ANALYZING CRASH POTENTIAL IN MIXED TRAFFIC WITH AUTONOMOUS AND HUMAN-DRIVEN VEHICLES

A Thesis

by

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ABSTRACT

Reducing crash counts on saturated road networks is one of the most significant benefits behind the introduction of Autonomous Vehicle (AV) technology. To date, many researchers have studied how AVs maneuver in different traffic situations, but less attention has been paid to the car-following scenarios between AVs and human drivers. A mismatch in the braking and accelerating decisions in this car-following scenario can lead to rear-end near-crashes and therefore needs to be studied.

This thesis aims to investigate the driving behavior of human-drivers that follow a designated AV leader in a car-following situation and compare the results with a scenario when the leader is a human-like driver. In this study, speed trajectory data was collected from 48 participants using a driving simulator. To estimate the near-crash risk between the participants and the leading vehicle, critical thresholds of six Surrogate Safety Measures (SSMs): Time to Collision (TTC), Inverse Time to Collision (ITTC), Modified Time to Collision (MTTC), Deceleration Rate to Avoid Crash (DRAC), critical jerk and Warning Index (WI), were used. The potential near-crash events and the safe driving events were classified using a random forest algorithm after performing oversampling and undersampling techniques.

The results from the two-sample t-tests indicated a significant difference between the overall deceleration rates, braking speeds, and acceleration rates of the participants and the designated AV leader. However, no such difference was found between the

participants and the human-like leader while braking and accelerating at stop-controlled intersections. Out of six SSMs, MTTC detected near-crash events 10 seconds before their actual occurrence at a range of 11.93 m with 83% accuracy. The surrogate measures identified a higher number of near-crash (high risk) events when the participants followed the designated AV and made braking maneuvers at the stop-controlled intersections.

Based on the number of near-crash (high risk) events, the designated AV's C-3.25 speed profile (with the maximum deceleration rate of 3.25 m/s^2) posed the highest crash risk to the participants in the following vehicle. For potential near-crash events classification, a random forest classifier based on undersampled data achieved the highest average accuracy rate of 92.2%. The deceleration rates of the designated AV had the highest impact on the near-crashes between the AV and the participants. However, shorter clearances during the braking maneuvers at intersections significantly affected the near-crashes between the human-like leader and the participants in the following vehicle.

DEDICATION

This thesis is dedicated to all my teachers and the people who have been there with me through thick and thin.

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CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a thesis committee consisting of Professor Dr. Dominique Lord [advisor] and Dr. Alireza Talebpour of the Department of Civil Department and Professor Dr. Jeffrey Hart of the Department of Statistics.

All other work conducted for the thesis was completed by the student independently.

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NOMENCLATURE

AV	Autonomous Vehicle
SSM	Surrogate Safety Measure
RF	Random Forest
NC-LR	Near-Crash (Low Risk)
NC-HR	Near-Crash (High Risk)
C-1	Speed profile with constant deceleration rate of 1 m/s^2
C-2.25	Speed profile with constant deceleration rate of 2.25 m/s^2
C-2.75	Speed profile with constant deceleration rate of 2.75 m/s^2
C-1	Speed profile with constant deceleration rate of 3.25 m/s^2
EF-1	Speed profile of experienced female driver 1
EF-2	Speed profile of experienced female driver 2
EM-1	Speed profile of experienced male driver 1
EM-2	Speed profile of experienced male driver 2

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1. INTRODUCTION

This chapter describes the problem statement, objectives and an overview of the thesis.

1.1 Problem Statement

With a boom in the Autonomous Vehicle (AV) technology over the past few years, predictions have been made on the safety benefits as well as the safety risks associated with this technology. The benefits, such as decreasing the human error accounting for 94% of the total crashes, improved mobility, and fuel savings, supplement the idea of adopting the AV technology. On the other hand, crash reports involving rear-end collisions between non-autonomous vehicles and AVs of Google, Nissan North America, and GM Cruise have recently been reported (Schoettle and Sivak, 2015). These reports involving AVs have raised doubts on the public acceptance of the technology, which in turn started the chain of testing AVs for different scenarios and driving conditions.

Since then, safety studies exploring the probability of failure of AV sensors leading to a complete vehicular failure, and measuring correlation between crashes and the number of miles travelled by an AV have been conducted by researchers to put forward the potential risks associated with this technology (Bhavsar et al., 2017; Favarò et al., 2017). A recent study by Rahmati et al. (2019) explored the influence of AV on the car-following behavior of human drivers and found a mismatch between the braking decisions of AV and human drivers at intersections. This raised the question of analyzing collision risk of rear-end crashes for a car-following scenario with an AV as the leading vehicle (referred to as the leader or lead vehicle) and a human driver that follows the AV vehicle.

Many studies have been conducted in the past using popular surrogate safety measures, such as Time to Collision (TTC), Modified Time to Collision (MTTC) to measure crash risks based on critical thresholds. However, limited research has evaluated the six surrogate measures to detect near-crashes in a car-following scenario 10 seconds before the actual near-crash occurrence. Also, no safety studies have explored the distance at which a surrogate measure can accurately predict a near-crash or crash in a car-following situation based on critical thresholds. Therefore, this study makes use of the popular Surrogate Safety Measures (SSMs) to detect near-crashes in car-following scenarios and identify the significant factors influencing the crash risk using a random forest methodology, a powerful machine learning classification algorithm.

Another issue that has failed to gain the attention of researchers is the imbalance in the near-crash data from a driving trip as only a minority of events account for near-crashes whereas most of the driving time can be deemed as safe or very low risk based on these popular surrogate measures. Therefore, it is important to perform a risk analysis and classification on a balanced dataset with an equal number of safe as well as near-crash data points to obtain fair and unbiased results. Novel data sampling techniques have recently emerged that allow the replication of data points in the minority to generate a greater number of similar data points and sometimes reduce the number of data points from majority group to match the minority count. Using these techniques, fair and unbiased results can be achieved while modeling near-crashes and obtaining accurate information on significant factors causing near-crashes. So, this research not only focuses on analyzing the potential safety risks and different driving aspects in the car-following behavior of AV and human drivers at stop-controlled intersections using a driving simulator, but evaluates the performance of surrogate measures based on near-crash detection rate, distance of detection and classifying near-crashes from safe-driving events using two sampling techniques with the help of random forest algorithm.

1.2 Research Objectives

The objectives of this thesis are to investigate the following:

1. Examine the braking behavior of participants in the following vehicle behind two different types of lead vehicles (designated AV and Human-like) while stopping at a stop-controlled intersection.
2. Analyze the acceleration behavior of test participants and the two kinds of leading vehicles after stopping at the stop-controlled intersection.
3. Evaluate the performance of popular Surrogate Safety Measures (SSMs) in detecting potential near-crash events (low and high risk).

4. Classify the potential near-crash events from the safe events using a random forest classifier for two different data sampling techniques and examine significant factors influencing near-crashes.

1.3 Thesis Organization

This thesis is organized into seven chapters. Chapter 2 outlines important information from previous literature on AV technology and safety risks associated with automation. Chapter 3 describes the various tasks of the research, which involves the experiment design, data collection for the study, and analysis techniques used for estimating crash risk. Chapters 4 and 5 cover the analysis results from participants driving behaviors in two-car-following scenarios, near-crash risk estimation, and factors influencing the near-crashes. Next, Chapter 6 compares the results between the two-car-following scenarios discussed in Chapters 4 and 5. Finally, Chapter 7 summarizes the results of the study and proposes recommendations for future research work.

2. LITERATURE REVIEW

This chapter provides important background information about the AV technology and crash risks involving AVs for various traffic conditions. This chapter is organized into five sections. Section 2.1 introduces AVs through a brief history and evolution of automated driving in terms of levels of automation. Section 2.2 then reviews the studies related to traffic safety risks associated with automation. Section 2.3 presents the analysis results on the braking maneuvers of the participants at stop-controlled intersections. Section 2.4 discusses the near-crash risk estimation using different Surrogate Safety Measures (SSMs) proposed in the past. Finally, Section 2.5 provides a summary for the chapter.

2.1 History of Autonomous Vehicles

Development of first real robot car was initiated in the early 1980s by Dickmanns and Zapp (1987) which evinced the ability to drive at high speeds but on empty streets. With the help of techniques involving convoy driving and tracking other vehicles, these vehicles were able to drive in busy traffic at speeds of 80 km/h (Dickmanns et al., 1994). In the early 1990s, Autonomous Land Vehicle in a Neural Network (ALVINN) gained attention due to its quick learning ability (few minutes) to drive on new types of the road after training from a human driver (Pomerleau, 1988).

In 2004, the Defense Advanced Research Projects Agency (DARPA) launched a challenge with a $1 million award for the AV capable of navigating a 150-mile course

(Thrun et al., 2006). Despite an improvement in the abilities of GPS systems during this period, the best teams were able to navigate just 7 miles of the route (Thrun et al., 2006). However, five AVs were able to complete a 132-mile route in a challenge organized in the following year. This progress led to a new challenge in 2007 which demanded the AVs to maneuver in an urban setting, i.e. negotiate blocked routes, fixed and moving obstacles, and also obey the traffic rules. Six teams were able to finish this challenge and presented great potential for automated driving in an urban environment (DARPA, 2014).

These developments attracted the attention of various major enterprises and government institutes as the process of formulating frameworks to test AVs on the streets of different nations was initiated (Burns, 2013; Marks, 2012; Reuters, 2013). Following the full autonomous test vehicle's introduction in 2017, Volvo aims to launch its unsupervised autonomous vehicle in the market by 2021. Initiating the development of a full AV, Google's Waymo reached a milestone of driving three million miles by 2017. Other giants such as BMW, Nissan, Audi, and Mercedes-Benz look forward to introducing their autonomous vehicle in their market by 2020 (Faisal et al., 2019).

2.2 Traffic Safety Risks Associated with Automation

With almost 90% of fatal crashes occurring in the US involve distracted driving, fatigue, alcohol or human error, autonomous vehicles are believed to be able to overcome these problems (Fagnant and Kockelman, 2015). Failure due to faulty hardware or software is often considered a major issue with the autonomous or complex electronic system and the frequency of experiencing these has also been a matter of concern for many researchers (Litman, 2017).

Researchers have also pointed out the potential risk compensation or offsetting behavior which can be seen in cases where drivers or travelers tend to over-trust the autonomous vehicle technology, leading to drivers taking additional risks (Ackerman, 2017; Millard-Ball, 2018). The potential threat of crashes due to human drivers joining platoons of autonomous vehicles has also been identified by a few researchers in the recent past. An increase in crash exposure by increasing the total vehicle travel is also thought of as a side effect of greater use of autonomous vehicles (Dawson, 2017).

A recent report by eight companies testing autonomous vehicles in 2017 to California DMV (Department of Motor Vehicles) brought the issue of disengagements into the light as humans often had to take over the control from the automated driving system during critical situations (Edelstein, 2018). Problems such as failure to brake adequately at a stop sign, difficulty in identifying vehicles in opposing lanes, inability to maintain GPS signals, failure to detect items indicating construction zones, failure to detect a signal saying no right turn on red, were found in the report in addition to hardware and software issues (Edelstein, 2018). Difficulty in designing an autonomous vehicle system which can perform safely in critical situations has been put forward as a demanding task by a few researchers (Campbell et al., 2010).

Mixed traffic streams involving human-driven and self-driving cars are also seen as a potential safety threat as autonomous cars often try to merge into traffic with inadequate gaps or space (Edelstein, 2018). These problems made researchers summarize that autonomous or self-driving cars might not be safer per mile than an average human driver and might also result in a greater proportion of crashes in mixed traffic streams (Schoettle and Sivak, 2015). Some researchers also argue that the introduction of autonomous vehicles would be a benefit for transport industry if they reduce crash rates by 10% but would be a concern if the total vehicle travel increases (Kalra et al., 2017). On the other hand, few researchers support the concept of autonomous technology by calling them 'crash-less cars' (Silberg et al., 2013).

Researchers have also stressed for the safety of automated driven systems through insufficient crash data available till date involving autonomous vehicles. Recent studies conducted by UMTRI (University of Michigan Transportation Research Institute) in 2015 and VTTRI (Virginia Tech Transportation Research Institute) in 2016 found much lower crash rates for self-driving systems as compared to conventional vehicles. However, these studies also quoted the insignificance of the obtained results due to a small number of crashes involving automated driving systems (Blanco et al., 2016; Schoettle and Sivak, 2015). For more accurate results on automated systems safety, miles traveled by these systems are required to increase proportionally to illustrate their harmless nature (based on fatality rate and injuries) (Kalra and Paddock, 2016).

2.3 Understanding Braking Behavior in Critical Events

Studying braking events of human-drivers at stop-controlled intersections have been a popular topic over the last few decades. However, identifying a braking profile which leads to comfortable braking before coming to a complete stop has posed serious challenges to researchers. The initial speed of the driver significantly affects their deceleration and acceleration at stop signs whereas time-of-day and driver demographics are not statistically significant (Haas et al., 2004). Modeling braking behavior using the coefficient of friction between pavement and car has been done to identify the comfort level of occupants during deceleration events (Wu et al., 2009). On the other hand, mathematical modeling of deceleration patterns which closely resemble those of an expert driver to achieve comfortable braking is also formulated by a few researchers (Wada et al., 2008).

However, a single threshold value accurately depicting an event of deceleration is still not agreed upon. A threshold deceleration rate of 0.3g, i.e. 2.94 m/s^2, is believed to depict emergency braking and a rate of 2 m/s^2 for comfortable braking (Miyajima et al., 2011; Naito et al., 2009; Wu et al., 2009). AASHTO sets the threshold deceleration rate at 3.4 m/s^2 for comfortable braking (Maurya and Bokare, 2012). To study emergency braking, learning about the maximum deceleration a vehicle can achieve is very important. (Kudarauskas, 2007) studied emergency braking of a vehicle and maximum longitudinal deceleration a_{xn} based on cohesion of vehicle's tires with the pavement coating. Utilizing the following formulas, theoretical value deceleration during braking was found:

$$a_{xn} = \varphi_x . g \quad (1)$$

$$a_{xn} \geq [0.1 + 0.85(\varphi_{x\,max} - 0.2)]. g \quad (2)$$

Where,

φ_x=coefficient of longitudinal cohesion of tire with road coating

g=acceleration due to gravity, i.e., 9.8 m/s^2

For roads with dry asphalt coating, φ_x = 0.8 resulted in a deceleration of 6.0-7.85 m/s^2 of a vehicle with tires in good condition. An emergency braking of 0.7g was assumed by (Anderson et al., 2013) while studying the effectiveness of Autonomous Emergency Braking (AEB) systems. In a previous study by (Glassco and Cohen, 2001), a braking level of 0.75g was used as a warning trigger during critical events in urban driving scenarios. Recently, (De Ceunynck, 2017) considered a maximum deceleration rate of 8 m/s^2 to be conservative which all vehicles can achieve. On the other hand, (Cunto, 2010) believed that a vehicle can achieve braking rate of 12.7 m/s^2 which was later considered to be a radical value. Therefore, a single value of maximum deceleration during critical events and emergency braking is still debated.

2.4 Collision Risk Between AV and Human Driver

(Rahmati et al., 2019) identified a mismatch in the braking decisions of AVs and human drivers and proposed a need for a detailed study on the associated risk of rear-end collisions. A Safety Surrogate Measure (SSM) is a traffic conflict indicator of the situation where there is a collision risk between vehicles (Ghanipoor Machiani and

Abbas, 2016). To accurately capture and detect traffic conflicts, many researchers have proposed using a combination of SSMs rather than just relying on one indicator (Johnsson et al., 2018; Zheng et al., 2019). Popular surrogate measures such as Time to Collision (TTC), Inverse Time to Collision (ITTC), Modified Time to Collision (MTTC), Deceleration Rate to Avoid Crash (DRAC), critical jerk and Warning Index (WI) have been very frequently used in risk analysis capturing different types of crash risks.

TTC can be explained as "the time required for two vehicles to collide if they continue at their present speeds and on the same path" (Hayward, 1971) and is calculated using the following equation:

$$TTC_t = \frac{x_{L,t} - x_{F,t} - D_L}{v_{F,t} - v_{L,t}}; \; \forall \left(v_{F,t} - v_{L,t}\right) > 0 \qquad \textbf{(3)}$$

Where, $x_{L,t}$ and $x_{F,t}$ are positions of the lead and following (ego) vehicle at time t, respectively; $v_{L,t}$ and $v_{F,t}$ are the vehicle speeds at t instant; D_L is the lead vehicle's length. Fixing the problematic assumption of constant speed assumption during the collision trajectory, MTTC was proposed with more advantages such as the inclusion of vehicles acceleration while evaluating the risk (Ozbay et al., 2008). It is calculated as follows:

$$MTTC_t = \frac{\Delta v_t \pm \sqrt{\Delta {v_t}^2 + 2\Delta a_t (x_{L,t} - x_{F,t} - D_L)}}{\Delta a_t} \qquad \textbf{(4)}$$

Where, $\Delta v_t = v_{F,t} - v_{L,t}$ is the relative speed of vehicles at risk at time t, and $\Delta a_t = a_{F,t} - a_{L,t}$ is the relative acceleration. As there are two outcomes of the equation, minimum MTTC is considered when both of the outcomes are positive; when one outcome is positive and the other is negative, yet, the positive outcome is selected as MTTC (Ozbay et al., 2008; Zheng et al., 2019). Deceleration Rate to Avoid Crash (DRAC) is defined as the required rate by the following vehicle to avoid a collision with the lead vehicle (Cooper and Ferguson, 1976; Gettman and Head, 2003) and calculated as follows:

$$DRAC_{F,t} = \frac{(v_{F,t} - v_{L,t})^2}{2(x_{L,t} - x_{F,t} - D_L)} \tag{5}$$

Another surrogate measure known as jerk, which is the rate of change of acceleration, has recently gained popularity in detecting safety-critical events (Mousavi, 2015). Jerk is calculated as:

$$j = \frac{da_F}{dt} \tag{6}$$

Where, da_F is the change in the acceleration between successive observations of the following vehicle in (m/s^2). Lastly, warning index (WI) is used in collision warning-algorithms makes use of factors such as tire-road friction, system delay with a lower value indicating a higher risk (Moon et al., 2009; Mullakkal-Babu et al., 2017). WI is calculated as:

$$w = \frac{s_n - d_{br}}{d_w - d_{br}}; d_{br} = \Delta v_F t_s + f(\mu)\left(\frac{v_F^2 - v_L^2}{2a_{max}}\right) \quad \textbf{(7)}$$

$$d_w = \Delta v_F t_s + f(\mu)\left(\frac{v_F^2 - v_L^2}{2a_{max}}\right) + v_F t_h \quad \textbf{(8)}$$

Where, d_{br} is the required braking distance; d_w= required warning distance; f(.) is the friction scaling function, μ is the estimated value of tire-road friction, and t_s is the system delay.

Many studies have been conducted on risk analysis using critical thresholds of these surrogate measures individually and proposed respective critical thresholds in the risk estimation during car-following situations, but no studies have tested/validated has compared these measures based on their thresholds and their ability to detect near-crashes 10 seconds before the actual occurrences.

2.5 Summary

In summary, this chapter has presented a review of literature on the potential safety risks associated with autonomous vehicles and human drivers and previous methods used to understand the driving behavior in a car-following situation and quantify the corresponding collision risk. As the literature on car-following scenario between AVs and human drivers is limited, it is necessary to better understand the driving behavior for this condition. The discussed SSMs have been widely used to detect actual near-crashes using field data but the performance of these SSMs in detecting near-crashes before their occurrences have not yet received adequate attention. This includes evaluating the accuracy rate of individual SSM in predicting a near-crash using a critical threshold and the distance at which a near-crash can be predicted using a single SSM. Therefore, the objective of this thesis is to bridge the gap in the literature on driving behavior of AVs and human drivers in car-following and the collision risks associated with it. The next chapter describes the methodology used for accomplishing the study objectives.

3. METHODOLOGY

This chapter describes the methodology used to achieve the study objectives. Section 3.1 briefly discusses the driving simulator equipment used in this study. Section 3.2 describes the experiment design adopted in this study. The data collection procedure and recorded variables are summarized in Section 3.3. The analysis technique adopted for near-crash risk estimation and factors affecting the near-crashes are explained in Section 3.4. Finally, Section 3.5 summarizes the key elements of this chapter.

3.1 Equipment

Figure 1 shows the equipment and the driving simulator setup used in this study. The simulator is composed of a 49-inch ultra-wide curved monitor display with a resolution of 3840 x1080 pixels and gas/brake pedals from Logitech. It also consisted of a PlayStation’s steering wheel which was in full accordance with a real vehicle. The curved monitor displayed a speedometer indicating the driving speeds in mph. The experiment setup did not provide any rear-view mirrors or gearbox to the participants. No sounds of the car engine or surroundings were played during the experiment.

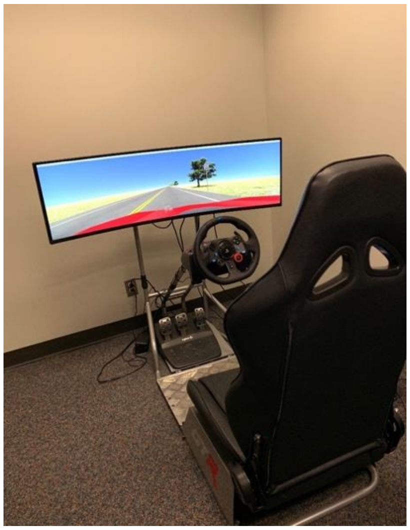


Figure 1. Driving Simulator Setup and Lead Vehicle in Car-Following Scenario

3.2 Experiment Design

Two car-following scenarios were designed using Unity-3D software to test the participants car-following driving behaviors. The test road was set up with straight alignment and a length of 4000 m or 2.48 miles. The test road with two lanes, each for one direction was separated by two parallel, solid yellow lines, to restrict the participants from overtaking the lead vehicle. Eight stop-controlled intersections were arranged on the test segment, each uniformly placed at 500 m apart. The speed limit during the entire segment was set at 30 mph (13.41 m/s). To adequately test the driving behavior of participants on the test segment during car-following, no other traffic was provided on the road. Two similar car-following scenarios were designed with the only difference being the assignment of the speed profiles of the lead vehicle in each scenario. Firstly, the design and assignment of speed profiles are discussed below.

3.2.1 Designing Speed Profiles

A total of eight different speed profiles for two kinds of the leading vehicle were tested in this study. Each car-following scenario tests four different speed profiles designated to the leading vehicle. The characteristics of the speed profiles used in the two test scenarios are explained below:

i) When the leader is an AV: (AV-HUMAN scenario)

Four-speed profiles with four different types of constant deceleration profiles, i.e. 1 m/s^2, 2.25 m/s^2, 2.75 m/s^2 and 3.25 m/s^2, were manually designed (see Figure 2). However, the profiles shared a common acceleration rate of 0.5 m/s^2 to depict a safe driving pattern by the designated AV leader. The speed profiles were split into three periods as follow:

Period 1: The lead car would accelerate at 0.5 m/s^2 until the speed of 30 mph (13.41 m/s)

Period 2: The lead car would maintain a constant speed of 30 mph (13.41 m/s)

Period 3: The lead car would decelerate at stop-controlled intersection at assigned deceleration rate of either 1 m/s^2 or 2.25 m/s^2 or 2.75 m/s^2 or 3.25 m/s^2, respectively

Period 4: The lead car would stop for 3 seconds after coming to a full stop and then accelerate again.

The speed profiles were assigned names based on their respective deceleration rates, i.e., C-1 means that the designated AV leader would decelerate at a constant deceleration rate of 1 m/s^2 and so on. Periods 1, 2, and 4 were kept the same for these four-speed profiles which can be seen in Figure 2. However, the only change was in Period 3, where the designated AV leader decelerates according to the assigned deceleration rate. The designated AV leader's maximum speed was limited to 30 mph (13.41 m/s), which was equal to the posted speed limit (see Table 1).

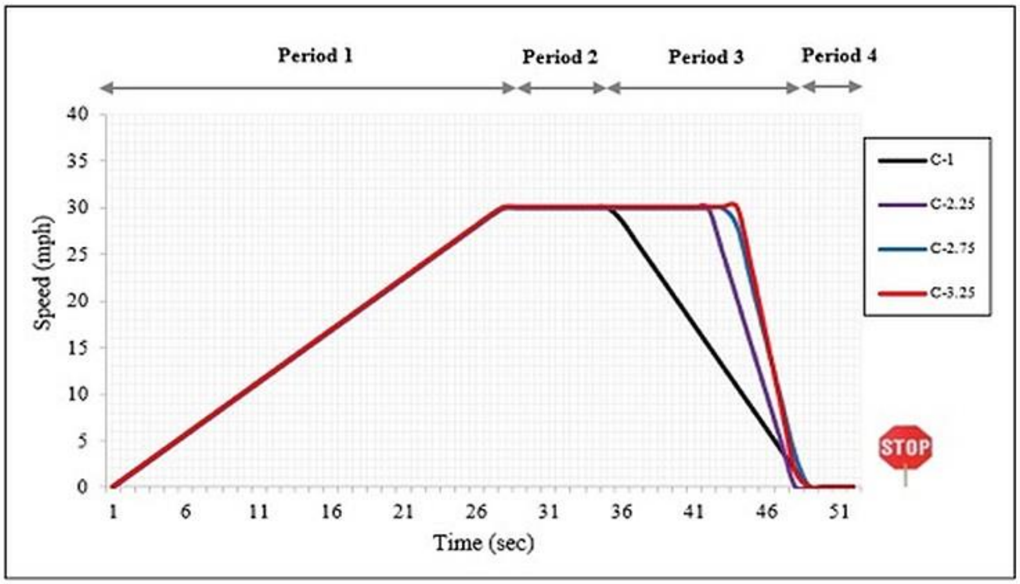


Figure 2. Four Speed Profiles for Designated AV Leader

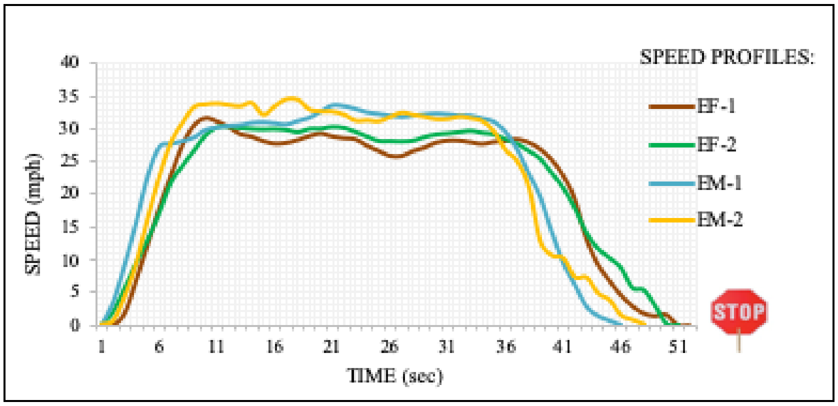
Table 1. Key Features of Designated AV Leader Speed Profiles

Features	C-1	C-2.25	C-2.75	C-3.25
Avg. Speed (mph)	15.97 (7.14)	17.67 (7.90)	18.30 (8.18)	18.33 (8.19)
Max. Speed (mph)	30.00 (13.41)			
Min. Speed (mph)	0.00	0.00	0.00	0.00
Avg. Acceleration (m/s^2)	0.50	0.50	0.50	0.50
Max. Acceleration (m/s^2)	0.50	0.50	0.50	0.50
Min. Acceleration (m/s^2)	0	0	0	0
Avg. Deceleration (m/s^2)	-0.96	-1.92	-2.24	-2.68
Max. Deceleration (m/s^2)	-1.00	-2.25	-2.75	-3.25
Min. Deceleration (m/s^2)	-0.60	-0.06	-0.85	-0.77

Note: C-1 refers to speed profile with constant deceleration rate of 1 m/s^2; C-2.25 refers to speed profile with constant deceleration rate of 2.25 m/s^2; C-2.75 refers to speed profile with constant deceleration rate of 2.75 m/s^2; and C-3.25 is the speed profile with constant deceleration rate of 3.25 m/s^2; speeds in ( ) are in m/s units.

ii) When the leader is HUMAN-like: (Human-Human scenario)

For modeling a human-like leader in the other car-following situation, four experienced drivers (two males and two females) were asked to drive on the test segment without any other traffic on the road. Their respective driving speeds were used to create four different speed profiles resembling their braking and acceleration behaviors. These drivers had at least five years of driving experience and a mean age of 25 years. Figure 3 and Table 2 illustrate the driving speeds of each profile before stopping at the first stop-controlled intersection.



Note: EF-1 refers to experienced female driver profile 1; EF-2 refers to experienced female driver 2 profile; EM-1 refers to experienced male driver 1 profile, and EM-2 is the experienced male driver 2 speed profile.

Figure 3. Four Speed Profiles of Human-like Leader

Table 2. Key Features of Speed Profiles

Feature	EF-1	EF-2	EM-1	EM-2
Avg. Speed in mph (m/s)	20.75 (9.28)	21.91(9.79)	24.33 (10.88)	23.28 (10.41)
Max. Speed in mph (m/s)	31.70 (14.17)	30.40 (13.59)	33.51(14.98)	34.47 (15.41)
Avg. Acceleration (m/s^2)	0.41	0.42	0.50	0.46
Max. Acceleration (m/s^2)	2.48	2.07	3.16	3.08
Min. Acceleration (m/s^2)	0.03	0.03	0.03	0.03
Avg. Deceleration (m/s^2)	-0.63	-0.74	-0.90	-0.89
Max. Deceleration (m/s^2)	-2.68	-1.68	-2.38	-3.73
Min. Deceleration (m/s^2)	-0.02	-0.02	-0.02	-0.02

Note: EF-1 refers to experienced female driver profile 1; EF-2 refers to experienced female driver 2 profile; EM-1 refers to experienced male driver 1 profile, and EM-2 is the experienced male driver 2 speed profile; speeds in ( ) are in m/s units.

3.2.2 Car Following Scenarios

Scenario 1: AV-HUMAN

In this scenario, the designated AV leader drove in front of the participants' vehicle based on the designed driving speeds in 4 profiles (C-1, C-2.25, C-2.75, and C-3.25), as discussed in the previous section. 24 participants (12 males and 12 females) were asked to follow the designated AV on the driving simulator. Each speed profile was assigned to the designated AV for one intersection and switched to a different profile for the next intersection. In this manner, the four-speed profiles were tested twice on a total of eight stop-controlled intersections.

The complete speed profile of the designated AV leader during the experiment can be seen in Figure 4. The lead car's (AV) assigned speed profile for each intersection is shown in Table 3.

Table 3. Leader (AV) Speed Profile Assignment at Each Intersection

Intersection	Leader's Assigned Speed Profile
#1	C-1
#2	C-3.25
#3	C-2.25
#4	C-1
#5	C-2.75
#6	C-3.25
#7	C-2.25
#8	C-2.75

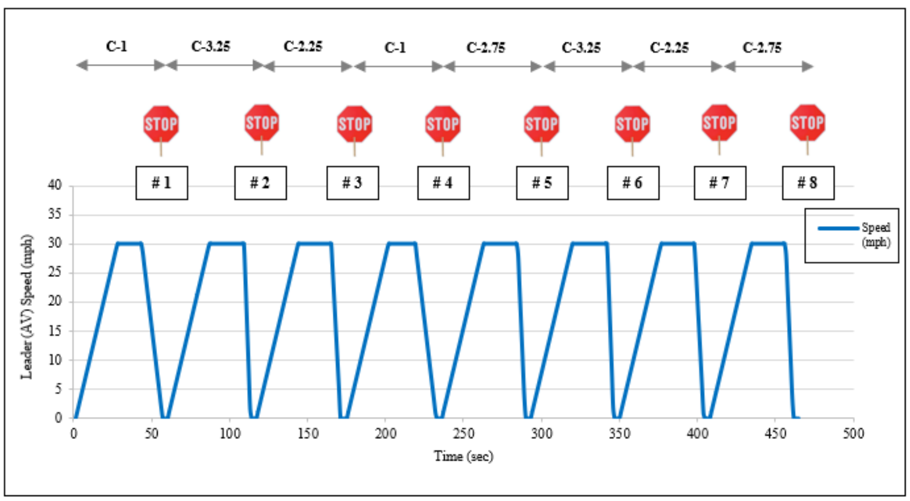


Figure 4. Designated AV Leader Speed Profile in Scenario 1

Scenario 2: HUMAN-HUMAN

In this scenario, the lead car was assigned with four-speed profiles extracted from four experienced human drivers (EF-1, EF-2, EM-1, and EM-2) discussed in the previous section. A new set of participants (12 males and 12 females) were asked to follow the lead car (Human-like) on the driving simulator. Except for the lead car's (Human-like) speed profiles at each intersection, all other conditions were unchanged in this scenario. The speed profile of the lead car (Human-like) during the experiment can be seen in Figure 5. Lead car's (Human-like) assigned speed profile for each intersection is shown in Table 4.

Table 4. Human-like Leader Speed Profile Assignment at Each Intersection

Intersection	Leader's Assigned Speed Profile
#1	EF-1
#2	EM-1
#3	EM-2
#4	EF-2
#5	EM-1
#6	EF-1
#7	EF-2
#8	EM-2

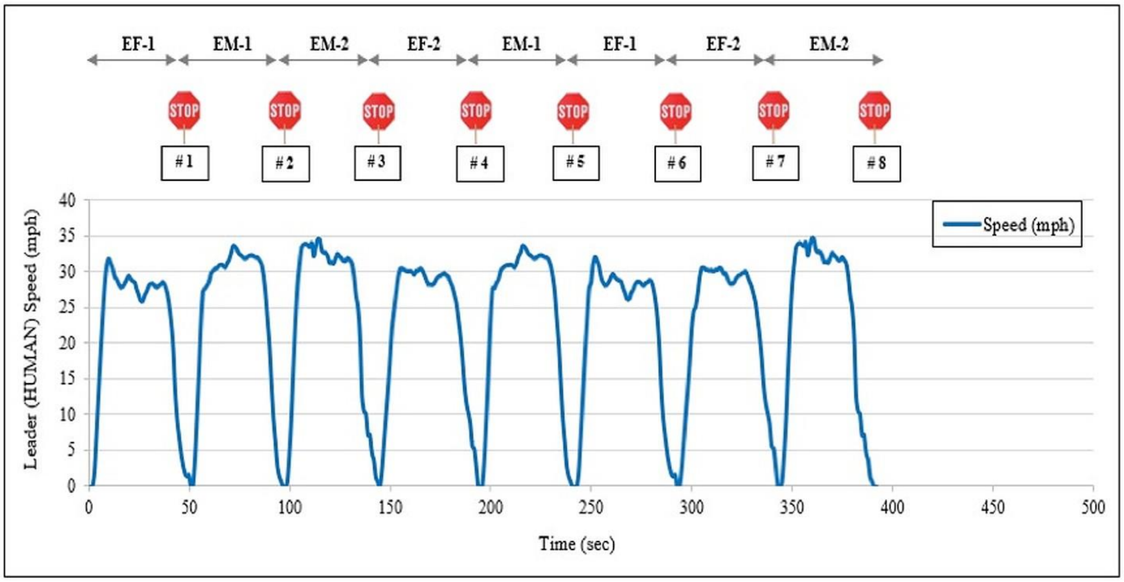


Figure 5. Human-like Leader’s Speed Profile in Scenario 2

3.3 Data Collection

In this experiment, a total of 48 participants (24 males and 24 females) were recruited through a recruitment email as per Institutional Review Board (IRB) guidelines. Each participant with age between 18 to 30 years, was required to hold a valid US driver’s license and at least one year of driving experience**.** The participants were compensated with USD 25 for their participation after completing the experiment. For the first scenario, the average age of the participants was 24.8 years, and a standard deviation of 2.43 years. For the second scenario, the average age of the participants was 25.3 years, and a standard deviation of 2.12 years.

3.3.1 Experiment Procedure

Upon arrival, each participant signed an informed consent form and completed a pre-test questionnaire. The pre-test questionnaire inquired the participants about their age, gender, years of driving experience, and any visual impairments. The participants were also checked for their valid permanent US driving license. Then, the participants were given a short introduction to the controls and functioning of the driving simulator. All participants were given at least a 5-min trial run on the driving simulator to gain familiarity with the setup and learn about the driving environment. After being familiarized with the simulator, the participants were given no strict instructions which could potentially influence their driving behavior during the experiment. However, the participants were instructed to "always be behind the lead vehicle". The participants were not given any information about the purpose of the experiment. Each participant was randomly assigned to one of the two car-following scenarios, i.e., AV-HUMAN or HUMAN-HUMAN. No participant took part in both test scenarios to minimize the risk of bias in driving behavior. In each scenario, the subject's vehicle or ego vehicle was initially kept at 6 m from the lead car to allow safe speeding. A speed limit sign with a posted speed limit of 30 mph (13.41 m/s) was also visible to the participants before starting the experiment. Once the simulation began, the participants could watch their driving speeds on the on-screen speedometer and were allowed to choose the speed they wanted to.

3.3.2 Variables Recorded

The simulator enabled the researchers to record the time taken by each participant to complete the experiment, the ego vehicle's lateral and longitudinal position, ego and lead vehicle speeds, and finally the input of accelerator/brake pedals. The clearance between vehicles, i.e., the distance from the front bumper of the ego vehicle to the rear bumper of the lead vehicle was also recorded in the output file. The simulator captured the driving data every 1 second.

The applied pressure on the accelerator and brake pedal ranged between -1 to +1 where -1 meant maximum possible brake application and +1 meant maximum possible acceleration input. The maximum deceleration rate was set to 0.81g or -8 m/s^2 and the maximum achievable acceleration to +3 m/s^2.

3.4 Risk Analysis

To estimate the collision risk during the two different car-following scenarios, six widely popular Surrogate Safety Measures (SSMs) were utilized in this study: Time to Collision (TTC), Modified Time to Collision (MTTC), Inverse Time to Collision (ITTC), Deceleration Rate to Avoid Crash (DRAC), critical jerk and Warning Index (WI). The procedure is shown in Figure 6. This approach allowed a high detection rate of traffic conflicts and near-crashes in the trajectory data obtained from 48 participants.

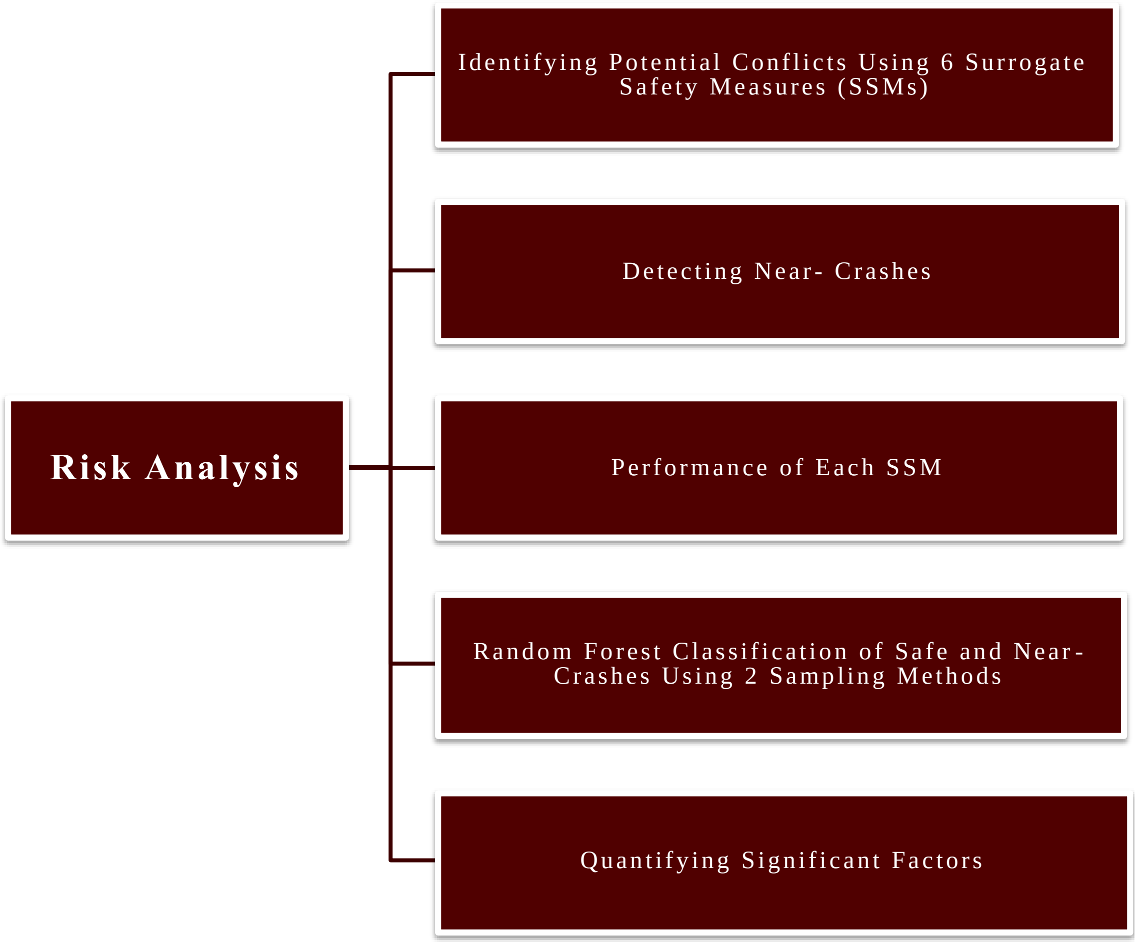


Figure 6. Risk Analysis Procedure

In this study, a time instant was characterized as a traffic conflict event when the assigned threshold of any one or more surrogate measures was violated. The critical thresholds of each surrogate measure were chosen from previous literature, which has been universally tested to capture accurate traffic conflicts (see Table 5). A potential traffic conflict may or may not lead to a near-crash, so these conflict events were used as an initial indication of near-crashes. If the clearance between vehicles drops to less than

4 m in the next 10 seconds of driving after a traffic conflict event is detected, then the event is called a near-crash (low risk) event.

Table 5. Thresholds Adopted for Each Surrogate Measure

SSMs	Thresholds
Time to Collision (TTC)	2 s
Inverse TTC (ITTC)	0.5 s^{-1}
Modified TTC (MTTC)	4 s
Deceleration Rate to Avoid Crash (DRAC)	-3.40 m/s^2
Critical Jerk	-9.9 m/s^3
Warning Index (WI)	< 0 or Negative Value

If the clearance between vehicles drops to less than 2 m in the next 10 seconds of driving after a traffic conflict event is detected, then the event is called a near-crash (high risk) event. Figure 7 illustrates an example of a participant experiencing a near-crash (high risk) occurring at 112th sec after the start of the experiment. The figure shows that the participant driving at 34 mph (15.20 m/s) following the designated AV leader with an initial clearance of 29.69 m suddenly brakes at 108th sec to as hard as -5.11 m/s^2 deceleration rate. During this maneuver, the clearance between the vehicles dropped to 1.38 m at 112th sec, which classified the event as near-crash (high risk).

Therefore, the traffic conflict event identified by MTTC at 108th sec resulted in a near-crash (high risk). Another important application of this approach was the detection range, i.e., the distance at which a surrogate measure can accurately identify a near-crash and alert the driver if a forward-collision warning system is developed with this feature. Surrogate measure with high accurate detection rate and considerable detection distance could be influential in reducing the near-crashes in car-following scenarios.

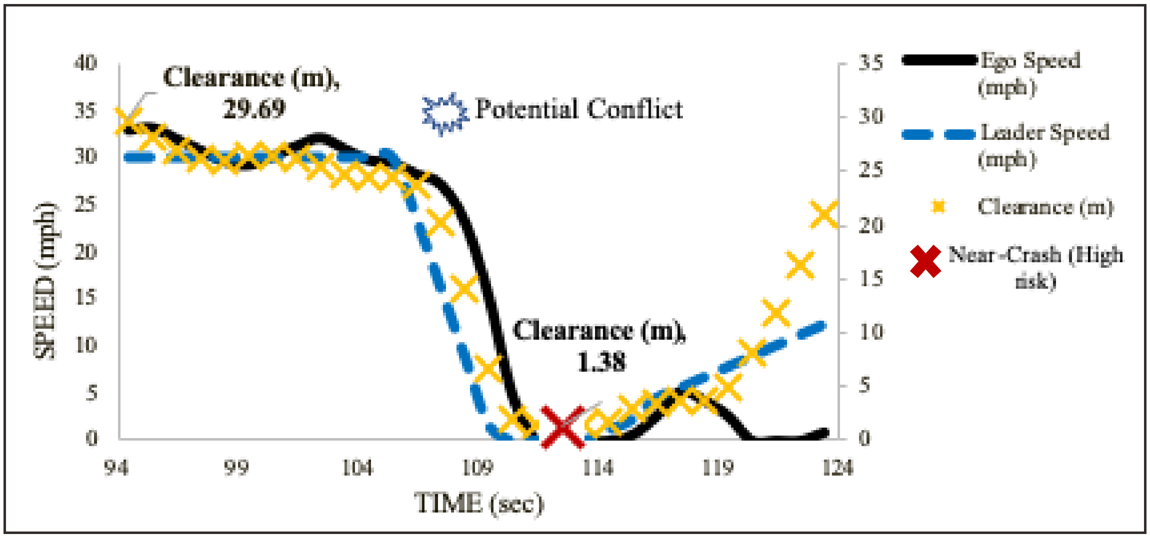


Figure 7. Example of Detected Near-Crash (High Risk) Event

The study used Random Forest (RF) algorithm to classify the detected near-crash events from safe driving events. As these detected near-crash events were rare events that occurred during car-following, so there was a significant imbalance in the distribution of safe and detected near-crash events. Hence, it was essential to balance the classes to apply the random forest classifier as performing classification on unbalanced dataset leads to biased results. Figure 8 shows the steps of the class balancing and RF classification algorithm.

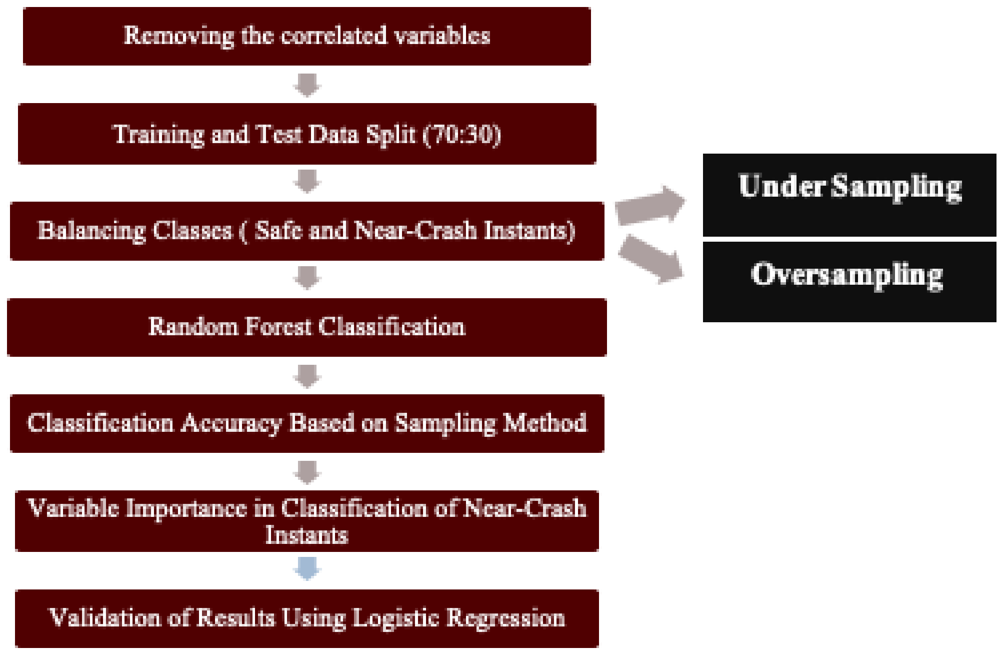


Figure 8. Classification of Safe and Near-Crash Events Using Random Forest

The ROSE library in R (Lunardon et al., 2014) used two sampling techniques to balance the number of events: minority oversampling and majority-class undersampling. Both undersampling and oversampling was performed to obtain the best performance measures from the random forest (RF) classifier. Finally, for validating the results, logistic regression was performed on the data (either oversampled or undersampled) based on the accuracy results achieved in the random forest classification algorithm. The training and test split remained constant at 70/30 during the classification process.

3.5 Summary

This chapter described the methodology adopted in this study for the design of the simulation environment using Unity software and the procedure used for data collection from 48 test participants. Near-crash risk estimation method using six surrogate measures and classification of near-crash events from safe driving events using the RF algorithm was also described. The next chapter presents the analysis results of braking and acceleration behaviors and near-crash risk estimation performed in Scenario 1 (when the leader is a designated AV).

4. ANALYSIS RESULTS: AV-HUMAN

The chapter presents results based on the driving behavior of 24 participants using the methodology discussed above. It is divided into five sections. Section 4.1 presents the descriptive analysis of the measured variables using histograms and two-sample t-tests. Sections 4.2 and 4.3 show the results from braking and acceleration pattern analysis of participants and the designated AV leader. Section 4.4 describes the risk analysis results using the surrogate measures and the random forest algorithm. Finally, Section 4.5 summarizes the findings from this chapter.

4.1 Descriptive Analysis

Table 6 presents the descriptive statistics of the measured variables.

Table 6. Descriptive Statistics of Measured Variables

Variables	**Units**	**N**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Ego Speed	mph (m/s)	10934	18.48 (8.26)	11.21(5.01)	0	47.65 (21.30)
Leader Speed	mph (m/s)	10934	19.20 (8.58)	10.88 (4.86)	0	30.00 (13.41)
Clearance	m	10934	24.64	23.36	-6.77	135.53
Ego Acc./Dec.	m/s^2	10934	-0.17	1.04	-8.00	3.00
Leader Acc./Dec.	m/s^2	10934	0.02	0.79	-3.25	1.00

Table 6 shows a high standard deviation in the average speed of the participants and the designated AV. During the experiment, the participants were a little bit slower than the designated AV (see Figure 9). The AV leader reached a maximum speed of 30 mph (13.41 m/s); however, the maximum speed recorded from a participant was 47.65 mph (21.30 m/s). The analysis revealed a considerable average clearance of 24.64 m between the participants in the following vehicle and the AV leader. In some occasions, the participants did achieve the maximum acceleration rate of +3 m/s^2 as compared to +1 m/s^2 of the designated AV. Similarly, the participants occasionally applied emergency brakes (deceleration rate of -8 m/s^2) while performing braking maneuvers at the intersections.

Table 7 shows the correlation matrix of the five measured variables. The correlation test on measured variables showed a serious (uphill) positive correlation of +0.85 between the participants' and the AV leader's average speed. In other words, an increase in the leader speed would result in higher ego speed in this car-following scenario. Due to this serious correlation, the leader speed variable was omitted from the analysis and the relative speed variable was introduced. Table 8 shows that the serious correlation among measured variables was eliminated as no variable shared a significant correlation.

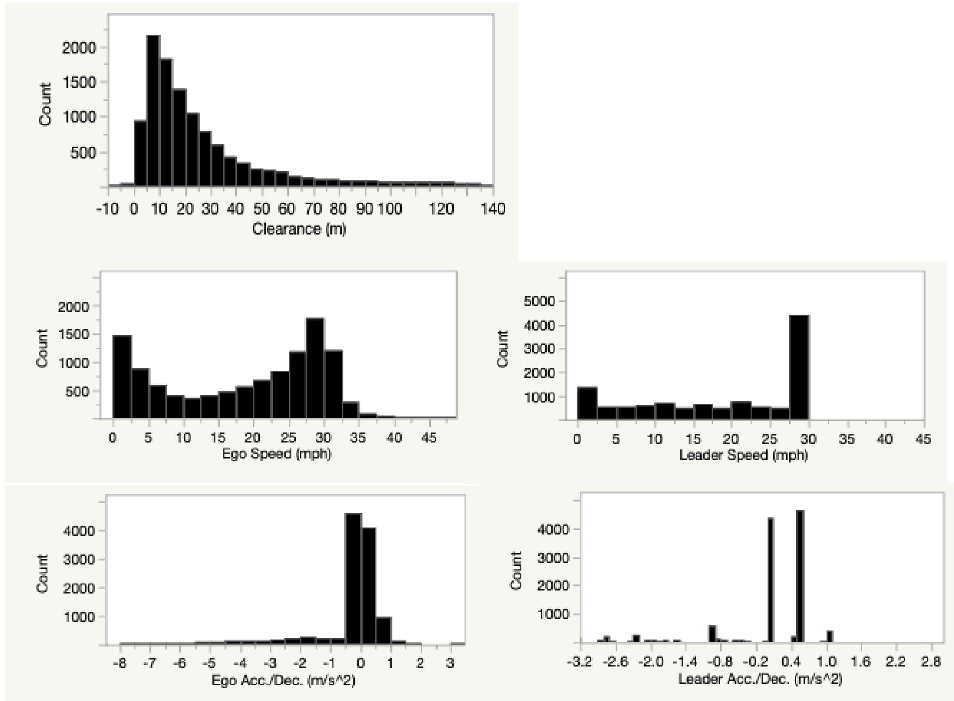


Figure 9. Histograms of Measured Variables

Table 7. Correlation Matrix of Measured Variables

Variables	Ego Speed	Leader Speed	Ego Acc./Dec.	Leader Acc./Dec.	Clearance
Ego Speed	1.00	0.85	0.18	-0.30	0.32
Leader Speed	0.85	1.00	0.28	-0.10	0.33
Ego Acc./Dec.	0.18	0.28	1.00	0.29	0.15
Leader Acc./Dec.	-0.30	-0.10	0.29	1.00	-0.17
Clearance	0.32	0.33	0.15	-0.17	1.00

Table 8. Correlation Matrix of Filtered Variables

Variables	Ego Speed	Relative Speed	Ego Acc./Dec.	Leader Acc./Dec.	Clearance
Ego Speed	1.00	0.32	0.18	-0.30	0.32
Relative Speed	0.32	1.00	-0.16	-0.38	0.00
Ego Acc./Dec.	0.18	-0.16	1.00	0.29	0.15
Leader Acc./Dec.	-0.30	-0.38	0.29	1.00	-0.17
Clearance	0.32	0.00	0.15	-0.17	1.00

4.2 Braking Behavior of Participants

Analysis of 192 average speed profiles from 24 participants (12 males and 12 females) depicted how participants began to decelerate or brake before coming to a stop at 8 stop-controlled intersections. Figure 10 illustrates a mismatch in the braking patterns of 24 participants and the designated AV as the participants decelerated to slow speeds of approximately 5 mph (2.23 m/s) and then slowly stopped at the stop-sign. Two-sample t-test also indicated a significant difference in the overall deceleration rates of participants and AV leader with two-tailed p-value of 0.04 (t=2.10, std. error =0.286) at the significance level of 5%.

Figure 11 presents a comparison between the average deceleration behavior of 24 participants behind the AV leader at 8 stop-controlled intersections. Participants demonstrated very similar late braking characteristics when following the AV leader with C-2.25, C-2.75, and C-3.25 profiles. However, participants made more gradual and smooth braking maneuvers when the AV leader decelerated at 1 m/s^2 (at C-1 profile).

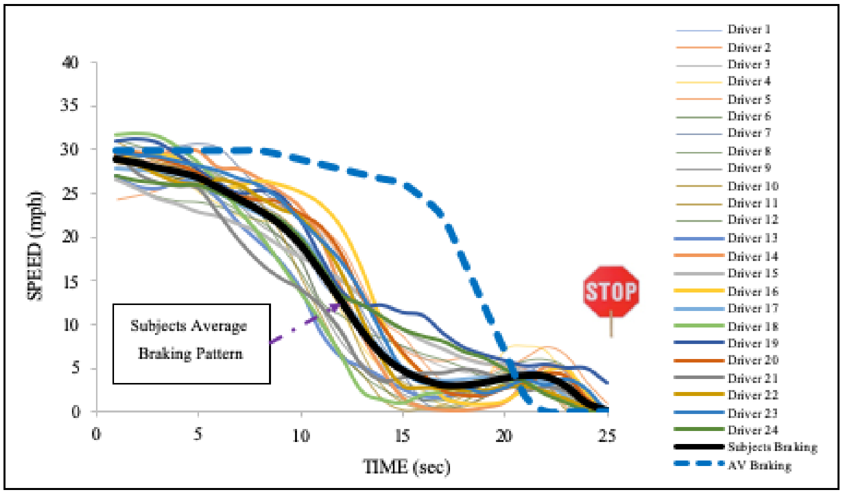


Figure 10. Participants Average Braking Speeds behind AV Leader

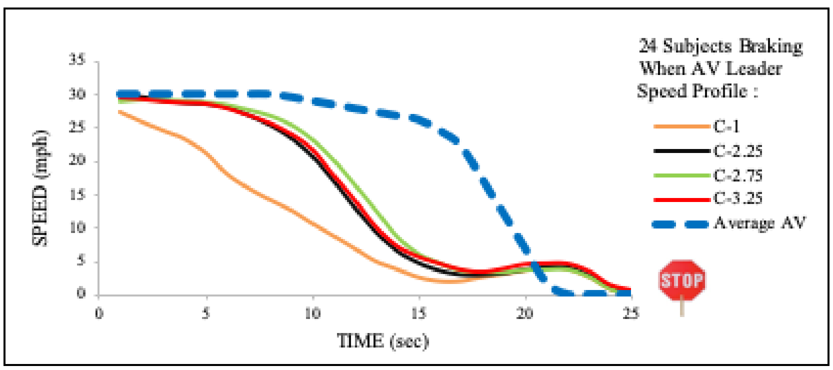


Figure 11. Participants Average Braking Speeds vs AV Leader Speed Profiles

Figure 12 shows the braking speeds of the participants based on the speed profile of the designated AV leader. The figure shows that the participants were likely to brake in the same way as the designated AV. Table 9 summarizes the results from the two-sample t-test comparing the means of participants and AV deceleration rates based on each profile. The table indicates that there was no significant difference in the braking rates. Therefore, the t-tests revealed a mismatch during the braking maneuvers only based on the approach speeds of the participants and the designated AV.

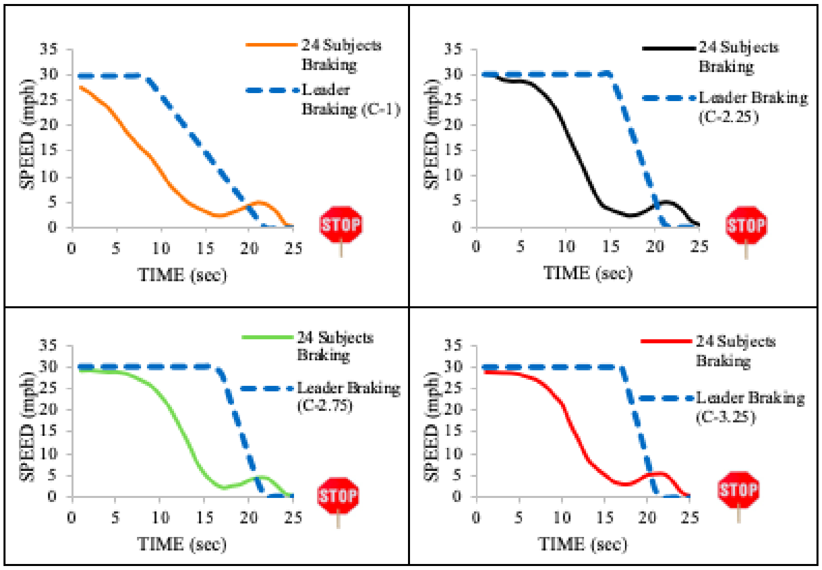


Figure 12. Participants Braking vs AV Leader Profile

Table 9. Two-Sample T-Tests Results of Participants and AV Leader Deceleration Rates

Comparison Pairs	Mean	Std. Dev.	t-value	p-value	Different (p < 0.05)
Participants	-0.49	0.46	0.32	0.74	No
Leader (C-1)	-0.53	0.49			
Participants	-0.54	0.68	0.02	0.98	No
Leader (C-2.25)	-0.53	0.94			
Participants	-0.52	0.68	0.05	0.95	No
Leader (C-2.75)	-0.54	1.04			
Participants	-0.51	0.67	0.06	0.94	No
Leader (C-3.25)	0.54	1.18			

Figure 13 shows that the participants started decelerating from 30 m (approx.) to 8 m (approx.) in ~15 s behind the AV at the stop sign. The average clearance maintained by the participants during the braking maneuvers were similar to each other.

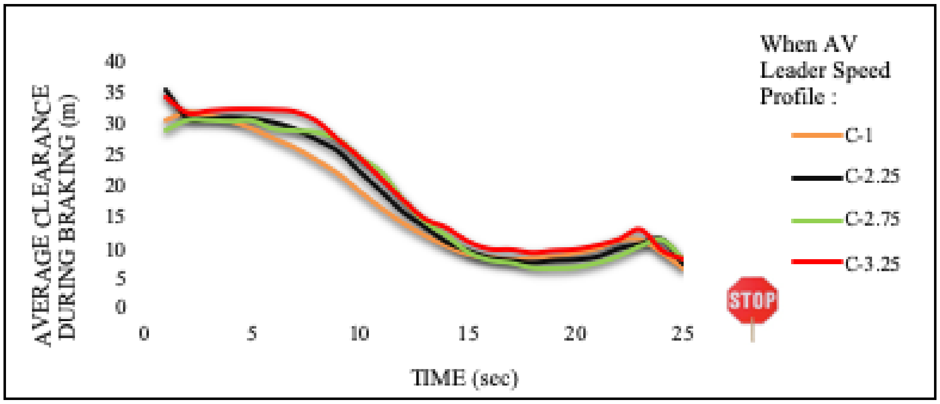


Figure 13. Average Clearance Between Participants and AV Leader During Braking Based on Speed Profiles

4.3 Acceleration Pattern After Stopping

The next topic deals with investigating how rapidly the participants accelerated after coming to a halt at a stop-controlled intersection and subsequently evaluate the mismatch in the acceleration rate of the participants and the designated AV.

The participants average acceleration rates (0.55 m/s^2) resembled the designed acceleration rate of the AV leader (0.5 m/s^2). However, Figure 14 shows that for the initial 7 seconds of acceleration, the participants accelerated at 1.25 m/s^2, i.e., 150% higher than the AV leader's rate. This revealed the willingness of the participants to quickly accelerate behind a slow leading vehicle, which in turn led to higher acceleration rates. The two-sample t-test with a p-value < 0.0001 (t =5.80; std. error = 0.12) confirmed the significant difference in the acceleration rates of the participants and the AV leader during the initial 7 seconds of speeding.

For the next 18 seconds, the participants accelerated at slower rates (0.26 m/s^2). A possible explanation could be the restriction faced by the participants while accelerating as the participants could not continue accelerating at 1.25 m/s^2 due to the slower accelerating lead car (AV). This ongoing acceleration increased the likelihood of a front-end collision with the AV leader, which compelled the participants to reduce their acceleration rate (see Table 10).

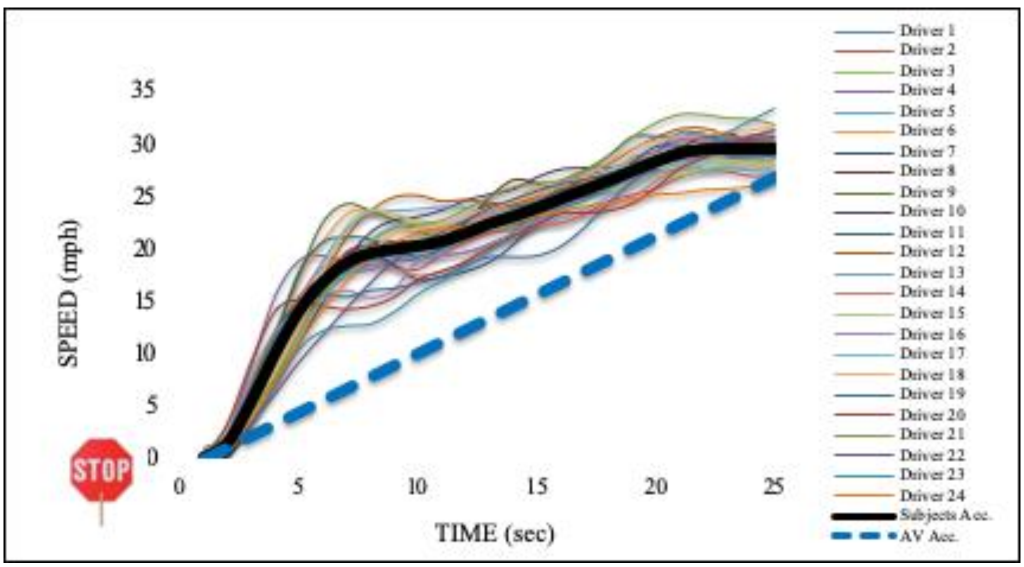


Figure 14. Participants Acceleration Behavior After Stopping at Intersection Behind AV Leader

Table 10. Summary-Acceleration Behavior (Scenario 1)

Acceleration Rate (m/s^2)	24 Participants	Designated AV Leader
Overall	0.55	0.5
Initial 7 seconds	1.25	
Last 18 seconds	0.26	

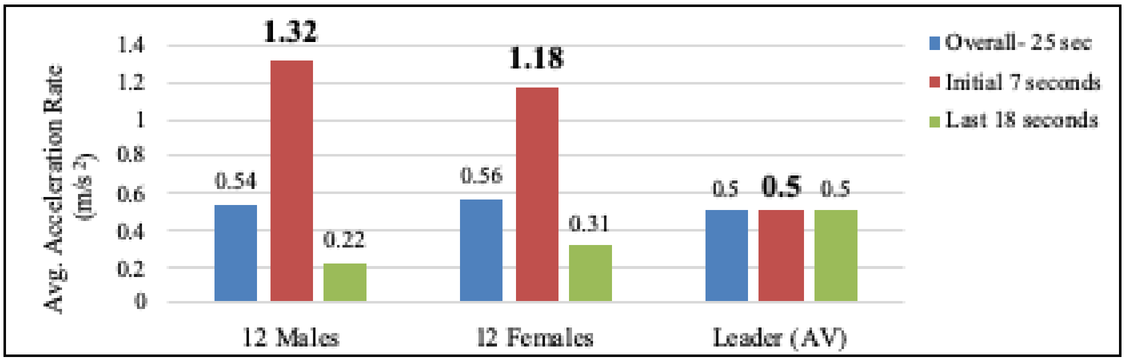


Figure 15. Participants Acceleration Behavior Based on Gender

The acceleration rates comparison between the 12 male and 12 female participants revealed slightly higher acceleration rates for the male drivers than for female drivers, as shown in Figure 15. Before achieving the free-flow speed, the male drivers accelerated at slightly slower rates than the female drivers.

Due to higher initial acceleration rates, male drivers drove closer to the AV leader, increasing the probability of a front-end collision. Due to the short proximity with the AV leader, male drivers lowered their acceleration rates during the next 18 seconds. On the other hand, the female drivers initially accelerated at a slightly slower rate than the male participants. The female drivers were relatively slower in accelerating, but they did not reduce their accelerations significantly as much as the male drivers. However, both the male and female participants did accelerate at a higher non-uniform rate than with the AV leader. This finding shows the discrepancy between the AV leader's designed constant acceleration rate and the non-uniform acceleration rate of the participants.

4.4 Risk Analysis

This section describes the results of near-crash risk analysis. Section 4.4.1 presents the characteristics of potential conflict and near-crash events detected by the surrogate measures. Section 4.4.2 outlines the performance of surrogate measures in detecting the near-crash events 10 seconds before their actual occurrence. Section 4.4.3 presents the near-crash risk based on the four designated AV speed profiles. Finally, Section 4.4.4 covers the classification results from the RF algorithm.

4.4.1 Potential Conflict and Near-Crash Events

Out of 10,934 recorded events extracted from 24 participants' data, critical thresholds for the six SSMs collectively identified 670 potential conflict events (6.13%) summarized in Table 11. On these potential conflict events, the average speed of the participants (18.41 mph/8.23 m/s) was higher than the AV leader (12.51 mph/5.59 m/s). Also, the AV leader decelerated at an average rate (-1.23 m/s^2) higher than the participants' average rate (-0.65 m/s^2). Higher relative speeds and harder leader deceleration rates indicate a potential front-end collision risk between the following vehicle and the AV leader vehicle.

Table 11. Summary of Potential Conflict Events

Parameters	Potential Conflict Events	Safe Events
Count	670	10264
Avg. Ego Speed in mph (m/s)	18.41 (8.23)	18.49 (8.27)
Avg. Leader Speed in mph (m/s)	12.51 (5.59)	19.64 (8.78)
Avg. Ego Acceleration/Deceleration (m/s^2)	-0.65	-0.14
Avg. Leader Acceleration/Deceleration (m/s^2)	-1.23	0.11
Avg. Clearance (m)	12.19	25.46
Avg. Long. Position (m)	2168.11	1953.39

Out of 670 potential conflict events, a total of 378 near-crash events accounted for 56.4% of the total conflict events. Table 12 presents the summary of critical parameters at detected near-crash events using the thresholds of surrogate measures. Nineteen participants were involved in 233 near-crashes with low risk (nine males and ten females) and nine participants (three males and six females) in 145 near-crashes with high risk. Figure 16 depicts the higher count of detected near-crash events for female participants, indicating that the female drivers were more likely to involve in a near-crash event while following the AV leader.

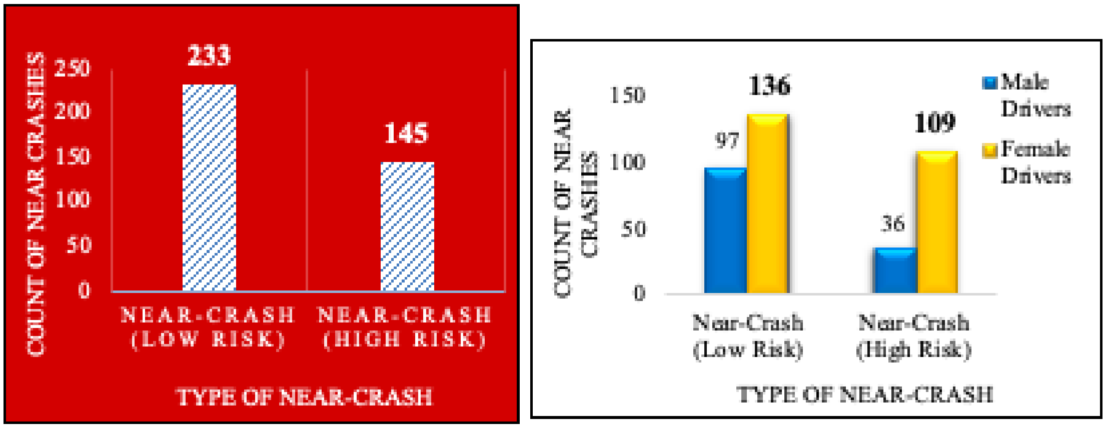


Figure 16. Number of Near-Crashes Based on Gender and Type (Scenario 1)

Table 12. Brief Statistics of Detected Near-Crash Events

Parameters	Near-Crash (Low Risk)			Near-Crash (High Risk)		
	Mean	**Max.**	**Min.**	**Mean**	**Max.**	**Min.**
No. of observations	233			145		
Ego Speed (mph)	18.38 (8.22)	35.71 (15.96)	3.15 (1.41)	17.48 (7.81)	33.10 (14.80)	3.19 (1.43)
Leader Speed (mph)	12.70 (5.68)	30.00 (13.41)	0.00	11.77 (5.26)	30.00 (13.41)	0.00
Ego Acceleration (m/s^2)	-0.67	1.71	-5.99	-1.09	1.00	-7.25
Leader Acceleration (m/s^2)	-1.46	0.50	-3.25	-1.51	0.50	-3.25
TTC (s)	22.75	2435.95	1.21	6.56	132.51	-3.22
Inverse TTC (s^{-1})	0.26	0.83	0.00	0.17	27.11	-32.98
MTTC (s)	2.97	5.20	1.46	2.53	4.09	0.04
DRAC (m/s^2)	0.44	2.75	0.00	0.47	42.99	-42.97
Jerk (m/s^3)	0.15	7.15	-5.96	-0.22	7.22	-6.09
Warning Index (WI)	1.11	5.58	-0.72	0.53	2.82	-4.02

4.4.2 SSMs Performance

This section discusses the reliability and accuracy of each measure in detecting a near-crash event 10 seconds before its actual occurrence.

Near-Crash Event Detection Ability of Each Surrogate Measure

Table 13 shows how the near-crash event detection rate for each SSM is calculated, i.e., the number of accurate near-crash detections made by a single measure divided by the total number of detected near-crash events (378). MTTC outperformed all other surrogate measures by accurately identifying 84% of the total number of near-crash events (319). The warning index (WI) with an accurate detection of only 21% implies that with the use of this measure, 79% of the near-crashes remained undetected.

Table 13. Individual Near-Crash Detection Rate of Each SSM (%)

SSMs	Identified Near-Crashes by Each SSM	Total Number of Near-Crashes	Individual Detection Rate of Each SSM (%)
TTC	74	378	74/378 = 19.57%
Inverse TTC	68		68/378 = 17.98%
Modified TTC	319		319/378 = 84.39%
DRAC	3		3/378 = 0.79%
Critical Jerk	0		0%
Warning Index (WI)	81		81/378 = 21.42%

The deceleration rate to avoid crash (DRAC) and critical jerk measures were less successful in detecting the near-crash events with the lowest detection rates of 0.79%

and 0%, respectively. The results were similar during near-crash (high risk) detection as the MTTC again outperformed other surrogate measures by correctly identifying 84% of the total near-crash (high risk) events (see Figure 17).

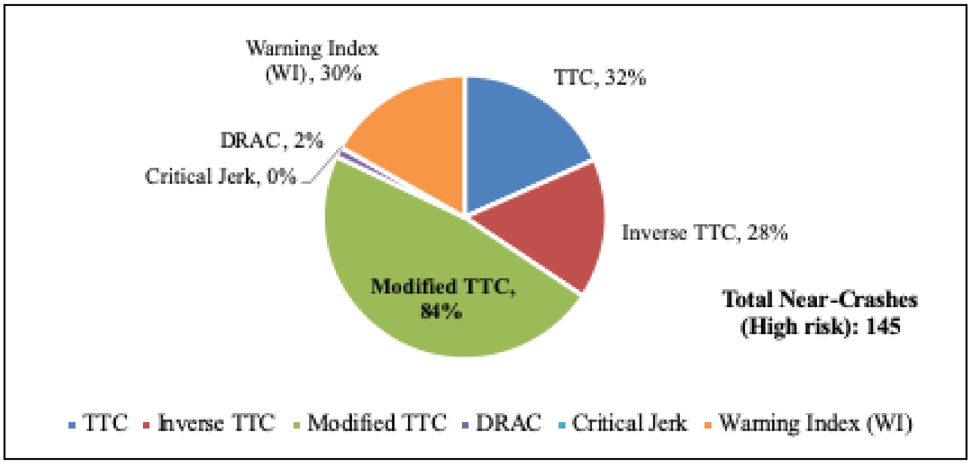


Figure 17. Accurate Near-Crash (High Risk) Detection Rate of Individual SSM (%)

Detection Range

Figure 18 and Figure 19 show an average detection range of 12.45 m and 8.98 m when all six surrogate measures collectively detected a near-crash (low risk) and near-crash (high risk) 10 seconds before their occurrence. Like the performance results reported in the previous section, MTTC again outperformed all other measures by detecting the near-crashes (high risk) at an average range of 13.34 m. For instance, if MTTC is used as a significant element in forward-collision warning systems (FCWs) in the real-world, a driver can be alerted to a possible near-crash at an average range/distance of 13.34 m in next 10 seconds of the car-following.

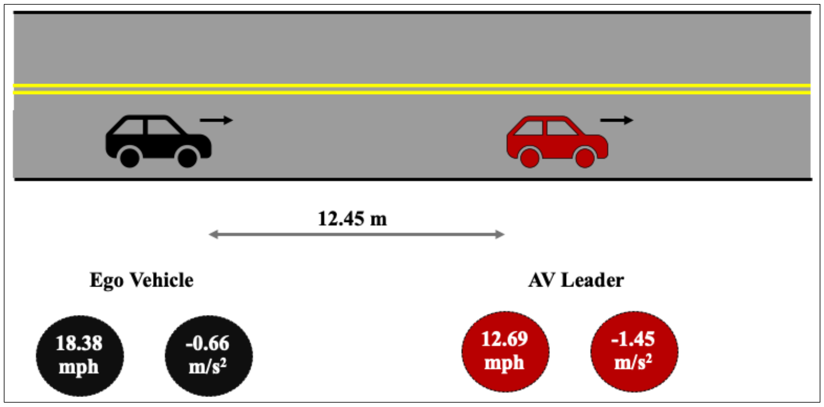


Figure 18. Near-Crash (Low Risk) Detection Range Using SSMs

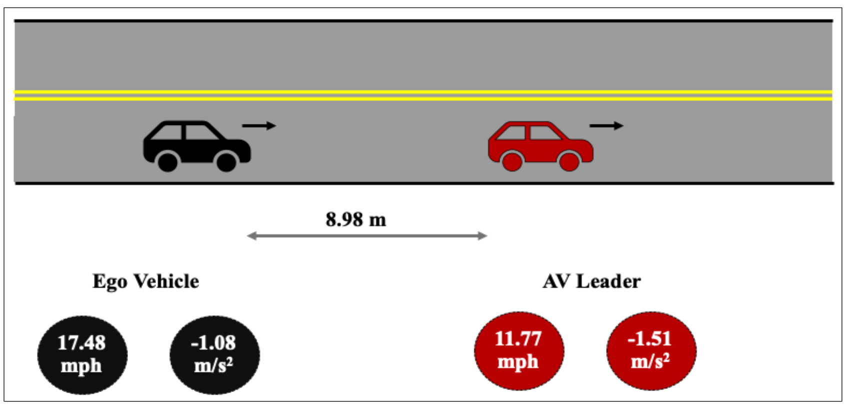


Figure 19. Near-Crash (High Risk) Detection Range Using SSMs

Figure 20 shows the average range at which each SSM detected the near-crashes 10 seconds before their actual occurrence. With a critical threshold of 4 sec, the MTTC measure detected the near-crash events at an average range of 11.57 m during the car-following. This is a significant finding because if used in a forward-collision warning system, detecting near-crashes at such range may allow more time for the driver to make a maneuver to avoid it. However, TTC, which is a common ingredient in some of the popular FCWs, detected the near-crash (high risk) events at an average range of 5.24 m.

This short detection range could allow less time to the following driver to prevent the imminent near-crash event.

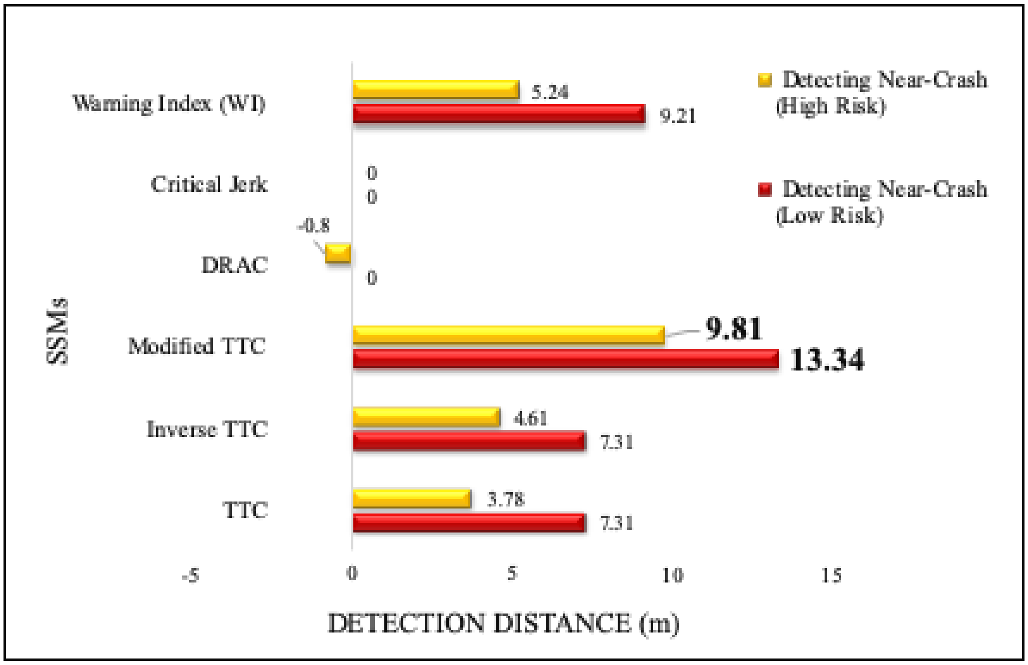


Figure 20. Average Detection Range (m) of Each SSM

4.4.3 Near-Crash Risk vs AV Leader Speed Profiles

Figure 21 illustrates the number of detected near-crash events participants involved based on the speed profile of the AV leader. Allocating the AV leader with C-3.25 (constant deceleration of 3.25 m/s^2) led to the highest number of near-crashes (high risk). This finding is in sync with the literature review finding as higher deceleration rates increase near-crash probability. The AV leader's C-1 speed profile with the lowest 1 m/s^2 deceleration rate had a significant number of near-crashes (high-risk). A possible explanation could be the close car-following of the participants at an average clearance of 7.42 m when the surrogate measures detected an elevated risk of a potential near-crash.

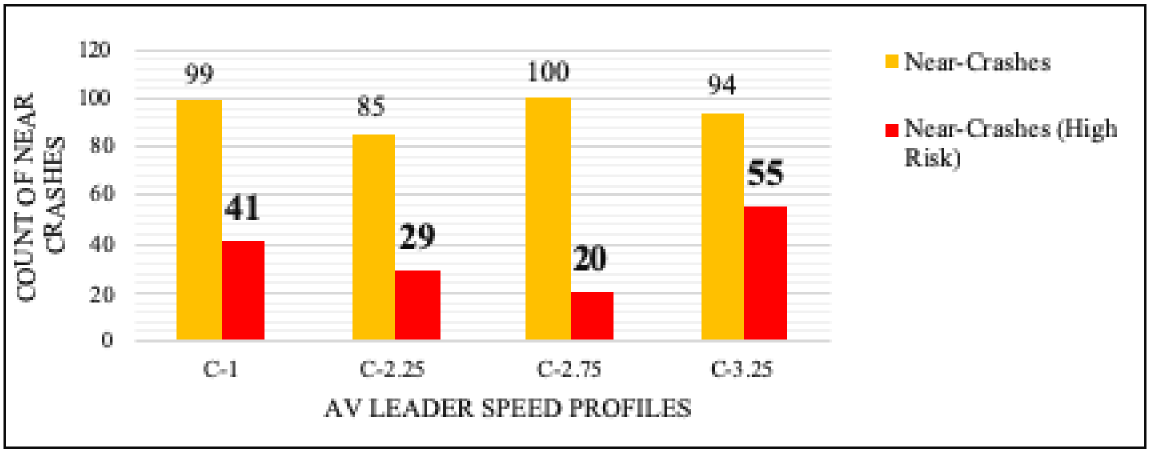


Figure 21. Count of Near-Crashes Based on AV Leader Speed Profiles

4.4.4 Classification Results

Figure 22 and Figure 23 show that after splitting the near-crash data, a considerable imbalance in the two classes (safe events and potential/detected near-crash events) was still present.

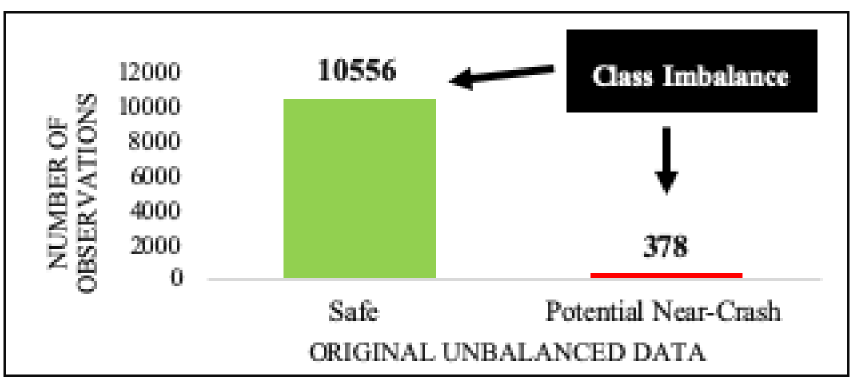


Figure 22. Initial Class Imbalance in Near-Crash Data

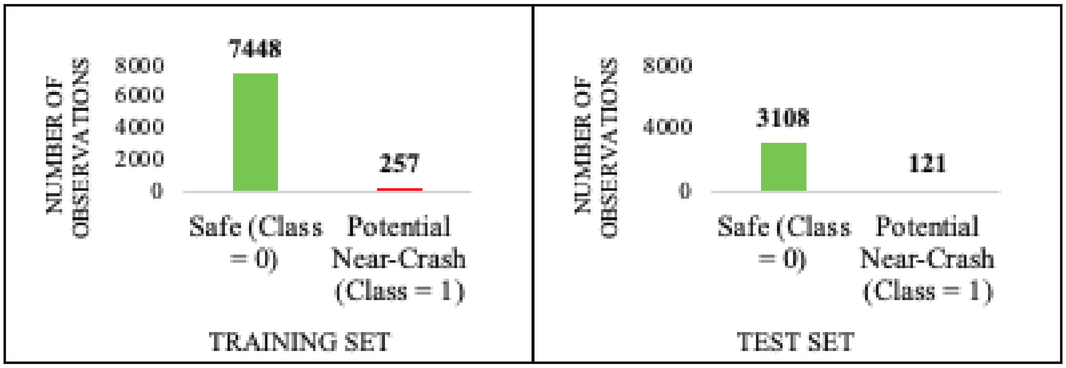


Figure 23. Class Distribution of Training and Test Set

Performing oversampling technique on the minority class (potential near-crash events), the total number of potential near-crash events were increased from 257 to 7448 in the training data. This technique created a 50/50 proportion of two classes in the data and doubled the total number of recorded events to 14,896 (See Figure 24). After undersampling of the majority class (safe events), 7448 safe events reduced to 257 in training set, i.e., equal to potential near-crashes count.

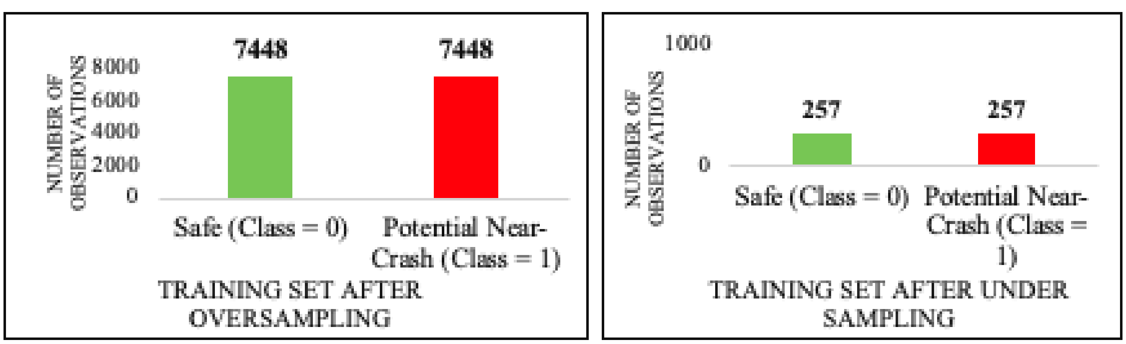


Figure 24. Balanced Classes after using two Sampling Methods

Three random forest classifiers were used for this part of the analysis: first based on the unbalanced training set, second on undersampled training set and the third on oversampled set were used to make predictions on the test dataset. Table 14 shows the results from the predictions in the form of a confusion matrix. After undersampling the training data, the maximum number of true positive predictions for class 1 or detected near-crash events, i.e., 115 out of 121 was achieved.

Table 14. Confusion Matrix of Predicted vs Actual Values of Near-Crash Events (RF)

Prediction	Unbalanced		After Undersampling		After Oversampling	
	Reference					
	0	1	0	1	0	1
0	3098	62	2837	6	3082	51
1	10	59	271	115	26	70

Where 0 = Safe Driving Events, 1 = Potential Near-Crash Events

Table 15. Summary of RF Models on Near-Crash Data (AV Leader)

Statistics	Results from Random Forest		
	Unbalanced	**Undersampling**	**Oversampling**
Accuracy	0.977	0.914	0.976
P-Value [Acc > NIR]	6.824e-07	1	8.864e-06
Kappa	0.610	0.420	0.633
Sensitivity	0.487	0.950	0.578
Specificity	0.996	0.912	0.991
Balanced Accuracy	0.742	0.931	0.785
Area Under the ROC Curve (AUC)	0.746	0.931	0.785

The RF classifier based on undersampled data achieved higher sensitivity (95%), specificity (91.2%) and balanced accuracy rate of 93.10% (see Table 15). This result indicated that undersampling the majority class (safe events) leads to a more accurate prediction of the minority class or potential near-crash events in the test data. ROC curves and area under the curve (AUC) value of 0.931 also illustrated better performance of RF classifier after performing undersampling technique (See Figure 25).

Figure 26 shows the importance of all the features or variables based on the Mean Decrease Gini or Gini index. AV leader's acceleration/deceleration and relative speeds came out as the most significant variables in predicting potential near-crash events (See Figure 26). In other words, a change in the AV leader deceleration rate did have an impact on the count of potential near-crash events that occurred during the experiment.

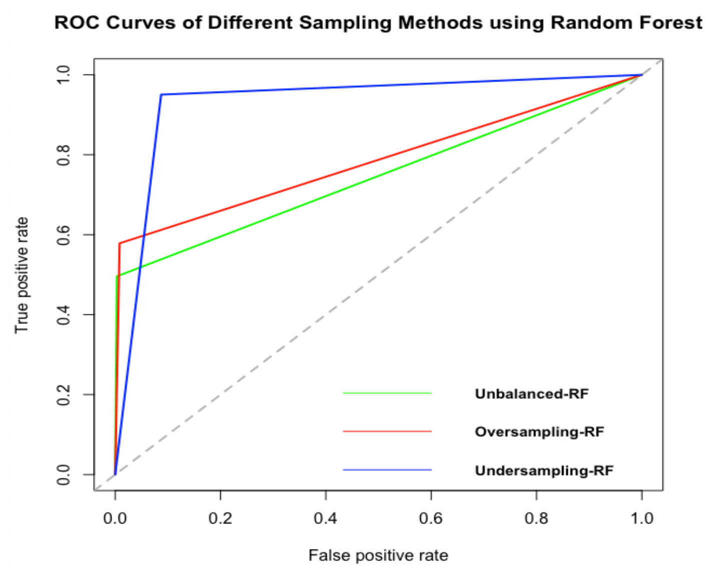


Figure 25. ROC Curves of Random Forest Classification vs Sampling Method

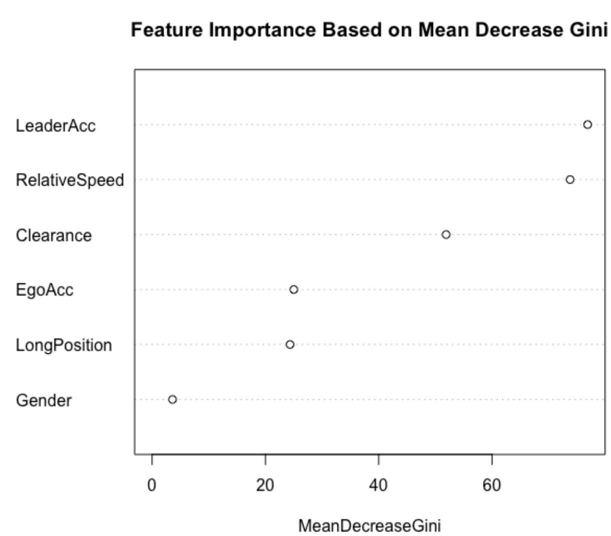


Figure 26. Feature Importance in Near-Crash Classification Using Mean Decrease Gini

Performing logistic regression on the undersampled data (N = 514: 257 potential near-crash events and 257 safe events), a high R^2 of 0.86 and 97.2% sensitivity indicated an improvement in the classification performance as the misclassification rate was as low as 0.04. The significance of AV leader's acceleration/deceleration and relative speed was again found with parameter estimates of -2.44 and +1.43 respectively. Results from Table 16 validated the high and accurate performance of RF classifier after undersampling the data.

Table 16. Logistic Regression Results a) Summary of Results, b) Confusion Matrix, and c) Variable Importance

a)

Term	Estimate	Std Error	Chi Square	Prob>Chi Sq.
Intercept	0.56861744	0.5313891	1.15	0.2846
Long. Position	0.00024389	0.00017	2.06	0.1514
Clearance	-0.3908231	0.0478443	66.73	<.0001*
Relative Speed	1.43818486	0.1853836	60.18	<.0001*
Ego Acc.	0.90320181	0.1866967	23.40	<.0001*
Leader Acc.	-2.4457863	0.2842191	74.05	<.0001*
Gender	0.95224009	0.4071718	5.47	0.0194*

b)

Actual	Predicted Count	
Near-Crash	1	0
1	250	7
0	17	240

Table 16 Continued

c)

Predictor	**Contribution**	**Portion**	**Rank**
Leader Acc.	50.8467	0.3941	1
Relative Speed	35.1829	0.2727	2
Clearance	18.0660	0.1400	3
Ego Acc.	12.5391	0.0972	4
Long Position	9.8693	0.0765	5
Gender	2.5092	0.0194	6

4.5 Summary

This chapter presented the results from braking/acceleration pattern analysis and near-crash risk analysis for the participants following the designated AV leader. A high positive correlation of 0.85 in the AV leader’s and participant’s speed during the car-following indicated that the AV leader's driving speed had an impact on the participants' speed in the following vehicle. There was a higher discrepancy in the braking of human participants and the AV leader assigned with a constant rate of deceleration of 1 m/s^2 (C-1 speed profile) as compared to the other three test speed profiles. The average acceleration rate of 24 participants recorded as 1.25 m/s^2 for the initial 7 seconds after stopping at the stop-controlled intersection was 150 percent higher than the AV leader’s acceleration of 0.5 m/s^2.

Assigning the AV leader to the C-2.75 speed profile encountered the highest number of near-crashes (100 out of 378). However, the AV leader braking with the C-

3.25 profile experienced the highest number of near-crashes (high risk). Modified Time to Collision (MTTC) with a critical threshold of 4 sec outperformed five other surrogate measures in detecting 84% of the near-crashes at an average range of 13.34 m. Handling the unbalanced data with the majority of safe driving events and rare potential near-crash events, RF classifier based on the undersampled data achieved a 93.1% accuracy rate in classifying the potential near-crash events.

Finally, the acceleration/deceleration of the AV leader with a negative parameter estimate (-2.44) came out to be the most significant factor in influencing and classifying the potential near-crash events. The next chapter presents the results based on the driving behavior of 24 participants following the human-like leader.

5. ANALYSIS RESULTS: HUMAN-HUMAN

This chapter presents the results based on the driving behavior of 24 participants following the human leader. The chapter is divided into five sections. Section 5.1 presents the descriptive analysis of the measured variables using histograms and two-sample t-tests. Section 5.2 and 5.3 describe the results from braking and acceleration pattern analysis of the participants and the human-like leader. Section 5.4 describes the risk analysis results using surrogate measures. Section 5.5 compares the results from the two test scenarios. Finally, Section 5.6 summarizes the findings from this chapter.

5.1 Descriptive Analysis

Table 17 shows that the participants' and human-like leader's average speed, 21.36 mph (9.55 m/s) and 22.11 mph (9.88 m/s), respectively, is not significantly different from each other. A cluster of high-frequency count around 30 mph (13.41 m/s) ego and leader speeds is seen in the histograms in Figure 27. Ego speed above 45 mph (20.12 m/s) was a rare occurrence with a maximum speed of 63.45 mph (28.36 m/s). In this car-following situation, the participants maintained an average clearance of 46.06 m with the human-like leader. The clearance histogram illustrates a decreasing trend (towards the right) as the clearance increases from 20 m to 140 m. In contrast to the previous scenario, the average speed of the participants and the human-like leader share a moderate upward relationship with a correlation coefficient of 0.50. Table 18 shows that no other variable pair shared a high correlation.

Table 17. Descriptive Statistics of Recorded Variables

Variables	Units	N	Mean	Std. Dev.	Min.	Max.
Ego Speed	mph (m/s)	8093	21.36 (9.55)	13.23 (5.91)	0.00	63.45 (28.36)
Leader Speed	mph (m/s)	8093	22.11(9.88)	11.31(5.06)	0.00	34.58 (15.46)
Clearance	m	8093	46.06	37.35	-1.70	139.94
Ego Acc./Dec.	m/s^2	8093	-0.31	1.49	-8.00	3.00
Leader Acc./Dec.	m/s^2	8093	0.00	1.23	-8.00	3.00

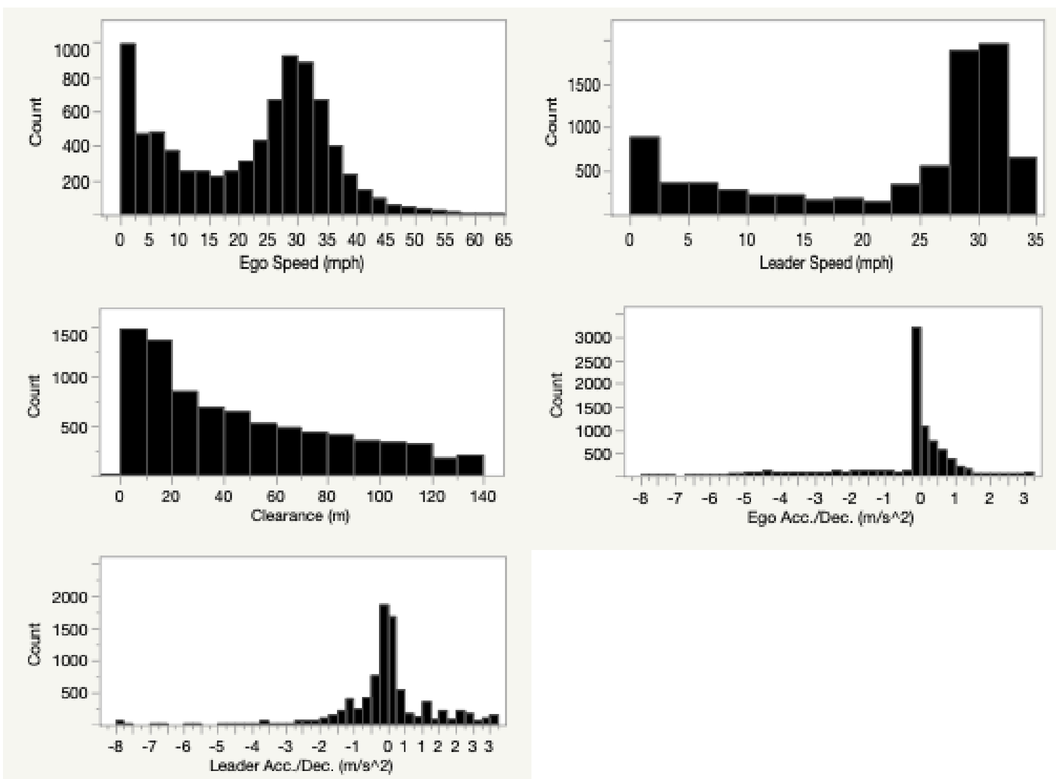


Figure 27. Histograms of Recorded Variables

Table 18. Correlation Matrix of Variables

Variables	Ego Speed	Leader Speed	Clearance	Ego Acc./Dec.	Leader Acc./Dec.
Ego Speed	1.00	0.50	0.37	0.14	-0.31
Leader Speed	0.50	1.00	0.42	0.24	-0.13
Clearance	0.37	0.42	1.00	0.27	-0.23
Ego Acc./Dec.	0.14	0.24	0.27	1.00	0.09
Leader Acc./Dec.	-0.31	-0.13	-0.23	0.09	1.00

5.2 Braking Behavior of Participants

The participants braking behavior behind the human-like leader in Figure 28 does not reveal any potential mismatch while stopping at the intersection. Also, the results from two-sample t-tests on the braking speed of the participants, and the human-like leader in Table 19 and Table 20 show no significant difference at the significance level of 5% (t=0.19; p-value = 0.85). This finding seems realistic in general as the human-like leader in this scenario was designated with speed profiles extracted from actual human drivers. Thus, the similarity in the braking behavior of the human leader and the participants seems logical. The participants' braking behind the human-like leader with the assigned EM-1 profile (green curve) were driving at a high speed before making the braking maneuver. This high speed, in turn, might be the potential reason behind the high average deceleration rate of participants (-1.76 m/s^2) in the last 18 seconds of approaching the stop-sign.

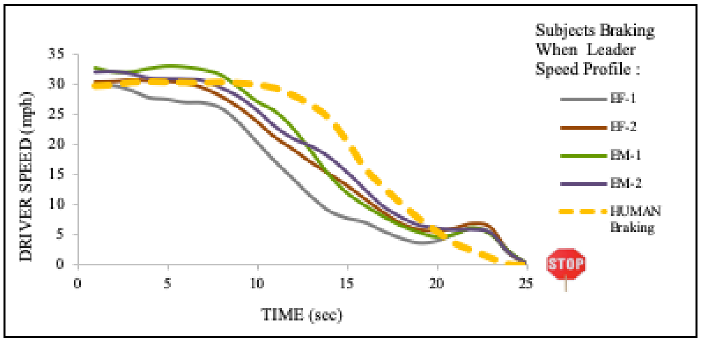


Figure 28. Participants Braking Speeds Based on Human-like Leader Speed Profiles

Table 19. T-Test Result on Avg. Dec. Rate of Participants vs Human-like Leader Profile

Avg. Dec. Rate (m/s^2)	Participants	Human-like Leader	t-value	p-value	Different ($p < 0.05$)
Overall	-0.56	-0.53	0.19	0.85	No

Table 20. T-Test Results on Avg. Braking Speeds of Participants Based on Human-like Leader Profile

Comparison Pairs	Mean	Std. Dev.	t-value	p-value	Different ($p < 0.05$)
Participants Leader (EF-1)	-0.53 -0.47	0.53 0.73	0.31	0.75	No
Participants Leader (EF-2)	-0.54 -0.50	0.56 0.57	0.22	0.82	No
Participants Leader (EM-1)	-0.59 -0.59	0.64 0.76	0.03	0.97	No
Participants Leader (EM-2)	-0.58 -0.56	0.49 0.85	0.13	0.89	No

Figure 29 illustrates the average clearance maintained by the participants during the braking maneuver based on the speed profile of the human-like leader. The participants maintained a greater clearance from the human leader with EM-1 and EM-2 assigned speed profiles. However, the figure depicts relatively close clearance measurements for EF-1 and EF-2 leader profiles. A gradual application of brakes leading to a more gradual decline in the clearance values was also observed.

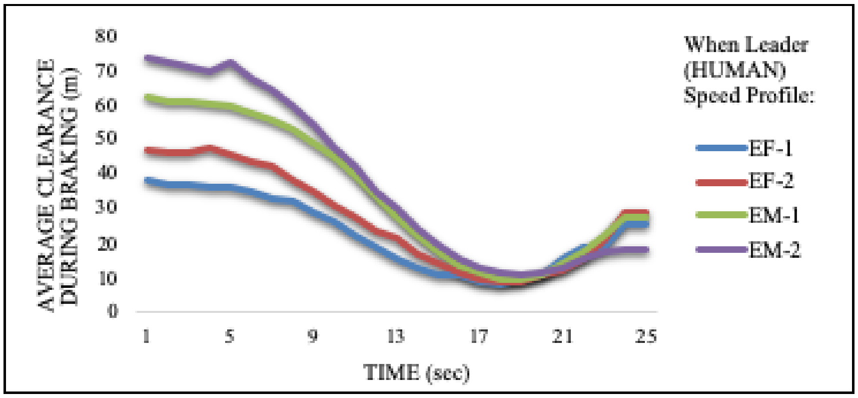


Figure 29. Average Clearance Between Participants and Human-like Leader Based on Test Speed Profiles

5.3 Acceleration Behavior of Participants

After stopping at the intersections, the average acceleration rate of the participants strongly resemble the acceleration rate of the human-like leader, as shown in Figure 30 and Table 21. Results from the two-sample t-test indicate no significant difference in the overall acceleration rate of the participants and the human-like leader at the significance level of 5% ($t=0.37$; p-value $= 0.70$).

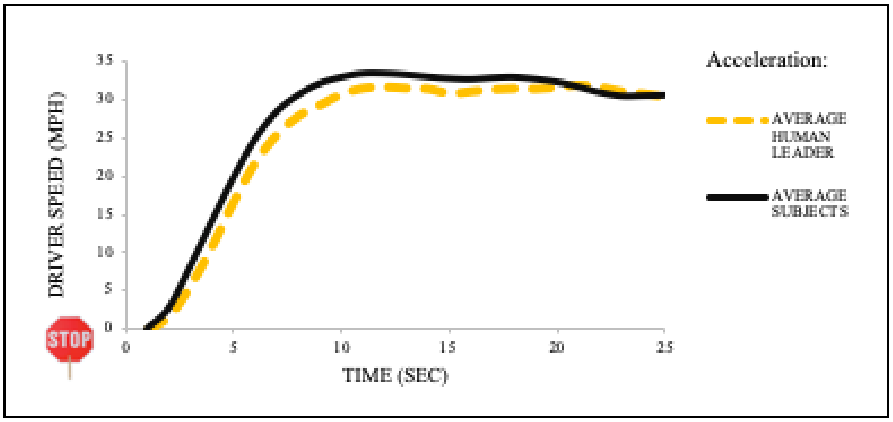


Figure 30. Participants Acceleration vs Human-like Leader

Table 21. Summary-Average Acceleration Rates (Scenario 2)

Acceleration Rate (m/s^2)	24 Participants	Leader (Human-like)
Overall	0.93	0.88
Initial 7 seconds	1.82	1.62
Last 18 seconds	0.03	0.14

Unlike the findings from the previous chapter, the acceleration rates of 12 male and 12 female drivers were found to be approximately equal in this scenario (See Figure 31). The average acceleration rates recorded in the initial 7 seconds of speeding after the stop at the intersection were identical with a magnitude of 1.82 m/s^2. Understandably, this acceleration was significantly reduced to as low as 0.06 m/s^2 later on as the participants achieved a speed equivalent to the posted speed limit and therefore did not continue acceleration any further.

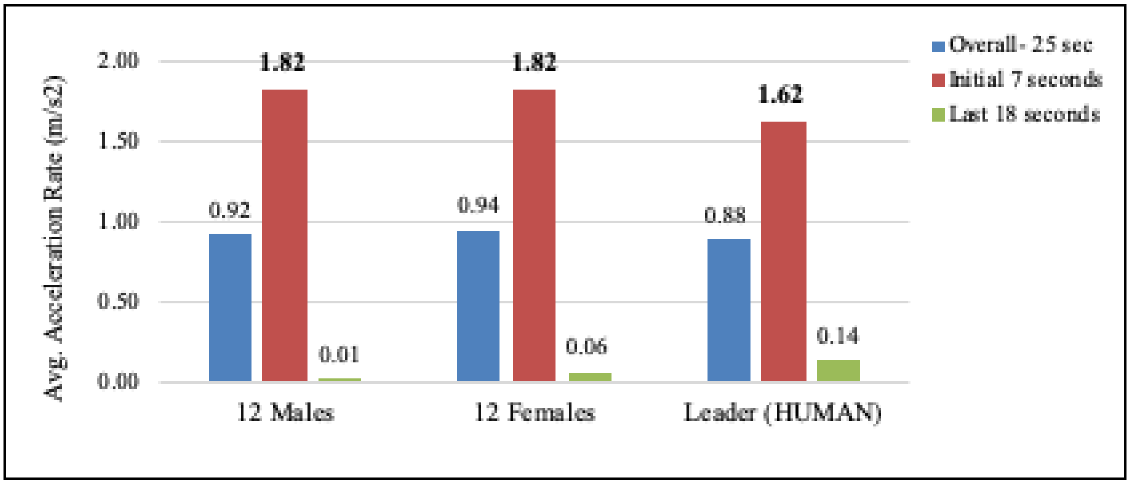


Figure 31. Comparison of Acceleration Rates Based on Gender

5.4 Risk Analysis

This section describes the results of near-crash risk analysis. Section 5.4.1 presents the characteristics of potential conflict and near-crash events detected by the surrogate measures. Section 5.4.2 outlines the performance of surrogate measures in detecting the near-crash events 10 seconds before their actual occurrence. Section 5.4.3 presents the near-crash risk based on the four human-like speed profiles and the classification results from the RF algorithm.

5.4.1 Potential Conflict and Near-Crash Events

In this scenario, 780 events were characterized as potential conflict events based on the thresholds of the surrogate measures. This count was higher than what was found in the previous scenario and higher driving speed of the participants and the human-like leader could be one of the factors in this identification. Again, the validity of surrogate measures and their respective thresholds could be seen as potential conflict events were detected at 15.44 m range/distance against the safe events (49.33 m). A total of 114 near-crash (high risk) events were detected in this scenario based on the clearance filter of 2 m and are summarized in Table 22. A slightly higher number of near-crash (high risk) events were observed for female participants as compared to the male participants.

Table 22. Summary of Potential Conflict Events

Parameters	Potential Conflict Events	Safe Events
Count	780	7313
Avg. Ego Speed in mph (m/s)	23.26 (10.40)	21.15 (9.45)
Avg. Leader Speed in mph (m/s)	14.69 (6.57)	22.90 (10.24)
Avg. Ego Acc./Dec. (m/s^2)	-0.70	-0.27
Avg. Leader Acc./Dec. (m/s^2)	-0.82	0.09
Avg. Clearance (m)	15.44	49.33

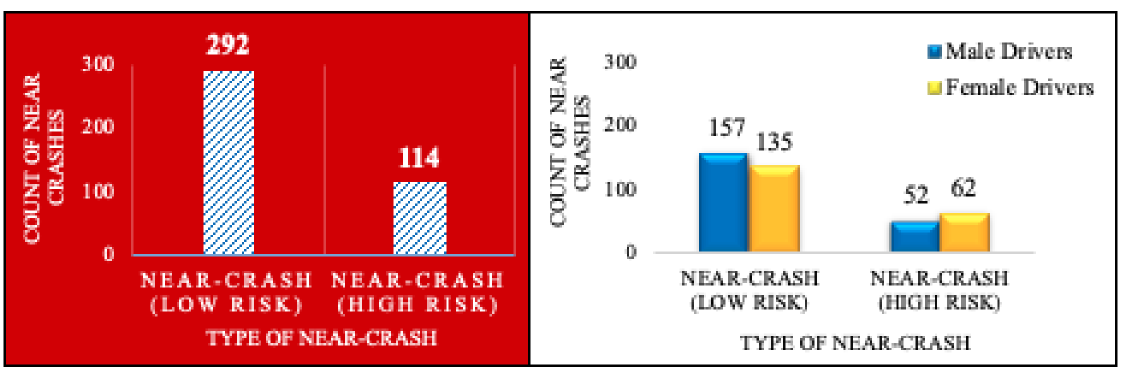


Figure 32. Count and Type of Near-Crash Events based on Gender

Table 23. Summary of Near-Crash Events

Parameters	Near-Crash (Low Risk)			Near-Crash (High Risk)		
	Mean	**Max.**	**Min.**	**Mean**	**Max.**	**Min.**
No. of observations	292			114		
Ego Speed in mph (m/s)	19.21(8.59)	44.11(19.72)	3.17 (1.42)	19.98 (8.93)	63.45 (28.36)	3.33 (1.49)
Leader Speed in mph (m/s)	12.02 (5.37)	31.59 (14.12)	0.00	12.22 (5.46)	34.47 (15.41)	0.00
Ego Acc. (m/s^2)	-0.78	2.84	-8.00	-1.15	2.74	-8.00
Leader Acc. (m/s^2)	-1.06	1.63	-4.50	-0.89	1.58	-3.73
TTC (s)	6.40	492.30	0.96	4.22	66.29	-1.14
Inverse TTC (s^{-1})	0.32	1.05	0.00	0.36	8.90	-16.65
MTTC (s)	2.79	5.66	1.06	2.57	4.59	0.16
DRAC (m/s^2)	0.61	4.55	0.00	0.95	17.64	-5.38
Jerk (m/s^3)	-0.21	7.68	-7.28	-0.38	6.40	-7.97
Warning Index (WI)	0.72	5.97	-1.37	0.31	2.34	-2.73

5.4.2 SSMs Performance

Similarly, MTTC outperformed all other surrogate measures in accurately detecting both, the total number of near-crashes and near-crashes (high risk) with an 82% accurate detection rate (See Figure 33).

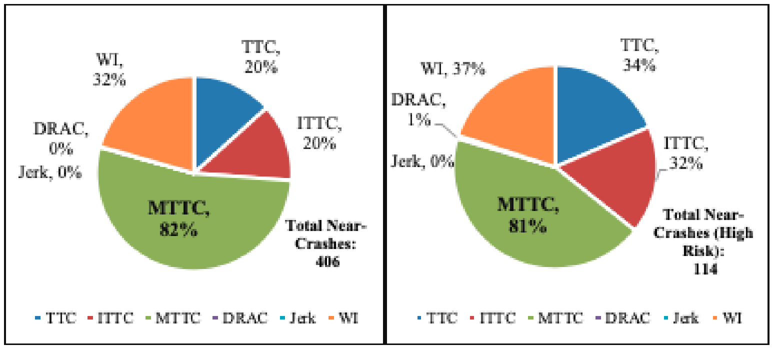


Figure 33. Near-Crash Event Detection Contribution of Each Measure

Measuring the detection range of these near-crashes, MTTC evinced capability of identifying a near-crash (high risk) at 12.22 m range, which was higher than any other surrogate measure (See Figure 34).

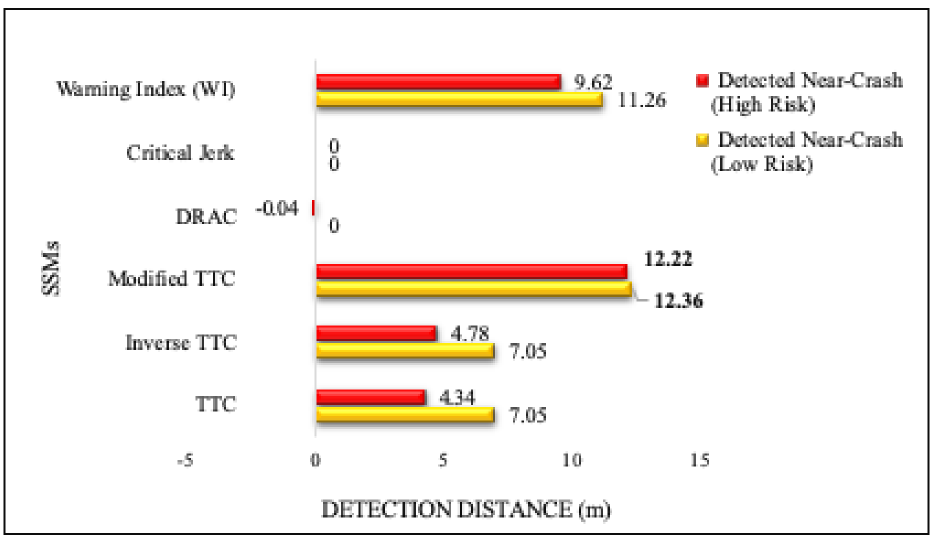


Figure 34. Detection Distance/Range of Each Measure

5.4.3 Near-Crash Risk vs Human-like Leader Speed Profiles

Figure 35 illustrates the number of detected near-crash events participants were involved in based on the speed profile of the human-like leader. Allocating the human-like leader with EF-2 (profile of experienced female driver 2) experienced the highest number of near-crashes (high risk).

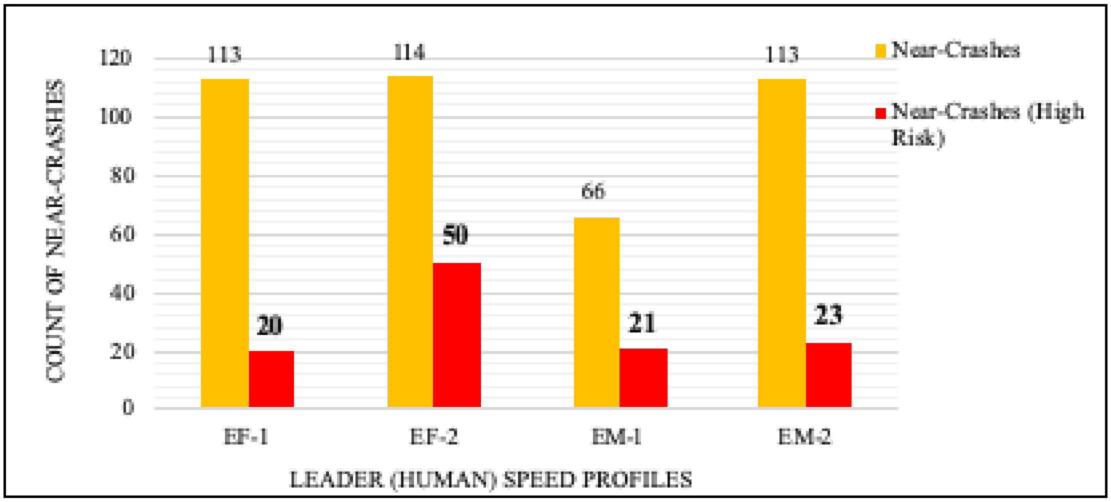


Figure 35. Number of Near-Crashes Based on Human Leader Speed Profile

Like the results documented in the previous chapter, the RF classifier on undersampled data achieved an accuracy rate of 91.30% in predicting the potential near-crash events. The confusion matrix in Table 24 also supports this performance of RF classifier on undersampled data by predicting the highest number of potential near-crash events.

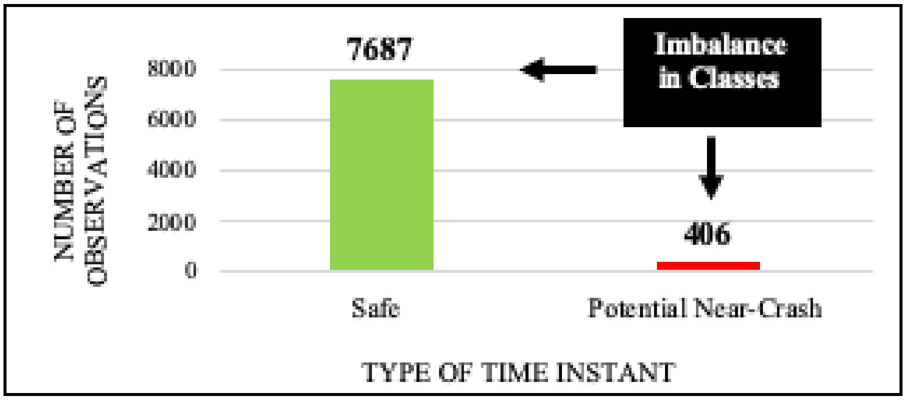


Figure 36. Imbalance in Near-Crash Data

The AUC value of 0.913 shown in Figure 37 confirms the high performance of the random forest classifier after undersampling the data.

Table 24. a) Confusion Matrix of Predicted vs Actual Values b) Summary of RF Models (0=Safe, 1=Potential Near-Crash)

a)

Prediction	**Unbalanced**		**After Undersampling**		**After Oversampling**	
	Reference					
	0	1	0	1	0	1
0	2273	61	2048	7	2253	45
1	21	46	246	100	41	62

Table 24 Continued

b)

Statistics	**Results from Random Forest**		
	Unbalanced	**Undersampling**	**Oversampling**
Accuracy	0.965	0.913	0.964
P-Value [Acc > NIR]	0.006	1	0.01
Kappa	0.512	0.400	0.571
Sensitivity	0.429	0.934	0.579
Specificity	0.990	0.892	0.982
Balanced Accuracy	0.710	0.913	0.780
Area Under the Curve (AUC)	0.710	0.913	0.780

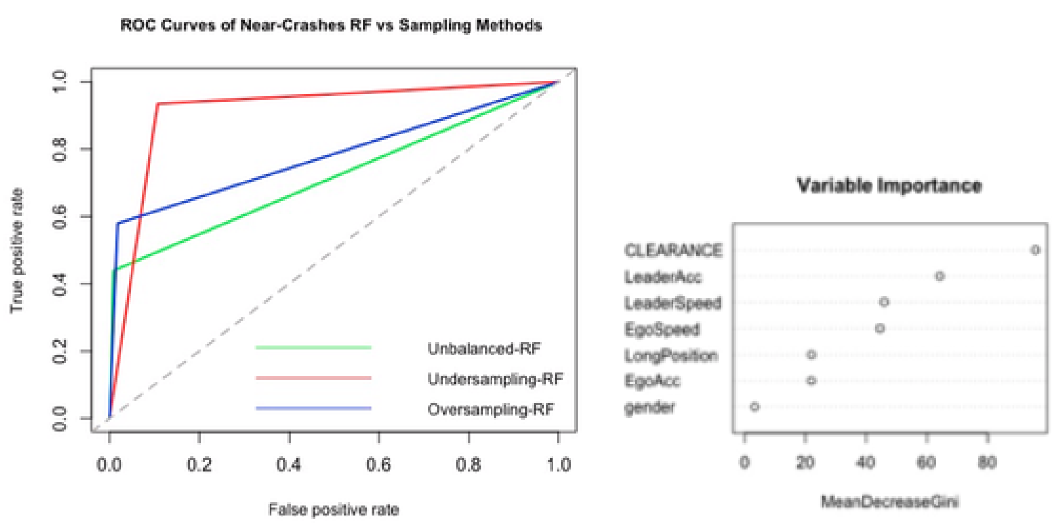


Figure 37. ROC Curves of RF vs Sampling Methods and Variable Importance

The clearance variable was found to be most significant in the classification of potential near-crash events from safe driving events. Further, the logistic regression is performed on the undersampled data to acquire the parameter estimates and significance of each variable and validate the results from RF classification.

Table 25. Variable Importance in Near-Crash Classification

Variables	Importance (Mean Decrease Gini)
Long. Position	21.90
Clearance	95.80
Gender	3.25
Ego Speed	44.65
Leader Speed	45.95
Ego Acc./Dec.	21.88
Leader Acc./Dec.	64.28

The logistic regression results also indicated clearance variable as most significant in the classification using independent uniform inputs with a parameter estimate of -0.296 (See Table 26). Human-like leader's acceleration/deceleration was ranked second in influencing the potential near-crash events with a negative parameter estimate (-1.58). With a generalized R^2 of 0.833 and higher accuracy rate of 92.14%, logistic regression on the undersampled data validated the results from RF classifier.

Table 26 indicates that the logistic regression on undersampled data accurately classified 286 potential near-crash events out of the 299-potential near-crash events in the regression dataset. It also validates the significance of clearance variable in influencing the near-crash detection and classification.

Table 26. Logistic Regression Results: a) Summary, b) Confusion Matrix, and c) Variable Importance

a)

Term	Estimate	Std Error	Chi Square	Prob>Chi Sq
Intercept	1.174	0.446	6.919	0.0085*
Long Position	0.000	0.000	0.913	0.3394
Clearance	-0.296	0.033	79.949	<.0001*
Gender	0.081	0.335	0.059	0.8087
Ego Speed	0.457	0.054	70.287	<.0001*
Leader Speed	-0.431	0.052	70.116	<.0001*
Ego Acc./Dec.	0.554	0.097	32.378	<.0001*
Leader Acc./Dec.	-1.582	0.220	51.534	<.0001*

b)

Prediction	Reference	
	0	1
0	265	13
1	34	286

Table 26 Continued

c)

Predictor	**Contribution**	**Portion**	**Rank**
Clearance	29.7922	0.3026	1
Leader Acc.	23.8478	0.2422	2
Leader Speed	19.2116	0.1952	3
Ego Speed	14.3613	0.1459	4
Ego Acc.	7.5258	0.0764	5
Long. Position	3.4342	0.0349	6
Gender	0.2718	0.0028	7

5.5 Results Comparison

In Scenario 1, the participants followed the AV leader more closely than the participants following the human-like leader in Scenario 2. The slower speeds of the AV leader had a significant impact on lowering the average speed of the participants with a high correlation coefficient of 0.85. However, the overall average speed of the participants did not share a high correlation with the human-like leader's average speed in Scenario 2. Table 27 shows the results from two-sample t-tests, which confirm the significance of the difference in participants' speed and clearance in the two scenarios at the significance level of 5%.

While stopping at the intersections, the participants decelerated in a distinct pattern compared to the designated AV leader resulting in a mismatch. On the other hand, the participants in Scenario 2 illustrated braking behaviors similar to the human-like leader. Also, the participants accelerated faster while driving behind the human-like leader (in Scenario 2) as compared to the AV leader (see Table 28).

Table 27. Comparison of Participants Overall Driving in Test Scenarios Using Two-Sample T-Tests

Overall	**Participants Driving in**	**Mean**	**Std. Dev.**	**t-value**	**p-value**	**Different ($p < 0.05$)**
Avg. Clearance (m)	Scenario 1	24.64	23.36	48.50	< 0.0001	**Yes**
	Scenario 2	46.06	37.35			
Avg. Ego Speed (mph)	Scenario 1	18.48	11.21	16.22	< 0.0001	**Yes**
	Scenario 2	21.36	13.23			

Where, Scenario 1: AV leader and Scenario 2: Human-like Leader

Table 28. Comparison of Participants Braking and Acceleration in Test Scenarios (Two-Sample T-Tests)

Parameters	Participants Driving in	Mean	S.D.	t-value	p-value	Different ($p < 0.05$)
Avg. Clearance During Braking (m)	Scenario 1	19.56	10.10	2.73	0.008	**Yes**
	Scenario 2	30.81	17.44			
Avg. Ego Speed During Braking (mph)	Scenario 1	13.35	10.76	1.25	0.21	No
	Scenario 2	17.27	11.29			
Avg. Dec. During Braking (m/s^2)	Scenario 1	-0.52	0.51	0.08	0.93	No
	Scenario 2	-0.53	0.61			
Avg. Acc. After Stopping (m/s^2)	Scenario 1	1.25	0.64	2.19	0.03	**Yes**
	Scenario 2	1.67	0.71			

In Scenario 1, the participants encountered higher near-crashes (high risk) due to a mismatch in the braking maneuvers made by the participants and the designated AV. Shorter clearances also played a significant role in the occurrence of near-crash events. In both scenarios, MTTC outperformed other five popular surrogate measures by accurately detecting 82% of the near-crashes 10 seconds before their actual occurrence at `~12m range.

The AV leader's speed profile with highest leader's deceleration rate (3.25 m/s^2) experienced the highest number of near-crashes (high risk) which is in tandem with the findings from previous literature indicating that high deceleration rates increase the probability of a near-crash. In Scenario 2, the highest number of near-crashes (high risk) were observed for the human-like leader designated with EF-2 speed profile with a maximum deceleration rate of -1.68 m/s^2 which is lowest among all other leader profiles.

The classification of potential near-crash events using random forest classifier achieved the best results after undersampling the majority class in the data (safe driving events) in both scenarios. Acceleration/deceleration of the AV leader and relative speed between the vehicles came out as the significant factors influencing the probability of near-crashes in Scenario 1. But, in Scenario 2, the relative speed and clearance had the highest importance in classifying the potential near-crash events. Logistic regression also validated the results of RF classification and variable importance after performing the undersampling and balancing the data.

5.6 Summary

This chapter presented the results from braking/acceleration pattern analysis and near-crash risk analysis for the participants following the human-like leader in Scenario 2. It also compared the results from the two-test car-following scenarios. The speed of human-like leader in this car-following scenario did not possess any serious correlation with the participants' driving speed. A noticeable similarity in the gradual braking and rapid acceleration behavior of 24 participants' in this scenario adds to the validity of the experiment. Similar to findings in Scenario 1, MTTC outperformed other surrogate measures by accurately detecting 82% of the near-crashes at a considerable average range of 12.22 m 10 seconds before their actual occurrences.

Of the 114 high-risk near-crash events, 50 occurred when an EF-2 profile was assigned to the human-like leader, whereas the least occurred (20) when the speed profile was EF-1. After undersampling the data, RF classifier produced the highest precision rate of 91.3%. Also, in classifying potential near-crash events, the importance of clearance/distance is validated by performing logistic regression on the undersampled data. The following chapter presents the conclusions of this research based on the analysis results.

6. CONCLUSIONS

This chapter provides the key summary conclusions of this research and provides further recommendations.

6.1 Summary of Key Results

This thesis provides valuable insights into different aspects of driving behavior of human drivers in two different car-following scenarios using a Unity-based driving simulator. Understanding how the participants decelerate behind two different types of leading vehicle (AV and human-like) at stop-controlled intersections and how quickly they accelerate after stopping were the key objectives of this study. Performing risk analysis by detecting near-crashes in car-following scenarios using six popular Surrogate Safety Measures was another vital aspect of this study.

The results from braking behavior analysis indicated a mismatch in the overall braking pattern of the 24 participants and the designated AV leader. On the other hand, two-sample t-tests did not yield any significant difference in the braking behavior of 24 participants and the human-like leader.

After stopping at the stop-controlled intersection, the participants accelerated at faster rates while following the human-like leader due to a greater available clearance. Results from two-sample t-tests indicated a mismatch in the acceleration rates of 24 participants (1.25 m/s^2) and that of the AV leader (0.5 m/s^2) at the significance level of

5%. However, there was no such mismatch in the scenario when the participants accelerated behind the human-like leader.

Out of the six surrogate safety measures used in this study to detect near-crash events 10 seconds before their actual occurrences, the MTTC evinced the highest accuracy rate of 83% in the detection. This finding of anticipating a near-crash 10 seconds before its real event at a range of 12.85 m in a car-following scenario using a critical threshold of 4 seconds would have significant safety advantages in near-crash avoidance.

The participants showed a higher tendency of near-crash involvement while following the AV leader designated with C-3.25 profile and the human-like leader with EF-2 profile. To avoid potential biased results due to an imbalance in two classes (safe and potential near-crash events) undersampling and oversampling techniques were performed to achieve a balanced dataset. RF classifiers on the undersampled data achieved the highest accuracy rates of 93.1% and 91.3% in predicting and classifying the potential near-crash events.

Variables, AV leader’s acceleration/deceleration in Scenario 1, and clearance between vehicles in Scenario 2 emerged as the most significant in classifying the potential near-crash events. Logistic regression successfully validated the results of RF classifiers on the undersampled data. The variable importance results were in sync with the characteristics of C-3.25, and EF-2 speed profiles as higher deceleration rates of the leader in these profiles increased the probability of near-crashes. The braking maneuvers by participants at shorter clearances led to the majority of near-crash events (high risk) during the experiment.

As the primary goal of the study was to study the safety risks associated with the car-following behavior of the participants under the influence of an AV, it was found that the participants were more likely to be involved in rear-end near-crashes involving high risk (145) with the designated AV leader in Scenario 1 as compared to human-like leader in Scenario 2 (112). The discrepancy in the participants' and the AV leader's braking behavior synchronizes with recent findings (Rahmati et al., 2019) indicating the potential disparity in the AV's and humans' decision making while braking at stop-controlled intersections.

6.2 Recommendations

This study recommends that researchers test different types of car-following behaviors between an AV and a human driver. Since this study involved the participation of 48 human participants, research with a larger sample size could further validate the findings from this study. The research demonstrates the efficiency of MTTC in predicting a near-crash with enough time and range to alert the driver and prevent a near-crash. The designers of forward-collision warning systems should take this result into account to achieve safer near-crash avoidance systems. To further assess this, designing more car-following scenarios on driving simulators and the real-world environment will provide validation to the findings from this study. Studies for the latter are currently being conducted at Texas A&M University.

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APPENDIX A

RECRUITMENT FORM

PARTICIPANTS NEEDED!

Howdy,

You are cordially invited to take part in a research study on **'understanding the braking behavior of human drivers when approaching stop signs'** being conducted by researchers in Department of Civil Engineering, Texas A&M University.

Your participation is greatly appreciated!

Eligibility:
Undergraduate or graduate students (**at least 18 years old and hold a valid driver's license**)

Session Duration:
Maximum 2 hours

Confidentiality:
The records of this study will be kept private. No identifiers linking you to this study will be included in any sort of report that might be published.

Contact:
For more information about this study, please contact Dr. Alireza Talebpour by email, atalebpour@tamu.edu, by phone at (979)8450875.

Thank you for your time and consideration!

Sincerely,
Alireza Talebpour, Ph.D.
Assistant Professor
Zachry Department of Civil Engineering

IRB Number: IRB2019-0235D
Approval Date: 04/11/2019
Expiration Date:

IRB NUMBER: IRB2019-0235D
IRB APPROVAL DATE: 04/11/2019

Figure 38. Image of the Email used for Recruiting Participants for the Study

APPENDIX B

PRE-TEST QUESTIONNAIRE AND CONSENT FORM

Driving Simulation Study

Pre-test Survey/ Questionnaire

Q1.

Age	
Gender	**Male / Female**

Q2. Do you currently have a valid drivers' license? (Circle one.)

1. **Yes**
2. **No**

Q3. Years of driving experience: _______________

Q4. Do you have any visual impairments or currently taking any medications?

1. **Yes**
2. **No**

Figure 39. Pre-test Questionnaire used for Recruiting Participants

TEXAS A&M UNIVERSITY HUMAN RESEARCH PROTECTION PROGRAM

INFORMED CONSENT DOCUMENT

Title of Research Study: Preventing Crashes in Mixed Traffic with Automated and Human-Driven Vehicles

Investigator: Alireza Talebpour, Ph.D.

Funded/Supported By: This research is funded/supported by _____SAFE-D_____.

Why are you being invited to take part in a research study?

You are being asked to participate because you are between the ages of 18 and 25 and have a valid drivers' license.

What should you know about a research study?

- Someone will explain this research study to you.
- Whether or not you take part is up to you.
- You can choose not to take part.
- You can agree to take part and later change your mind.
- Your decision will not be held against you.
- You can ask all the questions you want before you decide.

Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, you may contact the Principal Investigator , Alireza Talebpour, Ph.D., at 979-845-0875 or atalebpour@tamu.edu

This research has been reviewed and approved by the Texas A&M Institutional Review Board (IRB). You may talk to them at at 1-979-458-4067, toll free at 1-855-795-8636, or by email at irb@tamu.edu., if

- You cannot reach the research team.
- Your questions, concerns, or complaints are not being answered by the research team.
- You want to talk to someone besides the research team.

Document Version:

Page **1** of **3**

Figure 40. Informed Consent Form-Page 1

INFORMED CONSENT DOCUMENT

- You have questions about your rights as a research participant.
- You want to get information or provide input about this research.

Why is this research being done?

The purpose of this study is to evaluate how the human driving behavior is affected while following an automated vehicle at stop-controlled intersections.

How long will the research last?

We expect that you will be in this research study for ____1 hour____

How many people will be studied?

We expect to enroll about __120___ people in this research study at this site. Approximately __120___ people in the entire study nationally will be enrolled.

What happens if I say "Yes, I want to be in this research"?

You will be asked to perform the tasks of a driver on a driving simulator. After arrival, you will be given a short training to familiarize you with the driving simulator operation. You will be asked to drive the simulator four times during the experiment with a rest of at least 5 minutes between each trial.

The research will be conducted in Dwight Look Engineering Building, Texas A&M University, College Station.

What happens if I do not want to be in this research?

You can leave the research at any time and it will not be held against you.

What happens if I say "Yes", but I change my mind later?

You can leave the research at any time and it will not be held against you.

What happens to the information collected for the research?

Efforts will be made to limit the use and disclosure of your personal information, including research study and other records, to people who have a need to review this information. We cannot promise complete privacy. Organizations that may inspect and copy your information include the TAMU HRPP/IRB and other representatives of this institution.

What else do I need to know?

If you agree to take part in this research study, we will pay you __ $25 _____ for your time and effort.

Document Version:

Page **2** of **3**

Figure 41. Informed Consent Form-Page 2

INFORMED CONSENT DOCUMENT

Signature Block for Capable Adult

Your signature documents your permission to take part in this research.

Signature of subject	Date
Printed name of subject	
Signature of person obtaining consent	Date
Printed name of person obtaining consent	

My signature below documents that the information in the consent document and any other written and information was accurately explained to, and apparently understood by, the participant, and that consent was freely given by the participant.

Signature of witness to consent process	Date
Printed name of person witnessing consent process	

Document Version:

Page **3** of **3**

Figure 42. Informed Consent Form-Page 3

APPENDIX C

POST-TEST QUESTIONNAIRE

Driving Simulation Study

Post-test Survey/ Questionnaire

Q1. How difficult or easy was it for you to use the simulator?

Very easy. **Very difficult.**

1	2	3	4	5	6	7	8	9

Q2. How realistic did the simulator feel?

Very realistic. **Not at all realistic.**

1	2	3	4	5	6	7	8	9

Q3. How likely are you to drive in a similar way in the real world?

Very. **Not at all.**

1	2	3	4	5	6	7	8	9

Q4. Was there any time when you felt you were about to crash?

Yes. **Somewhat** **Not at all.**

Q5. At any time, did you feel frustrated while following the vehicle in front?

Yes. **Somewhat** **Not at all.**

Q6. Were you able to trust the driving behavior of the leading vehicle?

Yes. **Somewhat** **Not at all.**

Figure 43. Post-test Questionnaire

APPENDIX D

IMAGES OF SIMULATOR

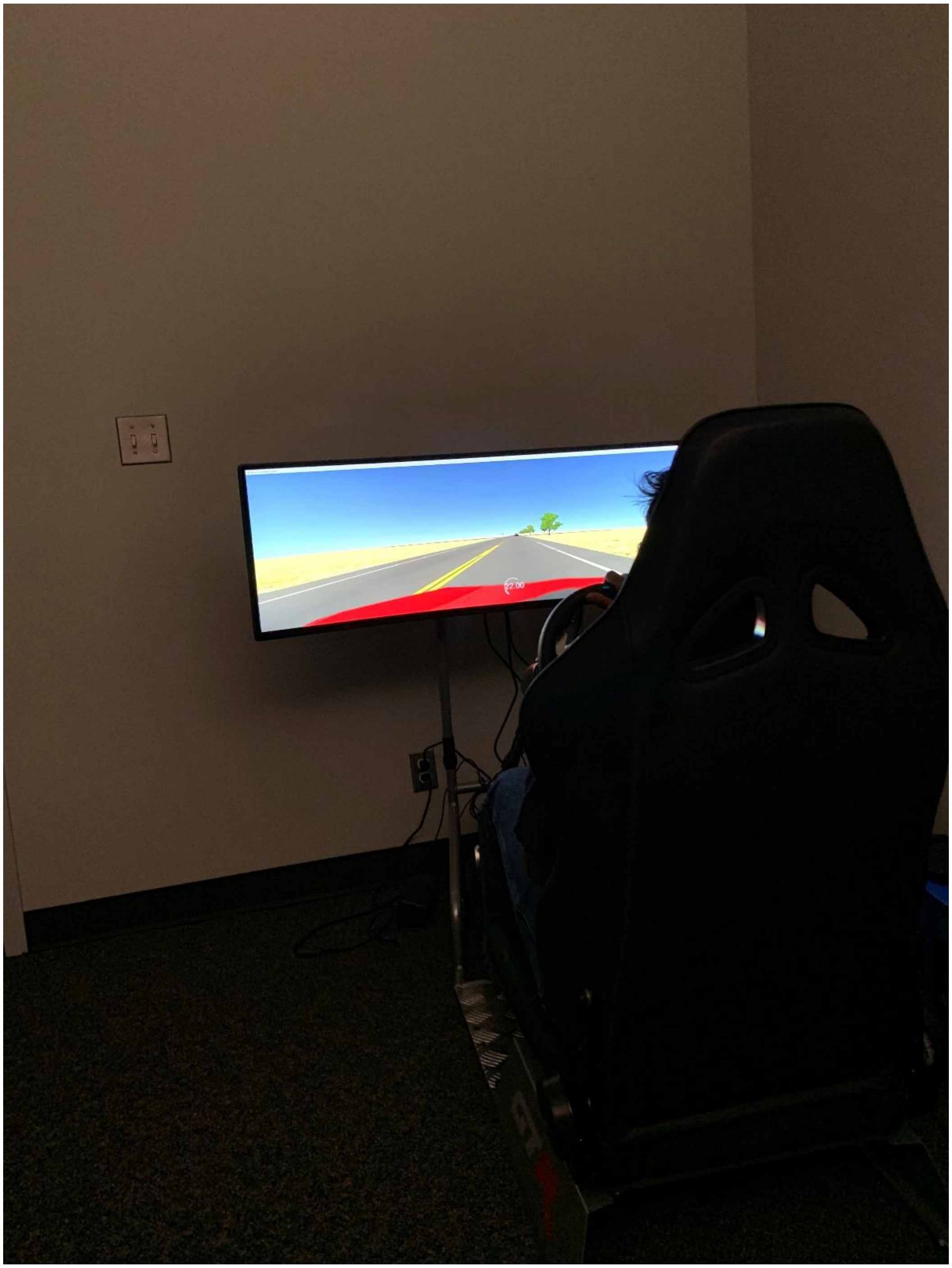

Figure 44. Image of the Driving Simulator During the Experiment

Figure 45. Image of the Following Vehicle Stopping at a Stop-Controlled Intersection

Figure 46. Image of the Participant Following the Leading Vehicle on the Driving Simulator