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Improving Safety under Reduced Visibility Based on Multiple Countermeasures and Approaches including Connected Vehicles

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IMPROVING SAFETY UNDER REDUCED VISIBILITY BASED ON MULTIPLE COUNTERMEASURES AND APPROACHES INCLUDING CONNECTED VEHICLES

by

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ABSTRACT

The effect of low visibility on both crash occurrence and severity is a major concern in the traffic safety field. Different approaches were utilized in this research to analyze the effects of fog on traffic safety and evaluate the effectiveness of different fog countermeasures. First, a “Crash Risk Increase Indicator (CRII)” was proposed to explore the differences of crash risk between fog and clear conditions. A binary logistic regression model was applied to link the increase of crash risk with traffic flow characteristics. Second, a new algorithm was proposed to evaluate the rear-end crash risk under fog conditions. Logistic and negative binomial models were estimated in order to explore the relationship between the potential of rear-end crashes and the reduced visibility together with other traffic parameters. Moreover, the effectiveness of real-time fog warning systems was assessed by quantifying and characterizing drivers’ speed adjustments through driving simulator experiments. A hierarchical assessment concept was suggested to explore the drivers’ speed adjustment maneuvers. Two linear regression models and one hurdle beta regression model were estimated for the indexes. Also, another driving simulator experiment was conducted to explore the effectiveness of Connected-Vehicles (CV) crash warning systems on the drivers’ awareness of the imminent situation ahead to take timely crash avoidance action(s). Finally, a micro-simulation experiment was also conducted to evaluate the safety benefits of a proposed Variable Speed limit (VSL) strategy and CV technologies. The proposed VSL strategy and CV technologies were implemented and tested for a freeway section through the micro-simulation software VISSIM. The results of the above mentioned studies showed the impact of reduced visibility on traffic safety, and the effectiveness of different fog countermeasures.

Keywords: traffic safety; fog; fog countermeasure; connected vehicle; variable message sign; variable speed limits; driving simulator; VISSIM

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LIST OF ACRONYMS/ABBREVIATIONS

Adaptive Cruise Control	ACC
Advanced Driver Assistance System	ADAS
Area under an ROC curve	AUC
Automated Surface Observing System	ASOS
Automatic Vehicle Identification	AVI
Automated Weather Observing System	AWOS
Automated weather Sensor System	AWSS
Brake Reaction Time	BRT
Changeable Message Sign	CMS
Component Object Model	COM
Crash Risk Increase Indicator	CRII
Crash Warning Systems	CWS
Dynamic Message Sign	DMS
Environmental Sensor Stations	ESS
Fatality Analysis Reporting System	FARS
Fog Detection and Warning System	FDWS

Fog Monitoring System	FMS
Geoffrey E. Heavers	GEH
Head-up Display	HUD
Highway advisory radio	HAR
Hosmer-Lemeshow	HL
Implementing VSL under CV environment	VSL&CV
Intelligent Driver Model	IDM
Lane Departure Warning System	LDWS
Loop and radar detector	LD
Market Penetration Rate	MPR
Microwave Vehicle Detection System	MVDS
Minimum time-to-collision	MTTC
Multivariate Analyses of Variance	MANOVA
National Advanced Driving Simulator	NADS
National Climate Data Center	NCDC
National Highway Transportation Safety Administration	NHSTA
National Oceanic Atmospheric Administration	NOAA
Perception Reaction Time	*PRT*

Rear-end Collision Risk Index	RCRI
Remote Processing Units	RPU
Remote Traffic Microwave Sensor	RTMS
Road Weather Information System	RWIS
Time-to-Collision	TTC
Traveler Information Station	TIS
Total Travel Time	TTT
Variable Message Signs	VMS
Variable Speed Limit	VSL
Vehicle-to-Vehicle	V2V
Vehicle-to-Infrastructure	V2I

CHAPTER 1: INTRODUCTION

1.1 Overview

The effect of weather events on traffic operations and safety has become a more important issue, and visibility reduction due to fog is a major concern. In recent years, the number of the fatal crashes involving fog shows a decreasing trend. However, there are still about 300-400 fog-related fatal crashes happening every year in the United States (Hamilton *et al.* 2014). Meanwhile, there are many crashes that occurred in Florida that were related to reduced visibility (Ahmed *et al.* 2013, 2014). In 2008, a 70 car pileup happened on I-4 in Polk County, Florida under reduced visibility conditions, which caused 5 fatalities and many injuries (Hassan *et al.* 2011). In January, 2012, 11 people were killed in a multi-vehicle involved crash that was related to fog and smoke on I-75 south of Gainesville, Florida (Ahmed *et al.* 2014).

In recent years, efforts to understand the fog impact on traffic and safety have been made. Traditionally, traffic safety analyses are conducted based on historical crash and traffic data. It was found that crashes that happened under low visibility conditions are prone to be more severe and more likely to involve multiple cars (Abdel-Aty *et al.* 2011). However , studies that utilized driving simulator experiments show that drivers would be more careful when they drive under reduced visibility conditions (White and Jeffery 1980, Van der Hulst *et al.* 1998). Some researchers tried to explain this pheonomon by pointing out the fact that driver's compensation (e.g., reducing speed, increasing headway, etc.) is insufficient under fog conditions (Sumner *et al.* 1977).

In the previous studies, a number of researchers have investigated the change of driver behavior under fog conditions. It was suggested that some drivers may reduce their headway distances to seek visible cues in fog (Broughton *et al.* 2007). Due to this phenomenon, drivers may not be able to have enough response time to react to imminent events even if they have reduced their speeds, which results in an increase of the rear-end crash risk.

In order to improve traffic safety under fog conditions, different methods have been proposed or employed to improve traffic safety under reduced visibility conditions, and Active Traffic Management (ATM) is one of the most common methods that has been utilized in recent years. ATM aims to smooth traffic flow and reduce congestion on freeways, and it usually relies on Variable Message Signs (VMSs) to change posted speed limits based on Variable speed limits (VSL) strategies (Wang *et al.* 2015, Lee *et al.* 2008, Kang *et al.* 2011, Abdel-Aty *et al.* 2006).

However, VMSs are placed discretely, and the deployment of VMSs can be expensive. This disadvantage could be improved by using Connected-Vehicle (CV) technologies, which include Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications. Recently, there have been considerable interests in using CV technologies to reduce crash potential. Some crashes may be prevented by systems based on CV technologies, such as Forward Collision Warning system (FCW), blind spot warning system, etc. Previously, crash warning systems technologies were based on radars or cameras. However, bad weather could reduce the systems' accuracy. CV could further improve the performance of crash warning systems by deploying V2V communications or V2I communications (Li *et al.* 2014). The V2V communications can provide the real-time position and speed of the lead vehicle. Thus, the crash warning systems could detect the sudden slow down or stop of the lead vehicle and timely alert the drivers of the following vehicle with an in-vehicle warning message (Benedetto *et al.* 2015). Moreover, ATM strategies could also be incorporated with CV technologies to further improve safety (Khondaker and Kattan 2015, Lee *et al*. 2013).

Although previous study has explored the effects of reduced visibility, there is no clear answer of how to evaluate the change of crash risk under fog conditions based on traffic data. Moreover, the effectiveness of different fog systems needs to be explored. Most of the VSL strategies that have been implemented under inclement weather are using pre-fixed speed limit values, which are according to practical experience. Hence, there is a need to propose VSL strategies for inclement weather. Meanwhile, there is a lack of studies on the safety effectiveness of CV technologies under fog conditions. Therefore, the changes of driving behaviors and traffic flow conditions should be examined under CV environment when fog is present. In this dissertation, there are two types of weather data sources. If fog events were reported from the airports, or visibility distance is less than 2000 m from the weather sensor, the corresponding time will be the start time for fog duration. Meanwhile, if the airports stop reporting fog events, or visibility distance equals or greater than 2000 m from the weather sensors, the moment will be the end of fog duration.

1.2 Research Objectives

The dissertation focuses on understanding the effects of reduced visibility on traffic safety, and evaluating the effectiveness of different fog systems. The specific objectives will be achieved by the following procedures:

1. Developing surrogate safety measurements to evaluate traffic safety under fog conditions.
2. Investigating the effects of fog systems on driver's speed adjustment behavior.
3. Investigating the impact of CV technologies under fog conditions.

4. Designing a VSL control algorithm to decrease crash risk under fog conditions, and evaluating its impact on traffic safety.

The first objective has been achieved in Chapter 3 and Chapter 4 by the following tasks:

a. Investigating the impact of fog on traffic flow.

b. Proposing a crash risk indicator to explore the changes of crash risk during fog.

c. Identifying the factors contributing to increasing crash risk during fog.

d. Proposing a new algorithm to evaluate traffic safety under fog conditions.

e. Exploring the impact of the reduced visibility together with other traffic parameters on safety based on the proposed algorithm.

The second objective has been achieved in Chapter 5 by the following tasks:

f. Proposing a hierarchical driving performance assessment method to evaluate the effect of the real-time fog warning system on driver's speed adjustments under different conditions.

g. Conducting a driving simulator experiment to support the proposed modeling framework.

The third objective has been achieved in Chapter 6 and Chapter 7 by the following tasks:

h. Examining the effectiveness of CWS on driver's rear-end crash avoidance behavior under fog conditions based on a driving simulator experiment.

i. Investigating whether warning systems (visual only vs. visual & audio) have significant effects on driver's read-end crash avoidance performance, when the lead vehicle makes an emergency stop by driving simulator experiment.

j. Evaluating the impacts of CVs under fog conditions by micro-simulation VISSIM.

The fourth objective has been achieved in Chapter 7 by the following tasks:

k. Proposing a VSL algorithm for fog conditions.

l. Investigating the feasibility of the proposed VSL control strategy.

m. Exploring the effects of the proposed VSL control strategy under reduced visibility conditions.

1.3 Dissertation Organization

The dissertation is organized as following: Chapter 2, following this chapter, summarizes the literature review, which includes visibility systems, traffic flow in inclement weather conditions, driver behavior in inclement weather conditions, and visibility-related crashes. Chapter 3 presents the crash risk analysis under fog conditions using real-time traffic data and airport weather data. Chapter 4 provides a rear-end crash risk algorithm under fog conditions based on field traffic and weather data. Chapter 5 offers the analysis of the impact of fog warning systems on driver's speed adjustments based on a driving simulator experiment. Chapter 6 evaluates the effects of Forward Collision Warning (FCW) systems on driver's crash avoidance behaviors. Chapter 7 proposes and evaluates a Variable Speed Limit (VSL) strategy, and its effectiveness under Connected Vehicle

(CV) environment is also evaluated in this chapter. Finally, Chapter 8 summarizes the overall dissertation and suggests future studies about inclement weather effects on traffic safety.

CHAPTER 2: LITERATURE REVIEW

2.1 Visibility Systems

2.2.1 Visibility Systems in the US

A typical visibility system includes four components (Figure 2-1). The visibility systems are highly dependent on the weather and traffic information. After gathering the data, decisions will be made at the Central Management Center to inform drivers about the current visibility conditions and maintain road safety.

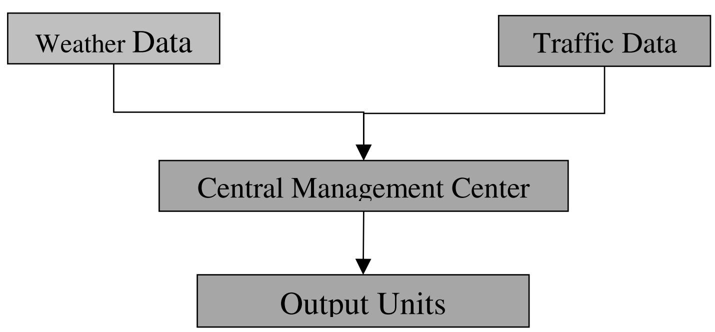


Figure 2-1 Components of a visibility system

Figure 2-2 shows the system architecture of the visibility system in Florida (Abdel-Aty *et al.* 2012a). There are four stations in the system, while one of the stations works as a base station. The stations detect the road visibility and continuously send information to the base station. Strategies, which include displaying warning messages on Dynamic Message Signs (DMSs) and changing speed limits by Variable Speed Limit (VSL) signs, could be implemented when specific hazardous conditions are detected.

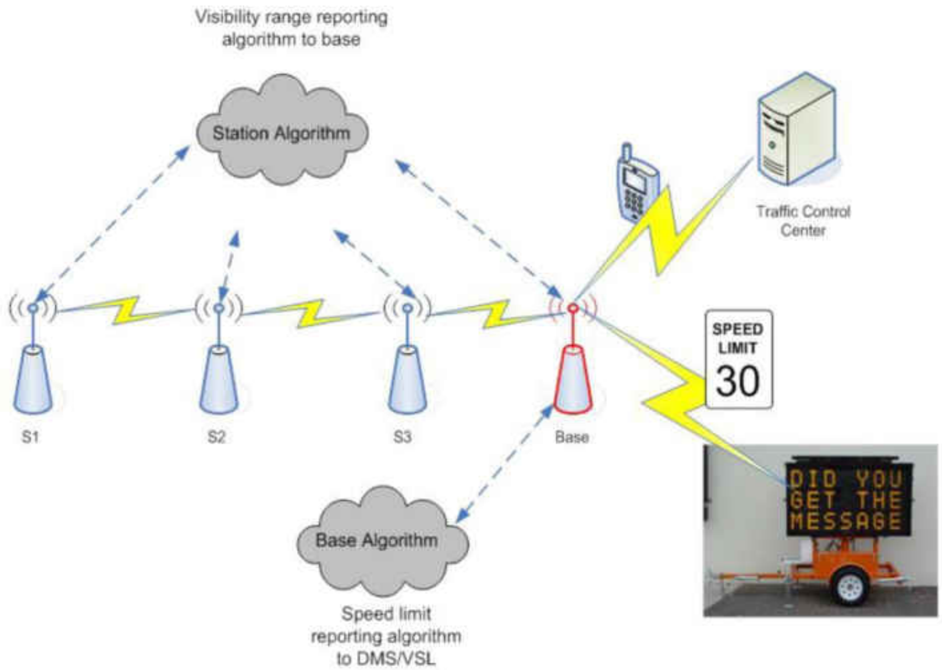


Figure 2-2 Visibility system proposed to FDOT (Abdel-Aty et al. 2012a)

In meteorological studies, the visibility distance is defined as the greatest distance that a black object can be seen (Hautiére *et al.* 2006, Hautiere *et al.* 2008). There are four common types of fog, which are radiation fog, advection fog, upslope fog and evaporation fog (sea fog) (Table 2-1) (Cereceda *et al.* 2002). In Florida, the fog is usually formed during cold months by air cooling and mixing with air parcels, which is known as radiation fog (Pietrzyk *et al.* 1997).

Table 2-1 Fog types

Fog Types	Causes	Characteristics
Radiation Fog	During night, the heats from earth's surface radiates into space, and the cooler earth's surface lead to the presence of the moist air layer. When the humidity reaches 100% the fog will be present.	It tends to dissipate very quickly once the sun comes up. This type of fog can be very dense and make driving dangerous in the low visibility environment.
Advection Fog	The condensation is caused by the horizontal movement of warm moist air, when the surface temperature is low.	It is prevalent on the Pacific coast of North America.
Upslope Fog	It occurs when moist air flows up a hillside or mountainside by light winds and becomes saturated.	It occurs in all mountain ranges in North America during winter.
Evaporation Fog	It occurs when the moist air, which contains sufficient water vapor, mixes with cooler air.	It leads to smoke rising off the surface of water, or frontal fog, which has the raindrops evaporate into the cool air near the ground.

A Road Weather Information System (RWIS) is used to detect the weather and pavement conditions (Guardian 2009). A typical RWIS usually includes Remote Processing Units (RPU), communication links and Environmental Sensor Stations (ESS) for collecting different types of weather data, such as temperature, precipitation, visibility, etc. Visibility sensors play an important role in the visibility systems. Figure 2-3 provides an example of a visibility sensor in Idaho.

Figure 2-3 Idaho DOT visibility sensor (Goodwin and Pisano 2003)

Other important weather information sources are the Automated Weather Observing System (AWOS), the Automated Surface Observing System (ASOS), and the Automated weather Sensor System (AWSS). Rivard (2014) gathered the AWOS/ASOS stations' data in Florida to analyze the Prospective Fog Warning Systems. He explained the meteorological data sources in Florida (Figure 2-4), which include primary stations (AWOS, ASOS, Florida Automated Weather Network, South Florida Water Management District site), and secondary sites (individual and privately owned weather stations). Florida has a total of 93 AWOS and ASOS stations, and 77 of them are located at airports.

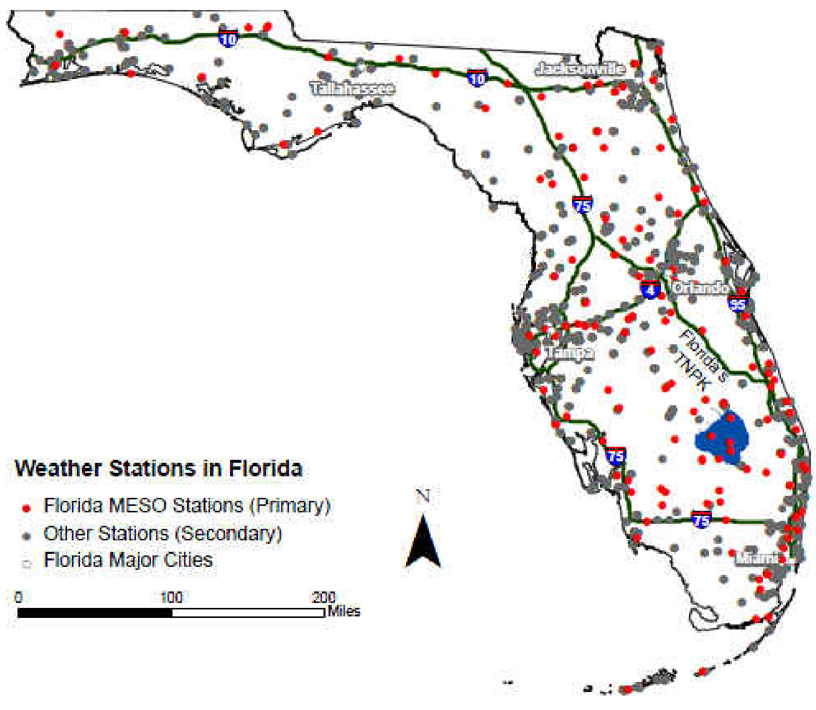


Figure 2-4 All Mesonet station in Florida (Rivard, 2014)

In general, the fog sensors can be divided into two types:

Transmissometers: A receiver is located 50 meters away from the transmitter, and collects the transmitted light source. During the fog conditions, the receiver will collect less light because the light will be scattered along the path. This type of sensor is normally used at airports, which is more expensive, inconvenient for transit when installing the sensors, and a long time of accurate alignment is needed (Figure 2-5).

Figure 2-5 Transmission method (Weisser 1999)

Backscatter and forward scatters: the other method of fog detection is measuring the light scattered. These two types of sensors will get the data from a small area of air, which are also called "point" detectors (Figure 2-6). The disadvantage of the sensors is that the maintenance should be done regularly.

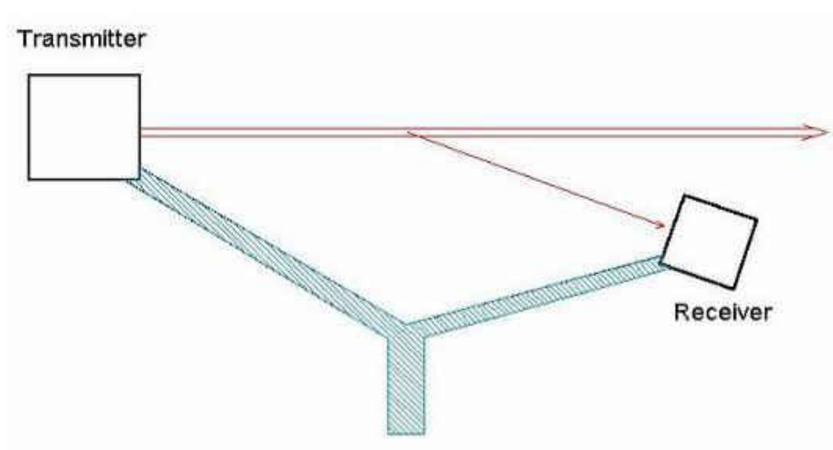


Figure 2-6 Backscatter and forward scatter methods (Weisser 1999)

Different types of road detectors can be employed to monitor the road traffic conditions, such as loop detectors, radar detectors, CCTVs, etc. Loop detectors are used to detect traffic to obtain the traffic parameters, while radar detectors can also be deployed to get the information about traffic flow and speed. CCTVs are widely applied to confirm the weather conditions and road conditions. Meanwhile, video imaging is another technique that has recently drawn much attention. The technique is designed to monitor the traffic even during low visibility conditions. However, the performance of this technique is still far from satisfactory and improvements are needed.

The operational strategies during fog conditions are implemented based on both weather information and traffic information. Alfelor *et al.* (2013) described the state-of-the practice in weather-responsive traffic management (WRTM) used in the US and Europe. Shahabi *et al.* (2012) also provided a description of the fog detection and warning system in the US.

Different weather conditions can affect the road safety in different levels. In 1995, Lavdas and Achtemeier (1995) proposed the "Low Visibility Occurrence Risk Index (LVORI)", and they also presented LVORI values as a function of Relative Humidity (RH) as well as Dispersion Index (DI) (Table 2-2). The Dispersion Index values describe the atmosphere's ability to ventilate smoke from areas of prescribed burning activity. From Table 2-2, we can find that the highest risk is presented when the DI value is low and the RH value is high.

Table 2-2 LVORI as a function of RH and DI (Lavdas and Achtemeier 1995)

DISPERSION INDEX												
	1-1	2-2	3-4	5-6	7-8	9-10	11-12	13-16	17-25	26-30	31-40	> 40
R.H.												
<55	2	2	2	2	2	2	2	2	2	2	1	1
55-59	3	3	3	3	3	2	2	2	2	2	1	1
60-64	3	3	3	3	3	3	2	2	2	2	1	1
65-69	4	3	3	3	3	3	3	3	3	3	3	1
70-74	4	3	3	3	3	3	3	3	3	3	3	3
75-79	4	4	4	4	4	4	4	4	3	3	3	3
80-82	6	5	5	4	4	4	4	4	3	3	3	3
83-85	6	5	5	5	4	4	4	4	4	4	4	4
86-88	6	6	6	5	5	5	5	4	4	4	4	4
89-91	7	7	6	6	5	5	5	5	4	4	4	4
92-94	8	7	6	6	6	6	5	5	5	4	4	4
95-97	9	8	8	7	6	6	6	5	5	4	4	4
>97	10	10	9	9	8	8	7	5	5	4	4	4

Note: 10 point scale is based on proportions of smoke and/or fog related accidents

In meteorological studies, the road visibility denotes the horizontal visibility 1.2 m above the roadway. The international classification of visibility is as follows (Table 2-3).

Table 2-3 International classification of visibility (Meteorological Office 1969)

Visibility	Description
Less than 40 m	Dense fog
40-200 m	Thick fog
200-1000 m	Fog
1-2 km	Mist (if mainly due to water droplets)
	Haze (if mainly due to smoke or dust)
2-4 km	Poor visibility
4-10 km	Moderate visibility
10-40 km	Good visibility
Over 40 km	Excellent visibility

In practice, the visibility can be classified into different levels by different visibility systems, and the information would be reported to the Central Management Center to implement different operational strategies. The display messages on the DMSs or the speed limit information on the

VSLs would be based on the current weather conditions (Rämä 1999, Perrin 2000). After collecting the information, the visibility system would implement corresponding strategies automatically or manually, which include displaying warning messages, speed advisories, changing speed limit, road closure, etc.

The DMSs, which are also known as Variable Message Signs (VMSs) or Changeable Message Signs (CMSs), are widely adopted in visibility systems nowadays (Rämä and Kulmala 2000, Kolisetty *et al.* 2006, Ali *et al.* 2013). DMS can provide information about the possible issues ahead and give corresponding advice to drivers. Williams *et al.* (2015) examined the effects of different color configuration, brightness levels, and flashing beacons on a VMS on drivers during the day and night under fog conditions (Figure 2-7). The experiments were carried out on Virginia Smart Road. The Virginia Smart Road is a 2.2 miles test road, and it was built to interstate standards. The smart road can produce fog, rain and snow in order to test their effects on traffic. During most of the situations in the experiment in this study, the VMSs with black-on-white, white-on-black, and amber-on-black color combinations had longer detection and legibility distances. The VMSs with flashing beacons, high brightness, and red-on-black color configurations would make the drivers feel more urgency.

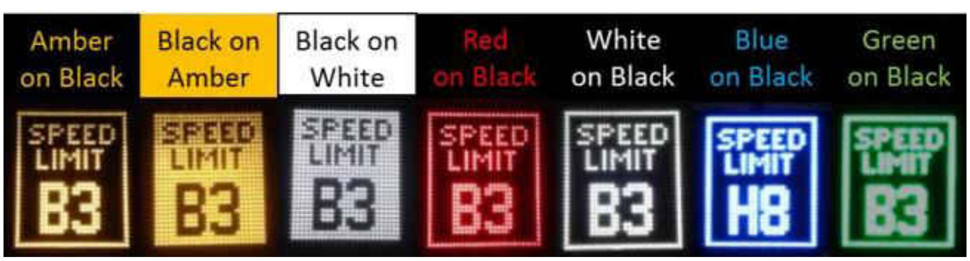


Figure 2-7 Tested color configurations (Williams et al. 2015)

The static warning sign is an alternative treatment for reduced visibility conditions. Figure 2-8 is the fog area sign in the Manual on Uniform Traffic Control Devices (MUTCD). The signs are typically located before the area where fog is likely to form frequently. In practice, the signs are sometimes placed with flashing beacons to draw drivers' attention during fog.

Figure 2-8 MUTCD fog area sign (MUTCD, 2009)

Highway advisory radio (HAR), which is also called Traveler Information Station (TIS), also plays an important role of communicating with vehicles. Permanent HAR transmitters are typically located on the Interstate and can be updated instantly during an emergency. The system provides road users with information such as incidents, fire, weather and other traffic conditions. For example, Virginia Department of Transportation (VDOT) broadcasts information on 1620 AM in VDOT's Northern, Southwestern and Central regions, and on 1680 AM in the Eastern Region. Figure 2-9 describes the locations of HAR stations in New York State and offers an example of current HAR signs. When the lights are flashing, the traffic information will be broadcasted.

(a) HAR stations (b) HAR signs

Figure 2-9 HAR (Highway Advisory Radio) system in New York State

Recent years have seen a trend in research on exploring the in-vehicle fog detection techniques, which still have not commonly been applied (Mori *et al.* 2007, Gallen *et al.* 2011, Pavlić *et al.* 2012). The basic concept of the camera-based visibility detection compresses the information from a 3D space to a two-dimension space. The depth information is lost during the compression process, so many studies are focusing on the methods of how to extract the depth information. However, the fog detection becomes more difficult when the vehicles are moving.

Advanced Driver Assistance System (ADAS), which is developed to help in the driving process, heavily rely on the camera-based detection technology to provide information during adverse weather conditions in order to improve safety and help the drivers have a better driving experience (Hummel *et al.* 2011, Borhade *et al.* 2012). Lane Departure Warning Systems (LDWSs) are one of the ADASs that can provide a warning to drivers when they are driving out-of-lane (Lo *et al.* 2013, Mahajan and Patil 2015). Figure 2-10 shows an example of the LDWS, which is named AutoVue. AutoVue can track the visible lane lines using the cameras, and it is designed to cope with the adverse weather conditions, such as rain, fog, etc.

(a) Camera and ECU (b) Lane Tracking

Figure 2-10 Bendix AutoVue (Hoover *et al.* 2014)

2.2.2 Visibility Systems in Other Countries

A 100-vehicle pile-up happened in foggy weather near South Korea's Incheon International Airport in 2015 (Telegraph 2015). Two people died and about sixty-five people injured due to the crash. The Korean authorities aim at developing a new visibility measuring and fog monitoring system using CCTV cameras. Figure 2-11 describes its image processing procedure.

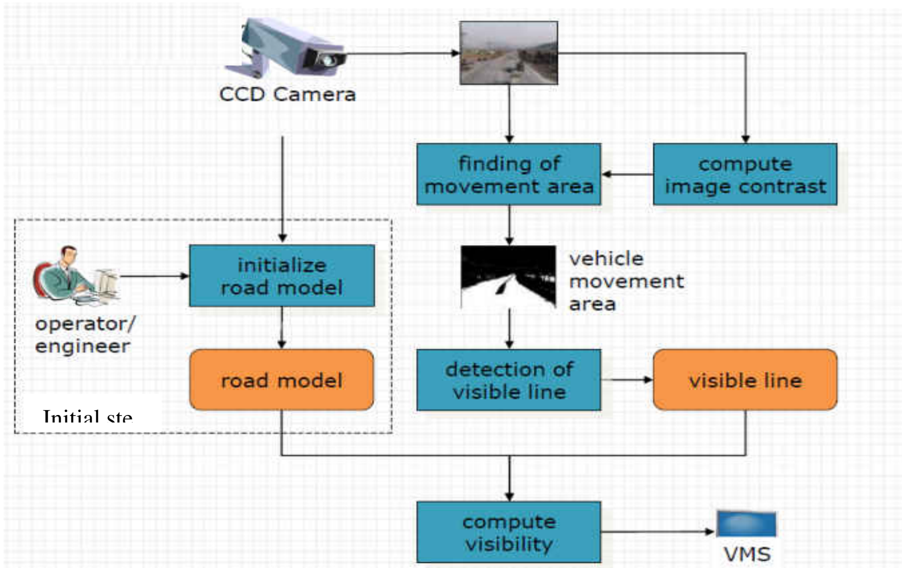


Figure 2-11 Image processing procedure in Korean visibility system (Lee and Kim 2014)

One important part of the system is to determine the current visibility by the images from cameras. Figure 2-12 offers an example of the system that they employed to determine the current visibility levels.

Figure 2-12 Road model (Lee and Kim 2014)

The Fog Detection and Warning System (FDWS) in South Korea includes a main controller, a visibility meter, a light bar, and a vehicle detector. The light bar is installed at every 30 m intervals to detect vehicles. If a vehicle passes the detection zone, the light bar will display red warning lights to inform the following vehicle of the leading vehicle's position in fog (Figure 2-13). *Lee et al. (2012)* conducted a study to evaluate the effects of FDWS on a section of National Highway No.37. The results indicate that FDWS will reduce the mean speed by about 3 kph during daytime and 10 kph during nighttime.

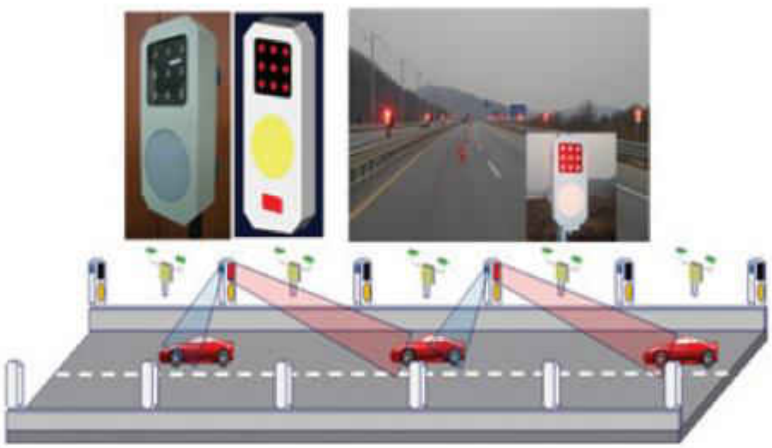


Figure 2-13 Light bars in FDWS (Lee et al. 2012)

In 2005, a severe multi-vehicle involved traffic crash happened in foggy weather in Sichuan, China. Two people died and thirty-four people were injured in the crash. Fog monitoring and warning system has been employed in many places of China. The weather information are collected based on CCTVs and satellite images. Both the real-time weather data and the fog forecasting data are sent to the traffic management center under low visibility conditions. The visibility conditions are divided into two levels: 1) visibility less than 200 m; 2) Visibility greater than 200 m and less than 500 m. The traffic management center implements relative strategies based on the weather information to cope with the situations. The traffic control strategies during fog conditions include: reducing the speed limits by DMSs or VSLs, road network management, roadway closing, etc. Sometimes, when fog last for a long time at mountainous regions, the road managers arrange that the vehicles pass the fog region by groups. The lead vehicle and the last vehicle of each group should be police cars, and other vehicles cannot pass the police cars when driving in the fog area. This method can increase the road capacity under fog conditions.

The Japanese government has funded many efforts to keep improving their Intelligent Transport Systems (ITSs) in order to help resolve road traffic problems. The ITSs include many parts, such as advances in navigation systems, electronic toll collection systems, assistance for safe driving, increasing efficiency in road management, support for public transport, etc. Figure 2-14 shows the structure of the Vehicle Information and Communication System (VICS). The basic concept of the system is using intelligent transportation technology to connect people (road users), vehicles and roads together.

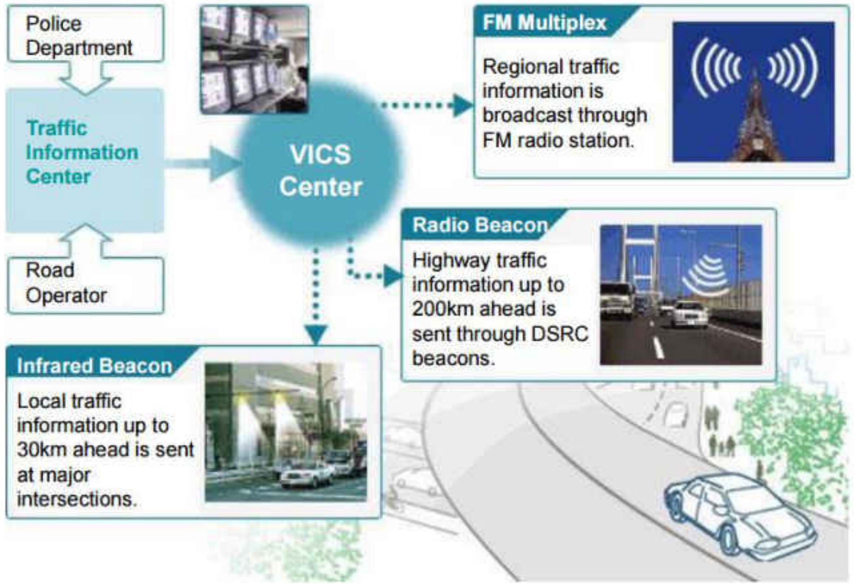


Figure 2-14 Structure of Vehicle Information and Communication Systems (Ministry of Land, Infrastructure, Transport and Tourism Japan 2013)

For example, the information of traffic and weather conditions can be provided to inform drivers about the potential issues ahead (Figure 2-15).

Figure 2-15 In-vehicle device in Japan (Ministry of Land, Infrastructure, Transport and Tourism Japan 2013)

Meanwhile, a guide-light delineation system has been employed in Japan since 2012 to overcome the problem of road marking being covered by snow. A green LED lamp is installed at the road shoulder and provides cues to drivers about the road geometry (Figure2-16). *Hagiwara et al. (2015)* evaluated the effects of the guide-light delineation system by driving simulator, and found significant positive effects of the system on driver mental workload under snow cover condition during nighttime.

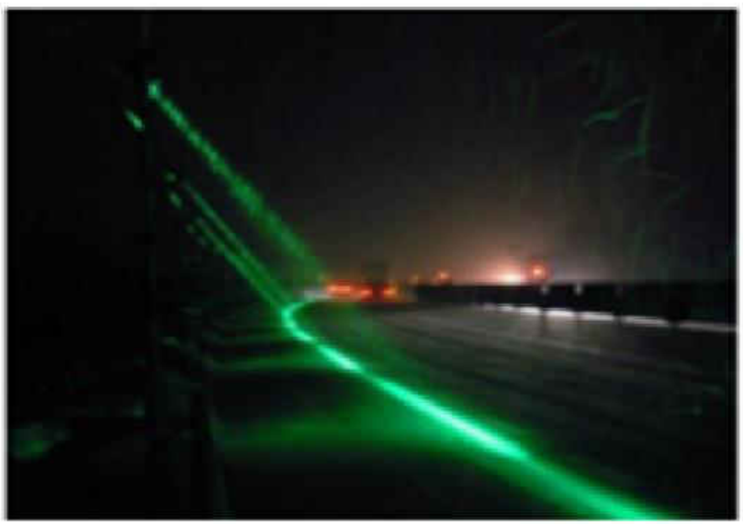


Figure 2-16 Guide-light delineation system in Japan (Hagiwara et al. 2015)

2.2 Studies of Visibility Systems

Previous analyses have revealed that rain or snow has significant impact on road traffic, such as speed and capacity (Ries 1981, Brilon and Ponzlet 1996, Manual 2000). Low visibility conditions, as one of the adverse weather conditions, also have significant impact on the road traffic flow (Table 2-4). The research performed by Agarwal *et al.* (2006) suggested that fog can lead to 12% capacity reduction.

Low visibility conditions will have significant impacts on the road traffic flow. Some of the drivers would decrease their speed, while others will not during the low visibility conditions (Al-Ghamdi 2007). It was reported that the average speeds of the freeway traffic flow during the low visibility could be reduced by 10%-12% (U.S.DOT 2014).

Table 2-4 Weather impacts on roads, traffic and operational decisions (Goodwin and Pisano 2003)

Road Weather Variable	Roadway Impacts	Traffic Flow Impacts	Operational Impacts
Fog	• Visibility • Distance	• Traffic speed • Speed variance • Travel time delay • Accident risk	• Driver capabilities/behavior • Road treatment strategy • Access control • Speed limit control

Agarwal *et al.* (2006) analyzed the capacities and speed reduction due to fog, and revealed the significant impacts of fog. From Table 2-5, we can observe that low visibility conditions will have negative effects on road capacities and average speeds. However, the selection of speed reduction is different, resulting in higher speed variation (Hawkins 1988, Abdel-Aty 2014).

Table 2-5 Comparison of percentage reductions in capacity and average operating speeds (Agarwal *et al.* 2006)

Variable	Range	Capacities (percentage reduction)	Average operating speeds (percentage reduction)
Visibility	1-0.51 mile	9	6
	0.50–0.25 mile	11	6
	< 0.25 mile	10.5	11

Abdel-Aty (2014) explored the relationship between reduced visibility and traffic flow characteristics. The study concluded that the variation of both headway and speed, and the average headway are higher while the average speed is lower in reduced visibility conditions.

Differences in traffic flow patterns are also pointed out under adverse weather conditions. Hou *et al.* (2013) used systematic procedures to calibrate weather effects on traffic flow models. The results shows that visibility and precipitation intensity significantly impact on traffic flow. Seeherman and Skabardonis (2015) studied the variability in bottleneck discharge flow during adverse weather that includes rainfall, wind and reduced visibility. The study found that reduced visibility would lead to a lower discharge flow. Elhenawy *et al.* (2015) developed an automated congestion identification algorithm that includes the weather and visibility impacts using a mixture linear regression model to identify and rank traffic bottlenecks. Bartlett *et al.* (2015) tried to validate the traffic model during the inclement weather conditions. They attempted to model the average speed and the hourly volume while taking weather into consideration. From the results, they recommended that a separate speed prediction model under the inclement weather condition could improve the model performance. Weng *et al.* (2015) attempted to study the traffic flow at signalized intersections under adverse weather conditions. The study concluded that the saturation flow rate would be decreased while the start-up lost time will increase under the adverse weather conditions. Qing *et al.* (2015) conducted a GPS based trip analysis and taxi services analysis during adverse weather in New York City. The results indicate that average trips of the travelers will be shorter and slower during the storm conditions. However, the taxi trips in the storm conditions during the regular work hours are similar to the taxi trips during the regular workdays.

Theofilatos and Yannis (2014) offers a review of the current studies about the effects of weather characteristics on road safety. They found that there is a trend of using real-time data to conduct the traffic safety impact analysis. However, the combined effects of the weather and other factors are needed to be identified, while the different effects in different areas (rural/urban or different countries) are needed to be explored. Also, more attentions should be paid to the vulnerable road users during the adverse weather conditions.

Under the fog conditions, drivers are prone to adjust their driving behavior, including changing their speeds and headways (White and Jeffery 1980, Van der Hulst *et al.* 1998). However, reaction to the low visibility conditions is quite different by drivers. For example, some of the drivers would decrease their speed, while others would not during the low visibility conditions (Al-Ghamdi 2007). Different reactions to the low visibility may result in a variation in traffic flow.

An important behavior during the low visibility condition is the drivers' car-following behavior, which can be used to explain the process of rear-end crashes (Oh *et al.* 2006, Oh and Kim 2010). The car following performance is found to be related to the drivers' age, experience and some other factors. The results from a questionnaire (Shepard 1996) indicated that 46% drivers were more prone to follow other vehicles, 29% drivers were prone to follow the pavement strips, and 5% of drivers said they will pull their vehicles off the road during low visibility conditions. A particular change of the behavior under low visibility situation is that drivers tend to reduce the gap (Hogema and Van der Horst 1994). Meanwhile, Ni *et al.* (2010) suggested that older drivers would like to maintain closer gap compared with young drivers during fog conditions. Serval studies have been conducted to explore the reasons of gap reduction. Previous studies have found that some drivers are likely to maintain shorter headways in the low visibility conditions. Some researches were trying to figure out the reason for the decrease in headway. Their results indicate that the drivers are trying to follow the front car and hope to maintain a visual contact with the front car (Evans and Rothery 1976, Saffarian *et al.* 2012). Besides, it was suggested that drivers are more likely to overestimate distance by as much as 60% in fog. Obviously, because of the reduced gap, drivers may not have enough space to brake which increases the risk of rear-end collisions (Shi and Tan 2013).

Even though drivers are prone to reduce their speed during the low visibility conditions, the reduction of the speeds is found to be insufficient. Sumner *et al.* (1977) found that the driver will reduce their speed when the visibility is below 100 m. However, half of the drivers were driving at a higher speed, which they could not stop safely. Some researchers have made efforts to find the reasons about the relatively high operating speeds of the drivers in reduced visibility conditions. The current studies reveal that the drivers could have false perspective of their operating speed when they are driving in a low visibility condition (Kang *et al.* 2008, Brooks *et al.* 2011). Their studies show that the low visibility will decrease the driver's ability to perceive speed (Snowden *et al.* 1998, Kang *et al.* 2008).

Driving simulators have been widely employed to investigate the changes of driver behavior under fog conditions. In 1998, Van der Hulst *et al.* (1998) found that drivers would increase time headways and prone to reduce speed in reduced visibility conditions. However, some studies pointed out that some drivers are likely to reduce headways during fog in order to maintain a visual contact with the front car (Caro *et al.* 2009, Saffarian *et al.* 2012). Broughton *et al.* (2007) pointed out that fog would separate drivers into two groups: "Lagger" and "Non-Lagger" at high speed scenarios, which means some drivers choose shorter headways during fog and are willing to stay within visible range of the lead car (Non-Lagger). Yan *et al.* (2014) conducted a driving simulator experiment and found that the driver's speed control behavior varied at different risk levels. They also concluded that the professional drivers tend to have lower speeds when they are facing low visibility conditions. Li *et al.* (2015b) investigated the driver behavior on s-curved road segments under fog conditions. The experiment results reveal the differences in control abilities between the professional drivers and the non-professional drivers. The results also indicated that non-professional drivers are less skilled in both longitudinal and lateral vehicles control.

Based on a driving simulator experiment with a repeated measures design, Hoogendoorn *et al.* (2010) quantified adaptation effects in case of low visibility condition and calibrated the parameters for mathematical models of car-following behavior. From the study, no significant effect of low visibility on deceleration was found. Basically, a smaller deceleration rate may be employed if the drivers think they have enough distance to decelerate, while an emergency brake may be employed when the drivers encounter a dangerous situation. Previous analysis showed that drivers will probably feel uncomfortable if the longitude acceleration is higher than 0.25 g (Wu *et al.* 2009). Bonsall *et al.* (2005) found that a reasonable deceleration rate is 5 m/s^2 for dangerous conditions and 2.5 m/s^2 for normal conditions in simulation analysis.

There are several research studies focusing on braking control. Hiraoka *et al.* (2005) proposed car-following behavior model based on a minimum jerk theory. It was expected that the proposed model can be employed to realize comfortable Adaptive Cruise Control (ACC) system. Ferrara and Pisu (2004) proposed a cruise control strategy to guarantee a bounded jerk so as to avoid too frequent changes between acceleration and brake. Wu *et al.* (2009) calculated the required car's deceleration rate when the front car has braked. Based on the relationship between calculated deceleration rate and comfort levels, the following car's status was divided into three zones: comfort, discomfort, and dangerous. However, few studies have been conducted for the braking control analysis under low visibility situation. The above mentioned studies may be limited since drivers can't immediately observe the situation ahead with reduced visibility.

Previous studies have found that there are more severe injury crashes and multi-vehicles crashes during fog (Abdel-Aty *et al.* 2011). Abdel-Aty *et al.* (2012b) examined the relationship between the traffic data and the reduced visibility crashes. The data was collected from loop/radar detectors and Automatic Vehicle Identification (AVI) sensors. The model has good prediction accuracy of the reduced visibility crash occurrence. Ahmed *et al.* (2014) developed a Bayesian logistic regression model using six years' (2005-2010) of crash and weather data from eight airports in Florida. The results show that crash risk can be predicted using the visibility conditions within 5 nautical miles radius from the center of the airports. Huang *et al.* (2010) conducted a hotspots analysis for the low visibility related crashes in Florida. They found that the morning hours in December to February are more likely to experience fog-related crashes, while head-on and rear-end crashes are the two most prevalent types of crashes. They also concluded that the road with higher speeds, undivided road segments and road without sidewalk are more prone to have crashes under reduced visibility conditions. In addition, low visibility related crashes are more likely to occur on two-lane rural roads. Meanwhile, recent studies also pointed out that the fog impact is more significant when visibility drops below a certain level, and the risk of rear-end crashes increases significantly during low visibility (McCann and Fontaine 2016). Zheng *et al.* (2015) studied the secondary crashes on statewide freeway networks in Wisconsin and revealed that low visibility can probably lead to secondary crashes, while the rear-end type of crashes is the most common secondary crash type.

There are some studies that have been conducted to examine the relationship between weather and crashes (Edwards 1999, Golob and Recker 2003). It was found that the average crash rates increase by 71% and 84% in rain and snow, respectively (Qiu and Nixon 2008). Yu *et al.* (2013) analyzed the hazardous factors on a mountainous freeway, and suggested that the weather conditions, especially precipitation, have significant impacts on crash occurrence. Li *et al.* (2015a) attempted to identify the weather-sensitive-hotspots in order to find better locations to place the environmental sensor stations.

Meanwhile, the increasing use of the multi-type of data has made the combined effect analysis more possible. There are many factors that may have influences on the crash likelihood or the crash severity. Wang *et al.* (2015) examined the crashes that happened on the expressway ramps and the results indicate that visibility is a significant factor for both single- and multi-vehicle crash occurrence. There are also some efforts to develop reduced visibility related crash prediction models. Hassan *et al.* (2013) developed a prediction model based on random forests and matched case-control logistic regression model. They concluded that the higher occupancy rate of the downstream at 10-15 minutes before the crashes would increase the low visibility crash likelihood. Xu *et al.* (2013) analyzed the crash likelihood in rainy and fog conditions. The results indicate that the reduced visibility crashes is highly related to the crash-prone speed difference between the upstream and the downstream.

2.3 Chapter Summary

This chapter introduced the state-of-practice of visibility systems in the US and around the world. Previous studies that are related to the low visibility effects on traffic flow and driver behavior are also reviewed. There are some limitations of the current visibility studies. First, many of the recent studies are based on driving simulator experiments, and there are few efforts that are based on field studies. Combing the information of real-time visibility conditions and visibility information may help improve the performance of visibility systems. Also, kinematics analysis is needed to have a better understanding of driver behavior under reduced visibility conditions.

CHAPTER 3: CRASH RISK ANALYSIS DURING FOG CONDITIONS USING REAL-TIME TRAFFIC DATA

3.1 Introduction

The effects of weather events on traffic operations and safety have become a more important issue, and visibility reduction due to fog is a major concern. In recent years, the number of the fatal crashes involving fog shows a decreasing trend. However, there are still about 300-400 fog related fatal crashes happening every year in the United States (Hamilton *et al.* 2014). It has been shown that low visibility conditions have significant impact on the road traffic flow. However, reaction to the low visibility conditions is quite different by drivers. For example, some of the drivers would decrease their speed, while others would not during the low visibility conditions (Al-Ghamdi, 2007). Different reactions to the low visibility may result in a variation in traffic flow.

Previous studies have found that there are more severe injury crashes and multi-vehicles crashes during fog (Abdel-Aty *et al.* 2011). Abdel-Aty (2014) explored the relationship between reduced visibility and traffic flow characteristics. The study concluded that the variation of both headway and speed, and the average headway are higher while the average speed is lower in reduced visibility conditions. Abdel-Aty *et al.* (2012b) examined the relationship between the traffic data and the reduced visibility crashes. The data was collected from loop/radar detectors and Automatic Vehicle Identification (AVI) sensors. The model has good prediction accuracy of the reduced visibility crash occurrence. Ahmed *et al.* (2014) developed a Bayesian logistic regression model using six years' (2005-2010) of crash and weather data from eight airports in Florida. The results show that crash risk can be predicted using the visibility conditions within 5 nautical miles radius from the center of the airports. Huang *et al.* (2010) conducted a hotspots analysis for the low visibility related crashes in Florida. They found that the morning hours in December to February are more likely to experience fog-related crashes, while head-on and rear-end crashes are the two most prevalent types of crashes. They also concluded that the road with higher speeds, undivided road segments and road without sidewalk are more prone to have crashes under reduced visibility conditions. In addition, low visibility related crashes are more likely to occur on two-lane rural roads.

There are some studies that have been conducted to examine the relationship between weather and crashes (Edwards, 1999, Golob and Recker, 2003). Theofilatos and Yannis (2014) offered a review of the current studies about the effects of weather characteristics on road safety. The review pointed out that that there is a trend of using real-time data to conduct the traffic safety impact analysis. However, most of the previous studies focused on the effects of precipitation, snow and some other weather conditions, but few have addressed the low visibility conditions. Yu *et al.* (2013) analyzed the hazardous factors on a mountainous freeway, and suggested that the weather conditions, especially precipitation, have significant impacts on crash occurrence. Li *et al.* (2015a) attempted to identify the weather-sensitive-hotspots in order to find better locations to place the environmental sensor stations.

Meanwhile, the increasing use of the multi-type of data has made the combined effect analysis more possible. There are many factors that may have influences on the crash likelihood or the crash severity. Wang *et al.* (2015a) examined the crashes that happened on the expressway ramps and the results indicate that visibility is a significant factor for both single- and multi-vehicle crash occurrence. There are also some efforts to develop reduced visibility related crash prediction models. Hassan and Abdel-Aty (2011) developed a prediction model based on random forests and matched case-control logistic regression model. They concluded that the higher occupancy rate of the downstream at 10-15 minutes before the crashes would increase the low visibility crash likelihood. Xu *et al.* (2012) analyzed the crash likelihood in rain and fog conditions. The results indicate that the reduced visibility crashes are highly related to the speed difference between the upstream and downstream.

Although there have been many efforts undertaken to evaluate traffic safety during fog conditions, most of the previous research studies have been based on crash data analysis or driving simulator experiments. Even though driving simulators could be a good tool to explore the driver behavior in fog, it cannot provide information about the traffic flow condition under the reduced visibility conditions. As for the studies based on crash data, they heavily rely on crash cases. A long study period is usually needed to obtain enough crash cases. Also, most of the previous research studied the locations with higher crash frequency during fog. However, it is difficult to identify the locations that crash risks increase because of the nature of rare traffic crash occurrence during fog. The possible solution to overcome this issue is to analyze the traffic change at the fog durations and identify the potential increase of crash risk based on the traffic data. Then, the locations which may experience higher crash risk under fog conditions can be identified.

In this study, both weather and traffic data are collected and the changes of traffic flow under fog conditions are investigated. Based on the changes of traffic flow, a concept of crash risk indicator is suggested in order to explore the changes of crash risk during fog. Subsequently, a logistic regression analysis is conducted to identify the factors contributing to increasing crash risk during fog.

3.2 Data Preparation

3.2.1 Study Area

This study based on two types of data sources: (1) weather data and (2) traffic data. The data for the study is from November 2014 to April 2015, when fog conditions are frequently present in Florida. The weather data were collected from the National Climate Data Center (NCDC), which archives weather data from nationwide weather stations operated by the National Oceanic Atmospheric Administration (NOAA). Two weather stations were selected in this study, which are Tampa Executive Airport and Orlando Executive Airport (Figure 3-1). According to previous research, both regions cover hotspots of fog-related crashes (Abdel-Aty *et al.* 2012a).

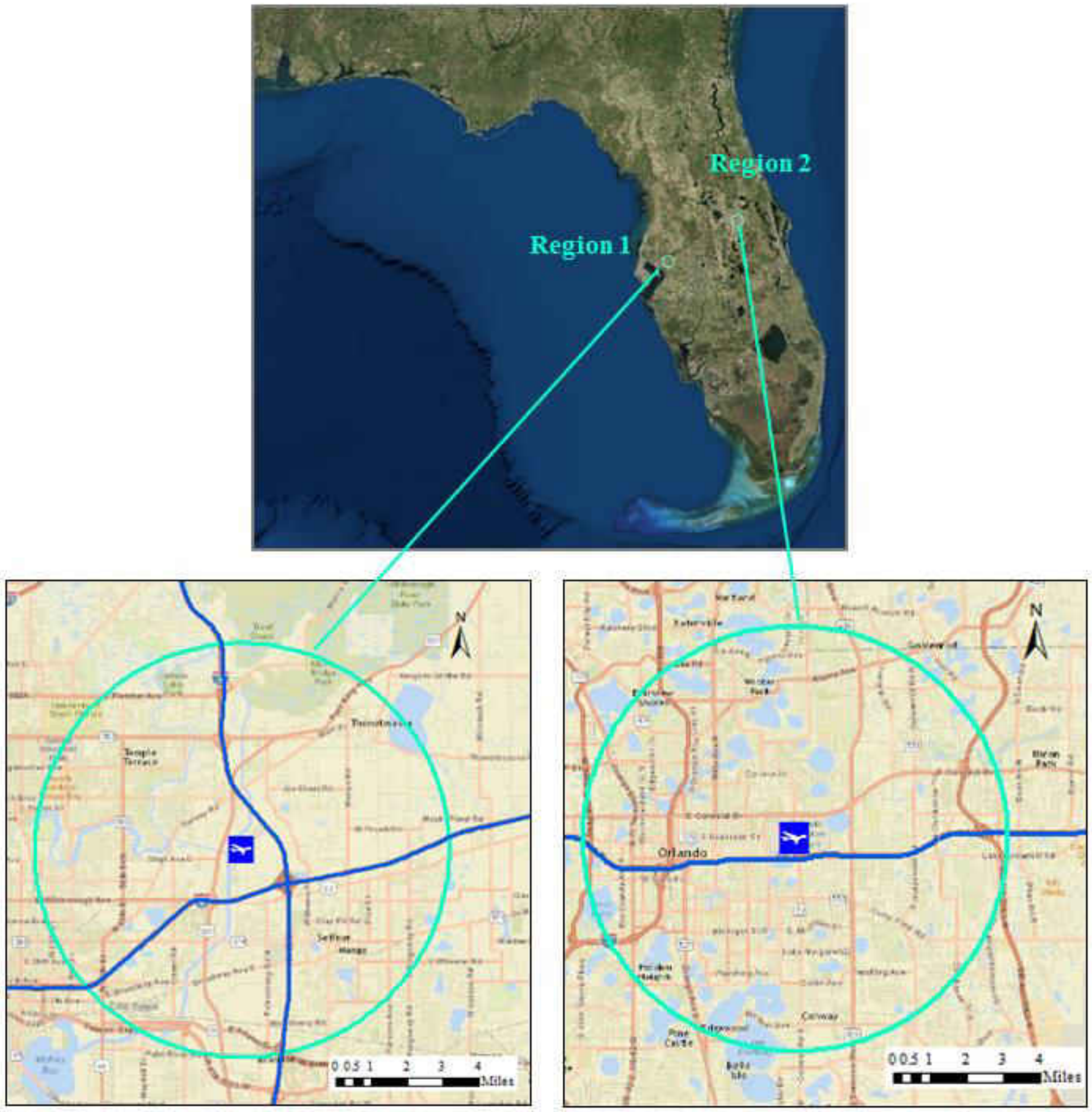


Figure 3-1 Study area

Previous research revealed that fog related data that was collected from the airports can be utilized to indicate the road weather conditions for adjacent areas within 5 nautical miles (5.8 statute miles) (Ahmed *et al.* 2014). Some of the traffic data was collected from LDs (loop and radar detectors) that are spaced at approximately 0.8 mile for about 7 miles and 11 miles of I-75 and I-4 in Tampa, respectively. The other traffic data was collected from Microwave Vehicle Detection System

(MVDS) sensors spaced at 0.4 mile for about 10 miles of SR-408 (East-West Expressway) in Central Florida.

3.2.2 Traffic Data and Detector Location Information

The detector system provides traffic volume (vehicle count), average speed (mph), and occupancy (the percent time that the sensor is occupied). The traffic information was aggregated to 5-minutes intervals, and the standard deviation for each 5-minute interval is calculated. In this study, there are a total of 43 detectors on I-75 southbound, I-4 westbound, and I-4 eastbound in Region 1, and 27 detectors on SR-408 in Region 2 for both eastbound and westbound directions. Thus, 70 detectors are included in this study. The three lanes that are closest to the median in both directions were used. Also, according to the Highway Capacity Manual (HCM, 2010), the influence area of ramp vicinities can be beyond 1500 ft. (0.3 mile). Thus, in this study, if a detector is located within 0.4 mile upstream/downstream of an off ramp/on ramp, the detector will be treated as within off ramp/on ramp vicinity.

3.2.3 Weather Data and Event

The weather data reported by the NCDC is not organized by a specific time interval, but the station will update the readings if there is a change in the weather conditions (e.g. fog, rain, etc.). The weather data include weather types, visibility (ranges from 0.25 to 10 miles), temperature, humidity, wind speed, etc. Thus, the fog event can be detected and the corresponding visibility distance can be obtained. According to the Highway Capacity Manual (2000), fog will impact traffic when the visibility is lower than 1 mile. Thus, fog events were selected when a fog event was reported while the corresponding visibility was less than 1 mile. The fog events are based on the starting and ending times of the fog. If rain was present before the fog duration, the corresponding fog events would be removed in this study in order to exclude the effects of the wet pavement. Based on the above selection rules, 55.56 hours of data in Region 1 and 32.25 hours of data in Region 2 were selected in this study.

3.3 Preliminary Analysis

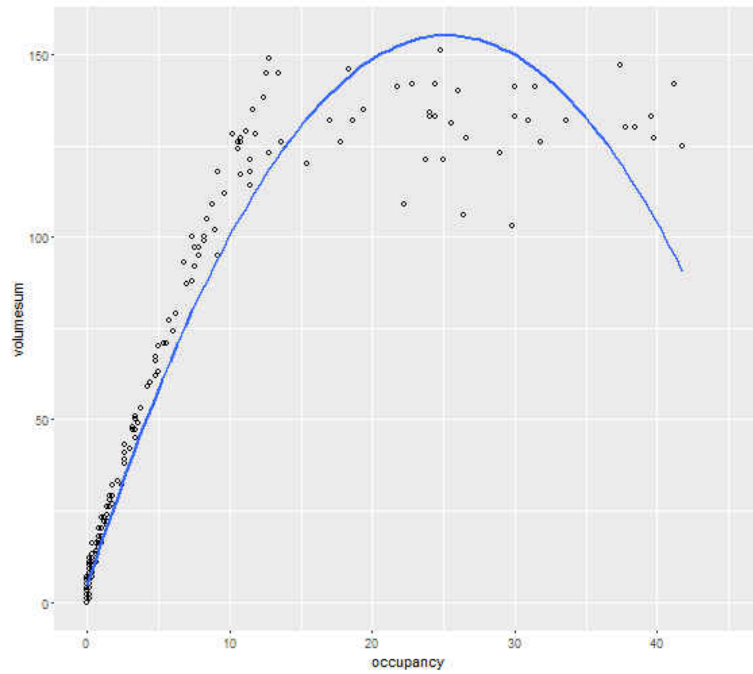
In order to analyze the fog impact on traffic flow, each event observation has a corresponding control observation, which has the same time period, similar day (weekday/weekend), and a clear weather condition. In total, there are 210 samples in this study. Each sample's traffic information was collected for both case and control (fog and clear) durations.

The differences in traffic characteristics between the case group (fog) and control group (clear) are analyzed in order to understand the fog impact on traffic flow. Fifty-five percent of the samples' speeds decreased significantly (p-value=0.10), which indicates that many drivers are prone to drive at a lower speed during fog. The results are consistent with previous research (Al-Ghamdi 2007). Also, there is a clear trend that drivers in the center lanes are more likely to decrease their speeds, where 67.1% of the samples' speeds decrease significantly at the 0.10 significant level. Meanwhile, 52.4% samples' volume decreases significantly at the fog duration. However, a difference between the two regions is observed, 74.2% and 14.8% of samples' volume decrease significantly in Region 1 and Region 2, respectively.

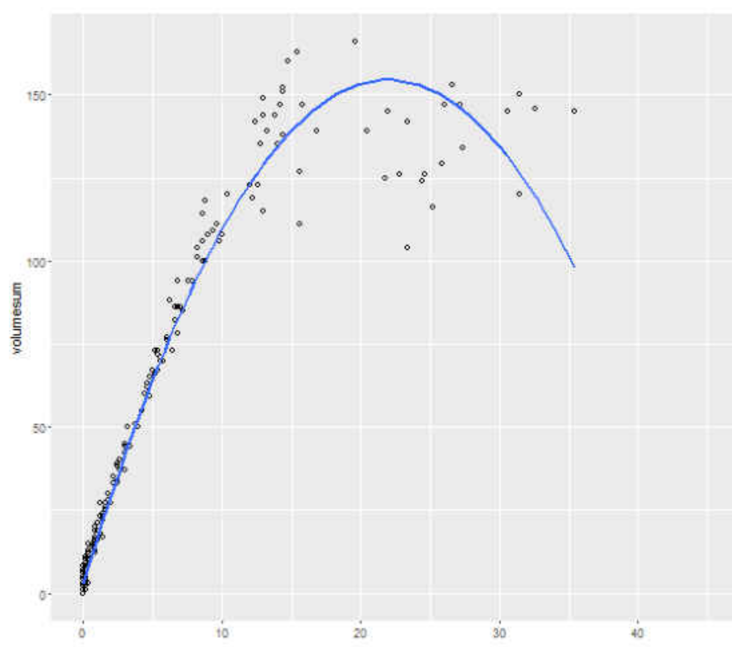
Figure 3-2 provides an example of the volume-occupancy relationship for the innermost lane during both fog and clear conditions at SR-408. The congestion percentage in fog conditions was 7.9%, while the congestion percentage decreases to 5.2% in clear conditions. Thus, more congestion situations were observed during fog. Meanwhile, a regression analysis was conducted for fog conditions and clear conditions, separately. The R-Square values are 0.96 for fog conditions and 0.98 for clear conditions.

Average volume during fog conditions= = $-0.23*(\text{occupancy})^2 + 11.82*\text{occupancy} + 5.47$

Average volume during clear conditions= = $-0.31*(\text{occupancy})^2 + 13.77*\text{occupancy} + 3.17$



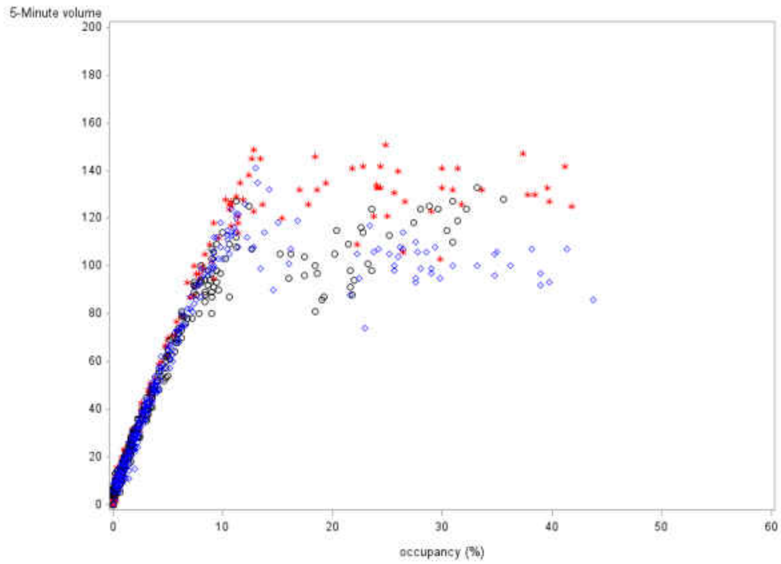
(a) Fog conditions



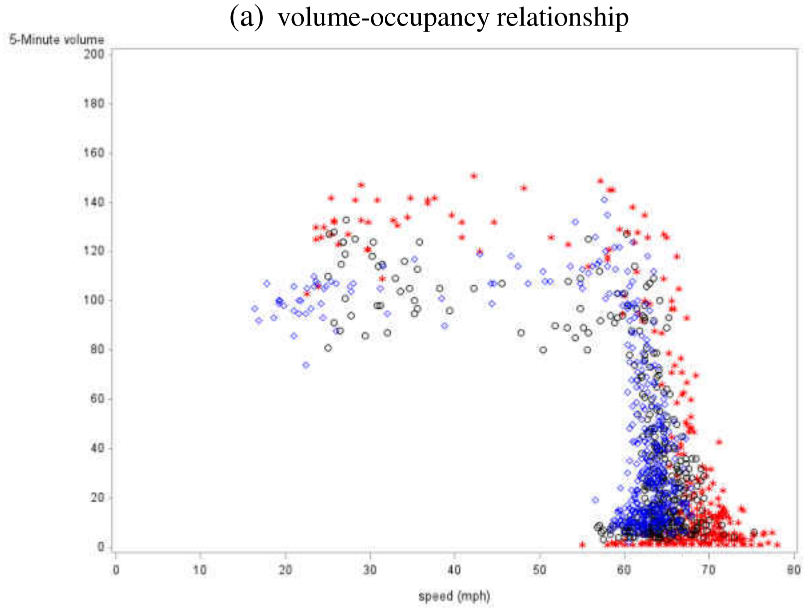
(b) Clear conditions

Figure 3-2 Volume-occupancy relationships in both fog and clear conditions

A slight difference between lanes can be observed at the fog duration, especially during congested conditions (Figure 3-3). There is a clear trend that the lane that is closer to the median has a higher capacity compared to the other lanes in fog conditions.



(a) volume-occupancy relationship



(b) volume-speed relationship

Lane 1(innermost lane) : *Lane 2*(middle lane): *Lane 3* (outer lane):

Figure 3-3 Traffic flow relationships in fog conditions by different lanes

3.4 Methodology

3.4.1 Crash Risk Increase Indicator (CRII)

Previous studies have shown that freeway crashes are found to be associated with certain traffic flow conditions. Traffic flow conditions could impact crash risk. It has been proven that a heavier traffic or a higher occupancy may lead to an increase of the crash risk (Madanat and Teng, 1995, Martin, 2002, Shi *et al.* 2014). Oh *et al.* (2005) explored the relationship between crash risk and real-time traffic data. They revealed that the standard deviation of speed in 5-minute interval can be a good indicator of crash likelihood increase. Meanwhile, previous studies have found that a higher speed can significantly increase the crash risks during fog (Owens *et al.* 2010, Mueller and Trick, 2012).

Crash risk would be higher when there is a significant transition of traffic status within a road segment. Previous results show that the average occupancy downstream coupled with the average speed downstream and upstream would increase the risk of reduced visibility related crashes (Hassan and Abdel-Aty, 2011, Abdel-Aty *et al.* 2012b). Lee *et al.* (2003) found that the difference between the speed at the upstream and the downstream detectors is higher if crashes occur. Xu et al. (2012) evaluated the impact of the traffic state on freeway crash risks. They concluded that the crash risk would be much higher than other statuses when the upstream has “uncongested” status and the downstream has “congested” status. In this study, at each five minutes duration, the studied locations’ statuses can be divided into “congested” and “uncongested”. The comparison between the studied location’s status and its two closest upstream locations that share the same lane is conducted in order to study the traffic flow condition at the fog duration (Figure 3-4).

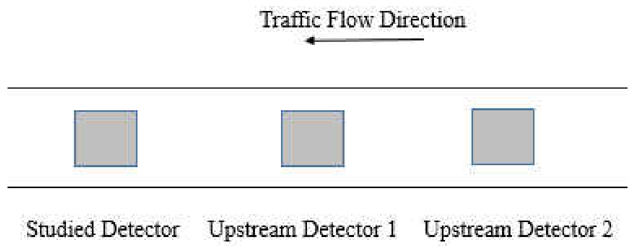


Figure 3-4 the relationship between the studied detector and its upstream detectors

Thus, the traffic flow statuses are divided into four categories (Table 3-1), while status 1 has the highest crash risk (Xu *et al.* 2012). Status 1 is defined as "dangerous status" in this study.

Table 3-1 Traffic flow categories (Xu *et al.* 2012)

		Sample status	
		Congested	Uncongested
Upstream sample status	Congested	Status 2	Status 3
	Uncongested	***Status 1***	Status 4

Based on the above analysis, Crash Risk Increase Indicator (CRII) is employed to describe the possible increase of the crash risks at a specific location and lane. The CRII value considered both local traffic flow characteristics status and traffic flow status. The local traffic flow characteristics status uses data from one detector and traffic flow status uses data from multiple detectors (the studied detector and the two closest upstream detectors). The CRII can only have two values: CRII=1 for crash risks possible increase, and CRII=0 for no crash risk increase.

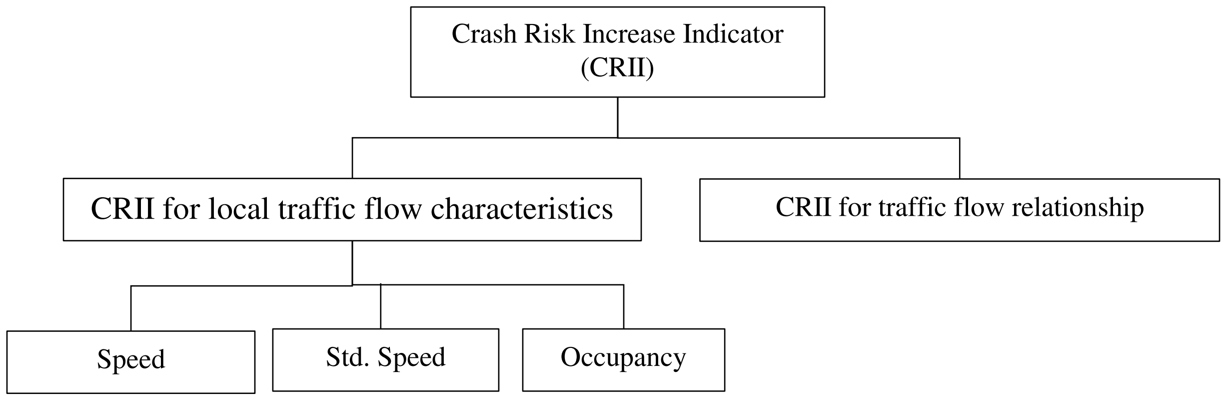


Figure 3-5 Crash Risk Increase Indicator (CRII)

The CRII includes the following parts (Figure 3-5):

a. CRII for Speed: if average 5-minute speed increases during fog (CRII for Speed=1: average 5-minute speed increases during fog; CRII for Speed=0: average 5-minute speed does not increase during fog).
b. CRII for Std. speed: if average 5-minute speed standard deviation increases significantly during fog at 0.10 significant level (CRII for Std. speed =1: average 5-minute speed standard deviation increases significantly during fog; CRII for Std. speed=0: average 5-minute speed standard deviation does not increase significantly during fog).
c. CRII for occupancy: if average 5-minute occupancy increases significantly during fog at 0.10 significant level (CRII for occupancy=1: average 5-minute occupancy increases significantly during fog; CRII for occupancy=0: average 5-minute occupancy does not increase significantly during fog).

d. CRII for traffic flow relationship: if the studied location has more dangerous status (status 1) during fog (CRII for traffic flow relationship=1: the duration of status 1 increased by 1% or more during fog; CRII for traffic flow relationship=0: the duration of status 1 increased less than 1% during fog.)

Thus, the CRII value for a specific location is based on four different CRII values, which is given by Eq. (3-1)

$$\text{CRII value} \\ = \max\{\text{CRII for Speed}, \text{CRII for Std. speed}, \text{CRII for occupancy}, \text{CRII for traffic flow relationship}\} \tag{3-1}$$

3.4.2 Logistic Regression Model

A binary logistic regression is proper to use to explain the increase of the crash risk (CRII) as a function of several factors. Table 3-2 shows the factors that were considered in this study. It should be noted that the "area dummy" variable is included in the logistic regression model to deal with the regional effect.

Table 3-2 Variables considered for the model

Symbol	Description
Onramp	The detector located within 0.4 mile downstream from the closest on ramp
Offramp	The detector located within 0.4 mile upstream from the closest off ramp
Innerlane	Lane location. Innerlane=1: the lane closest to the median Innerlane=0: Other lanes.
Volume	Average 5-minute volume at the fog duration
Speed	Average 5-minute speed at the fog duration
Stdspeed	Average 5-minute speed standard deviation at the fog duration
Area dummy	Regional Location. Area dummy=0: Region1; Area dummy=1: Region 2

A logistic regression model is developed to study the impact factors for the increase of the crash risk during fog. The probability that the crash risk possibly increase (CRII) with fog is modeled as logistic distribution in Eq. (3-2):

$$\pi(x) = \frac{e^{g(x)}}{1+e^{g(x)}} \tag{3-2}$$

The Logit of the logistic regression model is given by Eq. (3-3):

$$g(x) = \ln\frac{\pi(x)}{1-\pi(x)}=\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots\ldots + \beta_n x_n \tag{3-3}$$

where $\pi(x)$ is the conditional probability of crash risk possibly increasing with the presence of fog. $x_1, x_2 \ldots x_n$ are the independent variables that can be either categorical or continuous. The LOGIT procedure in the Statistical Analysis Software (SAS) is adopted to determine the variables in the model. The stepwise method is performed to select the independent variables with a significance level of 0.05. The final model is judged adequate for the Hosmer-Lemeshow statistic of model fit. The measurement AUC, which indicates the area under an ROC curve, is also used to assess the performance of calibrated models.

3.5 Results

3.5.1 Preliminary analysis results of Crash Risk Increase Indicator (CRII)

Local traffic flow characteristics indicators for the CRII include: the speed indicator, the standard deviation of speed indicator, and the occupancy indicator. Among all the risk indicators, the risks that are related to the average 5-minute speed and the average 5-minute occupancy are most common during fog conditions, where 15.7% of the samples' average 5-minute speed increase and 13.3% of the sample average 5-minute occupancy increase significantly.

Chi-Square tests were conducted in order to find the relationships between local traffic flow characteristics indicators and the samples' locations. The samples' on/off ramp locations and the lane locations are considered in this study. From Table 3-3, CRII for speed is significantly different between off-ramp vicinities and other locations. In this study, the percentage of the samples that have higher average 5-minute speed is 21.11% at off-ramp vicinities and 11.76% at other locations. The results indicate that drivers are more likely to decrease their speed when they are not driving near off-ramp vicinities under fog conditions. Meanwhile, the occupancy indicator is found to be highly related to its lane location and if it is located within an on-ramp vicinity. The percentages of locations that have observed a significant increase of the 5-minute occupancy during fog are 23.53% and 10.13% at on-ramp vicinities and other locations, respectively. Meanwhile, 22.86% of the samples' average 5-minute occupancy increase significantly at the innermost lane, while only 9.45% at the other lanes. Thus, if a sample is located on the lane closest to the median or within an on-ramp vicinity, it is more likely to have higher occupancy with the presence of fog.

Table 3-3 Chi-Square test for local traffic flow characteristics indicators

	On ramp		Off ramp		Lane position	
	Value	P-value	Value	P-value	Value	P-value
Speed	1.8177	0.1776	***3.3667***	***0.0665***	1.6228	0.4442
Std. speed	2.2408	0.1344	0.0153	0.9014	2.6603	0.2644
Occupancy	***5.9694***	***0.0146***	0.6347	0.4256	***9.0682***	***0.0107***

* Bold fonts stand for statistically significant ($p<0.1$).

If none of the three local traffic flow characteristics indicators show an increasing trend of crash risk during fog, the CRII value for the local traffic flow characteristics will equal 0, otherwise it will equal 1. In total, there are 66.2% of the samples for which no observation was found that any of the CRII value for local traffic flow characteristics increase. The Chi-Square test shows that the increase of the CRII for local traffic flow characteristics value is related to the location within an on-ramp vicinity (Chi-Square=3.5923, P-value= 0.0580).

More congestion is observed during fog conditions. There are 5 roadways that are included in this study, while only 3 of them have observed congestion during the studied periods (SR-408 westbound, I-4 westbound, and I-75 southbound). Among all the samples on the three roadways, 48.4% of the samples have more congestion during fog conditions when compared with the clear conditions. At the studied duration, 10.5% of the studied locations have more dangerous status (status 1) during fog compared to the clear conditions.

3.5.2 Modeling result considering main factors and interaction effects

According to the analysis above, the CRII value depends on both the local traffic flow characteristics CRII value and the traffic flow CRII value. Thus, 39.0% of the locations' CRII value equals1, which indicate these locations, were prone to have a higher crash risk during fog conditions.

Based on the main effect model (Model 1), the logistic regression analysis identified the significant factors directly associated with CRII value. The estimation results for the logistic regression model are shown in Table 4. Four variables (onramp, offramp, volume, and the interaction between volume and innerlane) were found to be significant. Table 3-4 shows that crash risk increases during fog is more likely to happen at locations that are within ramp vicinities or have a higher volume during fog. Also, the locations with a higher volume and located at the innermost lane are prone to have higher crash risk.

Table 3-4 Estimation results for the model (Model 1)

Parameter	Estimate	Std. Error	Wald Chi-Square	Pr > ChiSq
Intercept	-1.1904	0.4210	7.9959	0.0047
Onramp	0.4762	0.1927	6.1030	0.0135
Offramp	0.4031	0.1696	5.6473	0.0175
Volume	0.0301	0.0105	8.2450	0.0041
Volume*Innerlane	0.0106	0.00417	6.3970	0.0114

AUC: 0.675 p-value for Hosmer-Lemeshow test: 0.5513

3.5.3 Modeling result with regional effects

Since the data is collected at two different regions, regional effects should be considered in the analysis based on the above model. Therefore, a variable named "area dummy" is used for describing the regional locations of the detector (Area dummy=0: Region 1, Area dummy=1: Region 2). Meanwhile, the interaction effects between the area dummy and other variables are also considered in this study. Improvements of the model performance are observed after adding the new variables. Two measurements are employed to evaluate the model performance. The Hosmer-Lemeshow (HL) test for logistic regression is widely used to describe models' goodness of fit. A p-value is produced based on the HL test, while a higher p-value indicates better goodness of fit. The other measurement is the AUC, which is the area under an ROC curve. A higher AUC value usually means a higher model accuracy. If the AUC is greater than 0.7, the model will be considered as “acceptable” (Hosmer Jr *et al.* 2013). In this study, after adding the new variables, the p-value of HL test increases from 0.5513 to 0.7042, while the AUC increases from 0.675 to 0.716. It is worth mentioning that the "area dummy" is a significant variable if its interaction terms are not included in the model, which has a p-value equals to 0.6292 for the HL test and the AUC value is 0.688. However, the final model (Model 2) including the interaction terms has better performance while the dummy area variable becomes insignificant and was excluded from the model.

The estimation results for the logistic regression model with regional effects are shown in Table 3-5. The results indicate that the effect of the average 5-minute volume during fog is different by area, where crash risks of Region 2, which is the area within 5 nautical miles of the Orlando Executive Airport, are more likely to increase with a higher volume. The plausible reason is the differences in the land-use and trip characteristics between the two regions. Moreover, the innermost lanes in Region 2, which are all located on toll roads, have a higher probability to observe an increase in crash risk than those in Region 1. The possible reason is that people are prone to drive longer distance on toll roads and prefer to drive on the innermost lane in order to avoid conflicts with other vehicles. Other reasons that may cause the differences between the two regions are: (1) fog characteristics can be different in the two studied regions (such as fog present timings, duration, visibility levels, etc.).

Table 3-5 Estimation results for the model with regional effects (Model 2)

Parameter	Estimate	Std. Error	Wald Chi-Square	Pr > ChiSq
Intercept	-1.9504	0.5177	14.1941	0.0002
Onramp	0.5358	0.1993	7.2282	0.0072
Offramp	0.4037	0.1749	5.3266	0.0210
Volume	0.0604	0.0152	15.8597	<.0001
Volume*Innerlane	0.0200	0.00539	13.7061	0.0002
Area dummy*Innerlane	0.5984	0.2084	8.2435	0.0041
Area dummy*Volume	0.0182	0.00603	9.0998	0.0026

AUC: 0.716 p-value for Hosmer-Lemeshow test: 0.7042

3.6 Discussion

The aim of the current research is to investigate the change of traffic flow and traffic safety under fog conditions. The effect of fog on traffic flow was examined by comparing the traffic patterns under fog and clear conditions. It was found that the average volume and speed would be reduced under fog conditions. This finding corresponds to the previous study results of drivers' acceptances of larger headway and lower speed (Abdel-Aty *et al.* 2014; Al-Ghamdi, 2007). The result also indicates that drivers will be more cautious when fog is present.

In addition, whether the crash risk will be increased under fog conditions was analyzed based on traffic data. Since the fog crashes are very rare, a Crash Risk Increase Indicator (CRII) was suggested to indicate whether the crash risk can increase based on previous studies of the relationship between crash risk and traffic flow patterns (Hassan and Abdel-Aty 2011; Abdel-Aty *et al.* 2012b; Lee *et al.* 2003; Xu *et al.* 2012) . Specifically, the average speed, speed standard deviation, average occupancy, and upstream and downstream congestion status were adopted to develop the CRII. Based on the CRII value, nearly 40% of 210 samples were found to have increased crash risk under fog conditions (CRII=1). Therefore, this result suggested that the crash risk can increase under fog conditions (Abdel-Aty *et al.* 2011) and a further analysis to identify factors contributing such increase should be conducted.

Logistic regression models were estimated to explore the relation between exogenous factors and the increase of crash risk under fog conditions. The modeling result implied that crash risk would be more likely to increase near ramp areas. This finding agrees with the previous studies that mentioned that the existence of ramps can experience more lane changing behavior resulting in more crashes (Wang *et al*. 2015). Notably, this observed trend in this study implies that specific countermeasures are required at ramp areas to reduce the impact of fog on traffic safety. Besides, it was suggested that fog is more likely to increase the crash risk when the traffic volume is higher. The traffic should be definitely more congested when the volume increase and thus "dangerous status" should be more likely to be observed under fog conditions as suggested in previous studies (Hassan *et al.* 2013; Xu *et al.* 2012). Further, the crash risk is prone to increase in the innermost lane under fog conditions, indicating that specific countermeasures should be introduced to reduce the impact of fog on traffic safety for the innermost lane. Finally, the model considering the regional effect illustrated that the effect of fog on crash risk can vary in different regions. Given the fact that driving behaviors and roadway geometry can be quite different, the result is not surprising.

3.7 Summary and Conclusions

This study aims to identify the changes of traffic characteristics and investigate the situations in which crash risk are more likely to increase during fog. A comparative analysis of the traffic patterns between fog and clear conditions was conducted by using the traffic and weather data. The results reveal that the average volume and the average speed become lower under fog conditions.

A Crash Risk Increase Indicator (CRII) was defined in order to link the crash risk and the real-time traffic data. The CRII includes two parts: CRII for local traffic flow characteristics and CRII for traffic flow relationships. The average 5-minutes speed, the average 5-minute speed standard deviation, and the average 5-minute occupancy were considered for the local traffic flow characteristics CRII analysis. The traffic flow conditions of a location were divided into 4 categories based on the location's congested status and the two closest upstream locations. The traffic flow condition that has the highest crash risk was employed for the traffic flow CRII analysis.

A logistic model was applied to identify the contributing factors that increase crash risk during fog. The model estimation results showed that the crash risk is prone to increase at ramp vicinities and locations with heavier traffic in fog conditions. Also, the innermost lane with heavier traffic is more likely to experience an increase of crash risk during fog. The effect of differences between the regions was also analyzed in this study. The results show that locations that are at the innermost lane or have a heavier traffic in Region 2, which is the area within 5 nautical miles of the Orlando Executive Airport, would be more likely to observe an increase of crash risk in fog conditions.

Due to the lack of the real-time visibility and traffic data, few studies have been conducted to explore the change of traffic safety under fog conditions. This study proposed a Crash Risk Increase Indicator (CRII), which is employed to designate the potential increase of crash risk under fog conditions based on real-time traffic data. The analysis results indicate that the proposed indicator can work properly to reveal the potential crash risk increase under fog conditions and explore the factors contributing to the increase of crash risk. Based on the findings, more attention should be paid to the ramp vicinities when the visibility dramatically decreases due to fog, where there are more conflicts of vehicles. Also, it is important to identify the innermost lanes with heavier traffic since those locations can become more dangerous when fog is present. It is recommended to integrate the proposed indicator and modeling results with ITS technologies to enhance traffic safety under fog conditions. For example, ramp meters can be used in order to control the traffic volume during fog, and thus reduce the impact of fog on crash risk near ramp areas. Also, Dynamic Message Signs (DMS), beacons or road broadcasting could be employed near and at ramps during fog to notify drivers about the potential risk. Also, it is important to identify the innermost lanes with heavier traffic and apply proper countermeasures to improve safety management.

The indicator developed in this study only compares the crash risk between fog and clear conditions. An extension of this study is to compare the crash risk under fog conditions with different visibility levels to explore the impact of reduced visibility on traffic safety. Besides, the Crash Risk Increase Indicator (CRII) suggested in this study can be extended to adapt for the introduction of Connected Vehicles' systems under fog conditions.

CHAPTER 4: DEVELOPING AN ALGORITHM TO ASSESS THE REAR-END COLLISION RISK UNDER FOG CONDITIONS USING REAL-TIME DATA

4.1 Introduction

Fog is a weather condition that reduces visibility of the driving scene, which can cause a serious problem for traffic operation and safety. Usually, fog forms during the late night and early morning, which can increase crash severity (Al-Ghamdi, 2007). The crash data suggest an over-representation of fog crashes in crash fatalities. In the period of 2011-2016, nearly 11,600 fog-related crashes occurred in Florida. Nearly 1.53% of the fog-related crashes are fatal crashes while the proportion of fatal crashes for the total crashes is only 0.43%. Besides, the possibility of multiple vehicle involved crashes could be increased due to the reduced visibility (Abdel-Aty et al., 2011). For example, a fog-related crash with 70-vehicle pileup happened on I-4 in Polk County in January 2008, which caused five deaths and many injuries (Hassan and Abdel-Aty, 2011). Therefore, it is necessary to devote efforts to understand the impact of fog on traffic safety and propose appropriate countermeasures to enhance the safety under fog conditions.

Traditionally, traffic safety analyses are conducted based on historical crash data and identify roadway- and traffic-related factors contributing to the crash risk using statistical methodologies. Hence, the traditional method could suffer from problems such as small samples, underreporting, and misclassification. The problems could become even worse for fog crashes since the events are very rare. In addition, it would be difficult to rapidly evaluate the recent treatments due to the lack of after-treatment crash data, which require observations of a long period (several years) (St-Aubin et al., 2013). Considering the limitations of the traditional safety analyses, various studies have been conducted using individual vehicle data (e.g., vehicle speed and headway) to evaluate traffic safety (Oh et al., 2010; Son et al., 2011). Compared with the literature about traffic safety under clear conditions, traffic safety under fog conditions has attracted much less attention, especially studies based on individual vehicle data. Although some researchers have developed methods to investigate the traffic safety under fog conditions, the methods were proposed based on simplified conditions. Hence, the corresponding conclusions may be limited and biased.

This research aims to contribute to the literature by proposing a new algorithm to evaluate traffic safety under fog conditions and apply it to explore the impact of the reduced visibility together with other traffic parameters on safety.

4.2 Literature Review

In the previous research, only few studies have focused on the effect of fog on traffic crashes by using the historical crash data. Coding (1971) suggested that fog-related crashes were more likely to involve multiple vehicles. Edwards (1996) pointed that fog-related crashes were very rare and highly seasonal. It was found that speed remained a major contributing factor in many of multiple pileup crashes in fog (Edwards, 1998). Wanvik (2009) analyzed the effect of road lighting on fog-related crashes based on historical crash data in Netherlands and concluded that the effect of lighting was significant and underestimated in safety research. Abdel-Aty et al. (2011) conducted a comprehensive analysis of fog-related crashes in Florida. The authors found that the fog-related crashes tend to result in more severe injuries and involve more vehicles. They also concluded that head-on and rear-end crashes were the two most common crash types under fog condition.

Compared to the limited research about the impact of fog on traffic safety, a lot of efforts have been made to investigate the change of driver behavior during fog based on driving simulator studies. By using driving simulator data, Broughton et al. (2007) observed reduced headway distance under fog condition. The authors suggested that the headway distance reduced because the drivers wanted to seek visible cues since the scenery and roadway condition became obscure in fog. Caro et al. (2009) observed similar results of the reduced headway distance and they explained that the adjustment could be a way for drivers to achieve a perceptual control benefit. Ni et al. (2010) investigated the age-related differences in car following behavior in simulated fog condition. The authors found that older drivers would like to maintain closer headway distance (21% closer) compared to young drivers, indicating older drivers were at higher risk especially under heavy fog. Saffarian et al. (2012) found that drivers would feel risky under fog situation and they preferred to follow the leading vehicle as a guide instead of overtaking it. Yan et al. (2014) examined the effect of fog on speed control behaviors based on a driving simulator experiment. It was found that drivers would reduce their speeds significantly under fog condition. Wu et al. (2017) investigated the impacts of fog warning system on driving behavior under fog condition using the driving simulator. The authors found that the warning system may affect drivers' speed choice before they entered fog area. However, the effect of the warning system on drivers' final speed in the fog area is not significant.

Although drivers may reduce their speed under fog condition, they may still not have enough space to decelerate since drivers tend to reduce their headway distance, which may increase the rear-end collision risk (Shi and Tan, 2013). Thus, it would be necessary to evaluate the rear-end collision risk under fog condition and investigate the effects of reduced visibility together with traffic parameters on the rear-end collision risk. One of efficient methods to analyze the crash risk is to analyze the crashes based on the historical data. However, this approach may be limited since the fog-related crashes are very rare and the real-time traffic data are difficult to obtain. For example, only 0.32% of crashes occurred in Florida during the period 2011-2016 are fog-related crashes and the number of fog-related crashes that have available roadway and traffic data could be even smaller. The possible solution to overcome this issue is developing algorithm to calculate surrogate measures to evaluate the traffic safety. In previous studies, different surrogate measures have been calculated including time-to-collision (Oh and Kim, 2010), stopping distance index (Oh et al., 2006; 2009), modified time to collision (Ozbay et al., 2008), and individual vehicle speeds and headways (Hourdos et al., 2006). These earlier studies demonstrated the advantages of surrogate safety measures for traffic safety analysis. However, the algorithm of surrogate measures cannot be directly adopted for safety evaluation under fog condition since most of them were developed for clear condition without the consideration of the reduced visibility under fog condition.

Recently, Peng et al. (2017) assessed the impact of reduced visibility on traffic crash risk by calculating time-to-collision under fog condition. The authors calculated time-to-collision using the visibility distance to replace the actual clearance distance (the distance between the rear bumper of the leading vehicle and the front bumper of the following vehicle) when the visibility distance is less than the clearance distance. Li et al. (2014) used the same approach to develop an algorithm to evaluate the crash risk when they developed a variable speed limit strategy during inclement weather conditions. Although the reduced visibility was considered, the car-following process has been simplified. Specifically, it was assumed that the leading vehicle kept the same speed until the driver of the following vehicle can see the leading vehicle. Thus, it may lead to the inaccurate results regarding the traffic safety under fog condition.

This study contributes to traffic safety analysis under fog condition along two directions: (1) evaluating the rear-end collision risk under fog condition; and (2) exploring the effects of the reduced visibility together with other traffic parameters on the rear-end collision risk. Towards this end, a new algorithm is proposed to evaluate the rear-end collision risk under fog condition. Then, based on the proposed algorithm, the rear-end collision risk can be identified using real individual vehicular traffic and weather data. Finally, a logistic model and a negative binomial model are estimated to quantify the impacts of the reduced visibility and other traffic parameters.

4.3 Data Collection

To evaluate the rear-end collision risk under fog conditions, we collected data on a segment of I-4 in Florida, where severe fog-related crashes have happened (Hassan and Abdel-Aty, 2011). Figure 4-1 shows the layout of the data collection site. As shown in Figure 4-1, there are three lanes in each direction (totally six lanes) at the data collection site. A Remote Traffic Microwave Sensor (RTMS) augmented with a device to collect vehicle based data was installed on the light pole to collect traffic data. The added equipment not only captures the regular traffic parameters but also the headway between each vehicle on each lane. Meanwhile, a Fog Monitoring System (FMS) was installed close to the RTMS to collect the weather data. The FMS is a new visibility detection system by mounting visibility sensor arrays combined with adaptive learning modules to provide more accurate visibility data (Peng et al., 2017).

Figure 4-1 Data collection site

4.3.1 Weather data collection

A FMS consists of three sensors at increasing elevations beginning at one foot one inch. Wireless sensor node microprocessor circuit board to handle the multiple sensor inputs while providing extremely low power consumption, which enables a high rate of data transmissions. As shown in Figure 4-2, the FMS was installed close to the roadway. Beside the fog sensor, a camera was installed nearby to validate data from FMS units. It was indicated that the data collected from the FMS sensors could accurately reflect the visibility condition on the road. The weather data were collected from the FMS installed in the above-mentioned area. In total, 21 variables were collected from the sensors including air temperature, surface moisture, dew point, wind speed, etc. Also, the weather parameters such as rainfall and visibility distance (D_v) were also collected. The upper limit of visibility distance by the FMS is 2,000 m, indicating clear condition. Thus, the weather can be considered as rainy or foggy if the visibility distance is less than 2,000 m. Meanwhile, we can know whether the weather is rainy according to the rainfall data. Hence, we can find out the time when fog is present based on the rainfall and visibility distance data. In January and February 2016, nine days were found to have fog events and the corresponding date, time, and visibility distance were then obtained.

Figure 4-2 Fog Monitoring System (FMS) sensor

4.3.2 Traffic data collection

The RTMS sensors are installed on the side of the roadway, and do not cause temporary lane closures for installation or traffic flow interruption. Hence, this non-intrusive sensor has been widely used as an automatic traffic data collection approach (Ma et al., 2015). The traffic data were collected from the RTMS on I-4 (Figure 4-1). The variables including date, time, instantaneous speed of each vehicle, length of each vehicle, duration of detection, and lane assignment can be obtained directly from the sensors (Table 4-1). According to the study conducted by Yu and Prevedouros (2013), the data accuracy of RTMS can be up to 95%, which is higher than that of single loop detector. Based on the length of each vehicle, we can classify the vehicle type, denoted by V_{type}. In this study, vehicles are grouped into two categories: (i) passenger car and (ii) truck. Since the lengths of motorcycles should be shorter than 6.5ft (Minge et al., 2012), a vehicle is defined as a passenger car if its length is longer than 6.5ft and equal to or shorter than 30 ft. On the other hand, the vehicle is considered as a truck if its length is longer than 30 ft. Motorcycles are not considered in our current study. The headway (h) for each vehicle can also be calculated based on the time when the leading and following vehicles pass the same detector. Then the clearance distance (L) can be calculated as $L = v_F h - l_L$. Here, v_F is the speed of the following vehicle and l_L is the length of the leading vehicle.

Table 4-1 Sample of traffic parameter dataset

Date	Time	Lane	Speed(m/s)	Length(m)	Duration (0.001s)
1/9/2016	9:18:33	1	29.42	5.12	236
1/10/2016	9:18:58	1	29.91	5.36	240
1/11/2016	9:19:02	4	30.18	5.61	246
1/12/2016	9:19:13	3	32.72	4.91	205
1/13/2016	9:19:37	4	26.87	4.45	233
1/14/2016	9:19:40	4	30.18	6.00	258

Based on the recorded date and time, the traffic data under fog conditions can be subtracted and combined with the weather data. The combined dataset was then used to analyze the effects of reduced visibility on traffic under fog condition. The variables included in the combined dataset are presented in the following Table 4-2.

Table 4-2 Description of variables in the combined dataset

Variable	Definition of the variable	Measurement units
Date	Date of data collection	
Time	Time of data collection	
Visibility	Visibility distance	m
Speed	Speed of each vehicle	m/s^2
Length	Length of each vehicle	m
Lane	Lane number of each vehicle	

4.4 Methodology

4.4.1 Rear-End Collision Risk Index (RCRI)

4.4.1.1 Basic Rear-end collision risk Index

Rear-end crashes have been identified as one of the main crash types on freeways. The traffic conflict can be defined in different ways for the read-end crashes depending on the research purpose and design. One of the definitions is to compute vehicles' safe stopping distances. The concept of the safe stopping distance could be defined as the safe distance that the following vehicle could safely reduce speed to avoid the collision with the leading vehicle when the leading vehicles makes an unexpected stop. It assumes that the leading vehicle could respond to a stimulus by taking an emergency stopping maneuver, and then the following vehicle has to react to such a braking maneuver to avoid a collision. Based on the assumption, the stopping distance of the leading vehicle should be larger than that of the following vehicle to avoid the potential rear-end crash. Hence, the safe condition can be mathematically expressed as (Oh et al., 2006; Son et al., 2011):

$$MSD_L > MSD_F \tag{4-1}$$

$$MSD_L = L + \frac{v_L^2}{2 \times a_L} \tag{4-2}$$

$$MSD_F = v_F \times PRT + \frac{v_F^2}{2 \times a_F} \tag{4-3}$$

where, MSD_L and MSD_F are the minimum stopping distance of the leading and following vehicles, L is the clearance distance. v_L is the speed of the leading vehicle and v_F is the speed of the following vehicle. a_L is the deceleration rate of the leading vehicle and a_F is the deceleration rate of the following vehicle. Different deceleration rates will be employed for different vehicle types to estimate more reliable minimum stopping distance (3.42 m/s^2 for passenger cars and 2.42 m/s^2 for trucks). *PRT* is the perception reaction time of the following vehicle in seconds (1.5s was used in this study).

It is noted that the deceleration rate and perception reaction time used in this study are commonly accepted in the transportation practice (Highway and Officials, 2011). Based on the eq. (4-1), the rear-end collision risk index (RCRI) can be defined as

$$\text{RCRI} = \begin{cases} 0\ (safe) & if\ MSD_L > MSD_F \\ 1\ (dangerous) & otherwise \end{cases}$$

The index represents the car-following safety status under clear condition when the following vehicle can see the braking light of the leading vehicle. However, the following vehicle's driver can't see the braking light of the leading vehicle under fog conditions if the L is larger than the visibility distance (D_v) and the following vehicle will keep the speed until the driver can see the leading car. Hence, the above-mentioned index might not be appropriate for the car-following situation under fog conditions. In the following part, this study analyzes the stochastic vehicle kinematics when the leading vehicle makes an emergency brake considering different relations between L and D_v and extends the RCRI to evaluate the rear-end collision risk under different fog conditions.

4.4.1.2 Extending Rear-end Collision Risk Index under Fog Conditions

The following vehicle should employ different vehicle-following maneuvers under different relations between clear distance (L) and visibility distance (D_v). Thus, the rear-end collision risk index (RCRI) might change under different fog conditions. There are two general relations between L and D_v: (1) $L < D_v$; (2) $L \geq D_v$. In this section, the stochastic vehicle kinematics is discussed after the leading vehicle starts to brake and the RCRI will be subsequently modified (Wu *et al.* 2017).

Situation 1: L $<\mathbf{D_v}$: Under this situation, the driver of the following vehicle is able to see the braking light on when the leading vehicle starts to decelerate. As shown in Figure 4-2, the leading vehicle starts to make emergency brake at time t_1 and the driver of the following vehicle can see the braking light of the leading vehicle. After a perception reaction time (*PRT*), the following vehicle begins to brake to avoid the collision with the leading vehicle. Hence, the calculation of the minimum stopping distance of the two vehicles and the RCRI is the same as the calculation under clear condition.

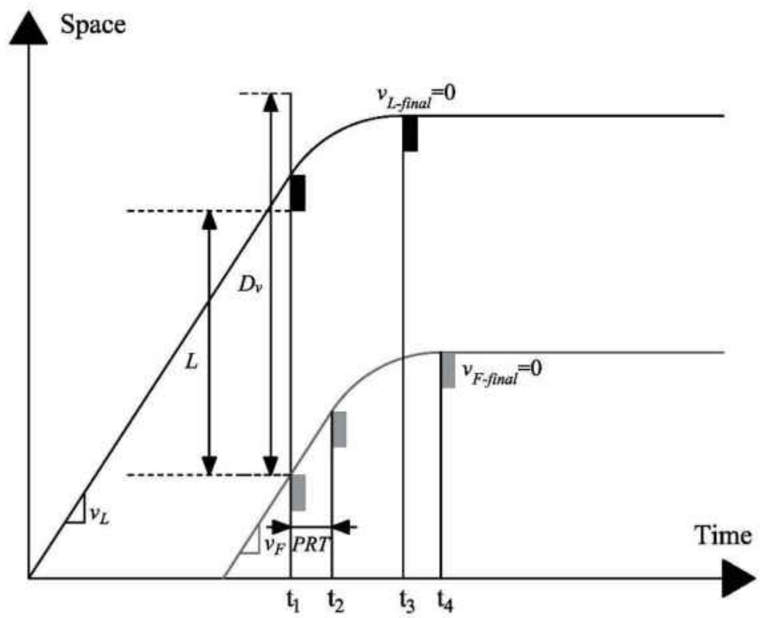
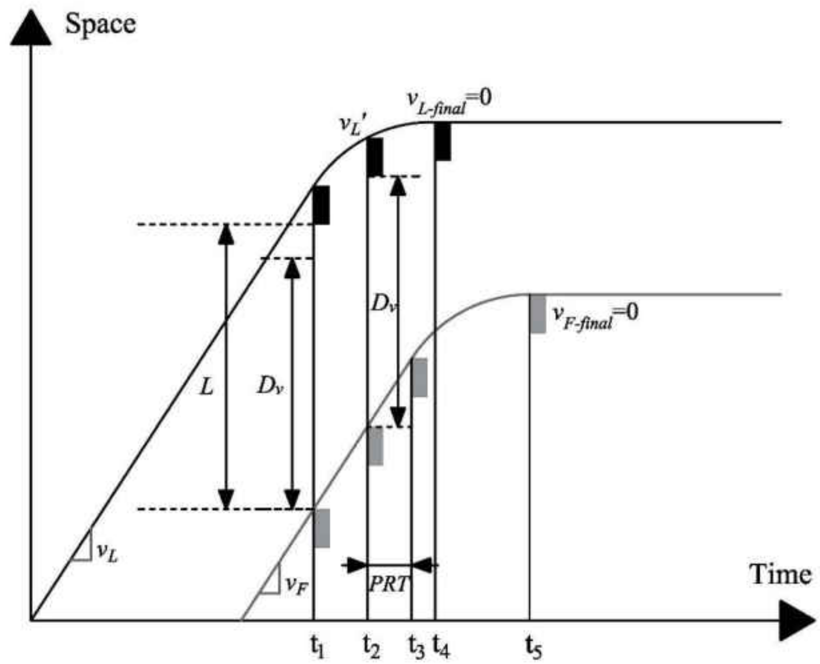
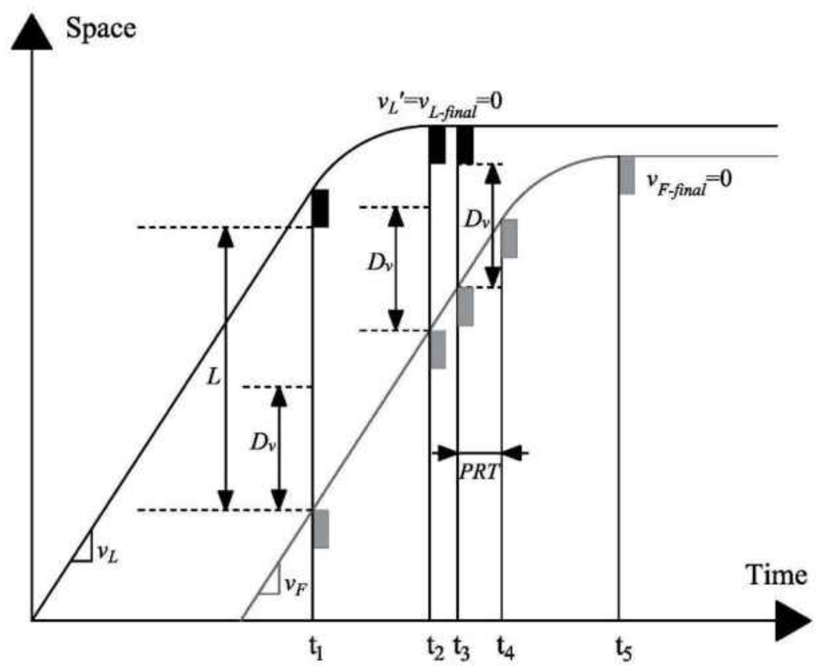


Figure 4-3 Rear-end collision risk index (RCRI) under Situation 1

Situation 2: L $\geq D_v$: Figure 4-4 shows the time-space diagram of vehicle trajectories under situation 2. When the leading vehicle starts to brake at time t1, the following vehicle will just keep its speed since the driver of the following vehicle cannot see the braking light of the leading vehicle. The following vehicle will not react to the leading vehicle's braking maneuver until t2 when the following vehicle's driver can see the leading vehicle, i.e., the clearance distance between the two vehicles becomes equal to the visibility distance (D_v). As shown in Figure 4-3, there are two possible speed statuses of the leading vehicle at time t2: (1) the leading vehicle decelerates to a lower speed; (2) the leading vehicle decelerates to a complete stop (speed=0).



(1) Status 1



(2) Status 2

Figure 4-4 Rear-end collision risk index (RCRI) under Situation 2

Let Δt be the time difference between time t_1 and t_2. Then the minimum stopping distance of the leading vehicle remains the same while the minimum stopping distance of the following vehicle will change as:

$$MSD_F = v_F \times (PRT + \Delta t) + \frac{v_F^2}{2 \times a_F} \tag{4-4}$$

Then, the rear-end collision risk index (RCRI) will change correspondingly.

There are two possible speed statuses of the leading vehicle at time t_2: (1) the leading vehicle decelerates to a lower speed; (2) the leading vehicle decelerates to a complete stop (speed=0).

If the leading vehicle still moves at time t_2 (Situation 2 Status 1), we have:

$$v_L \times \Delta t - \frac{1}{2} a_L \times \Delta t^2 + L = D_v + v_F \times \Delta t \tag{4-5}$$

Solving equation (4-2), the Δt can be calculated as:

$$\Delta t = \frac{(v_L - v_F) + \sqrt{(v_L - v_F)^2 + 2a_L(L - D_v)}}{a_L} \tag{4-6}$$

Then we have the speed of the leading vehicle at time t_2, $v_L{}'$ as:

$$v_L' = v_L - a_L \times \Delta t = v_F - \sqrt{(v_L - v_F)^2 + 2a_L(L - D_v)} \tag{4-7}$$

Since the vehicle of the leading vehicle at time t_2 is larger than zero, we will have the condition:

$$v_F > \frac{1}{2}v_L + \frac{a_L(L - D_v)}{v_L} \tag{4-8}$$

On the other hand, the leading vehicle will stop when the driver of the following vehicle can see the leading vehicle if $v_F \leq \frac{1}{2}v_L + \frac{a_L(L-D_v)}{v_L}$ (Situation 2 Status 2). Under this status, we will have:

$$\frac{v_L^2}{2a_L} + L = D_v + v_F \times \Delta t \tag{4-9}$$

Solving equation (4-9), the Δt can be calculated as:

$$\Delta t = (\frac{v_L^2}{2a_L} + L - D_v)/v_F \tag{4-10}$$

Based on the equations (6) and (10), the Δt can be calculated for the different relations between v_F and $\frac{1}{2}v_L + \frac{a_L(L-D_v)}{v_L}$. Then, the minimum stopping distance of the following vehicle can be modified while the minimum stopping distance of the leading vehicle is the same as that under Situation 1.

In summary, the minimum stopping distance and rear-end collision risk index (RCRI) can be modified in different situations under fog condition based on the above-mentioned algorithm. The implementation of the proposed algorithm is illustrated in Figure 4-4. To implement such algorithm, the first step is to decide which situation belongs to by checking the relation between L and D_v. If the algorithm belongs to Situation 1 (L<D_v), the minimum stopping distance of the two vehicles and the RCRI can be identified directly. If the algorithm belongs to Situation 2 ($L \geq D_v$), we should first determine which status the algorithm is by checking the speed of the leading vehicle when the driver of the following vehicle can see the leading vehicle. Then, the minimum stopping distance and the RCRI can be determined accordingly.

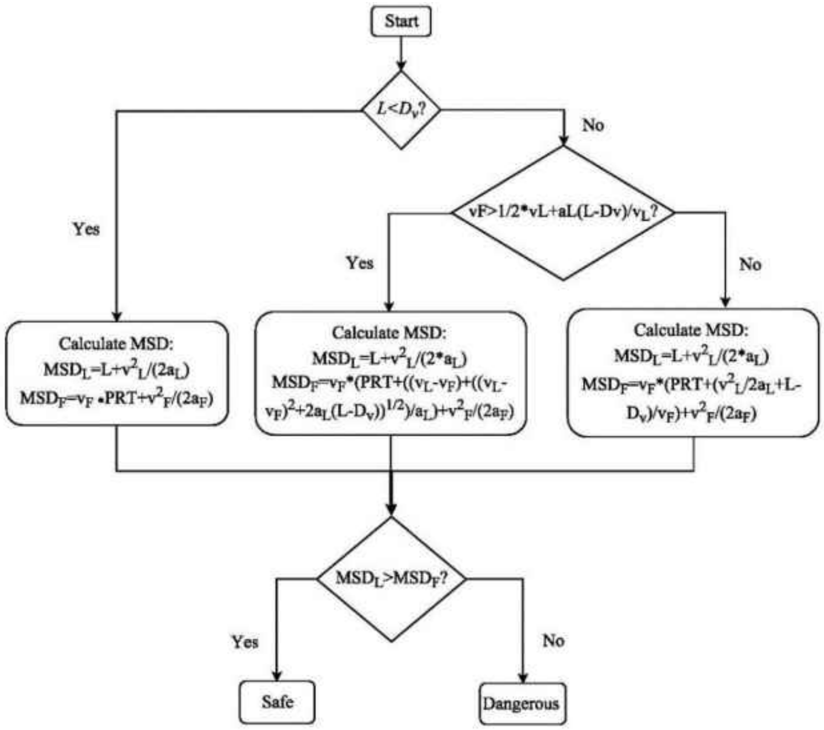


Figure 4-5 Flowchart of the proposed algorithm for rear-end collision risk index (RCRI)

4.4.2 Model Formulation

4.4.2.1 Individual factors affecting rear-end collision risk under fog condition

Based on the above-mentioned algorithm, we can determine whether the following vehicle has a potential rear-end crash (1=yes; 0=no) with the leading vehicle when the leading vehicle makes an emergency brake. Chi-square test is conducted to explore whether there are significant differences of the impact of reduced visibility under different fog levels. In addition, a logistic model is estimated to identify the impact of reduced visibility and other individual vehicular data on the rear-end collision risk under fog condition. The probability that the rear-end collision under fog condition can be calculated in Equation (4-11):

$$\pi(y_i) = \frac{e^{g(y_i)}}{1 + e^{g(x_i)}} \tag{4-11}$$

The logistic regression model is given in Equation (4-12):

$$g(y_i) = \ln\frac{\pi(y_i)}{1-\pi(y_i)} = \boldsymbol{\beta x} \tag{4-12}$$

where $\pi(y_i)$ is the conditional probability of potential rear-end collision. **x** is a set of the independent variables that can be either categorical or continuous and $\boldsymbol{\beta}$ is a set of corresponding parameters.

The following seven individual vehicle variables are taken into account for the estimation. For the fog level, there are two main reasons for the classification. First, National Oceanic and Atmospheric Administration (NOAA) standards suggest considering the effects of fog if the visibility distance gets reduced to less than 1,000m due to mist (NOAA, 1998). Since the maximum distance recorded by the weather sensor is 2,000m, the visibility is considered as light fog condition and classified as Category 1 when the visibility distance is greater than 1,000m. Second, significant change of driving behavior could be observed if the visibility distance is less than 200m (Li et al., 2015). In addition, the sample size of the dataset in the range of low visibility will be insufficient to conduct a statistically significant analysis if we selected another lower distance. Hence, the visibility is considered as dense fog condition and classified as Category 3 if the visibility distance is less than or equal to 200m. Finally, the visibility is considered as moderate fog condition and classified as Category 2 if the visibility distance is between 200m and 1,000m. Also, it should be noted that other classifications and more clusters could be specified in the future if more data would become available.

(i) The type of the following vehicle, V_{type}^{F}. If the vehicle is passenger car, $V_{type}^{F} = 0$; otherwise, $V_{type}^{F} = 1$.

(ii) The type of the leading vehicle, V_{type}^{L}. If the vehicle is passenger car, $V_{type}^{L} = 0$; otherwise, $V_{type}^{L} = 1$.

(iii) The speed of the following vehicle, v_F (m/s).

(iv) The speed of the leading vehicle, v_L (m/s).

(v) Headway level, H_{level}. If the headway between the two vehicle is larger than 10s, $H_{level} = 1$; if the headway is larger than 3s and smaller than or equal to 3s, $H_{level} = 2$; otherwise, $H_s = 3$.

(vi) Fog level, F_{level}. If the visibility is greater than 1,000m, $F_{level} = 1$ (light fog); if the visibility is greater than 200m and less than or equal to 1,000m; $F_{level} = 2$ (moderate fog); otherwise, $F_{level} = 3$ (dense fog).

(vii) Time of day, $Time_{d-n}$. If the observed time is between 7:00 am and 7:00 pm, $Time_{d-n} = 1$ (day time), otherwise, $Time_{d-n} = 0$ (night time). It should be noted that the time is determined based on the sunrise and sunset time in Florida.

4.4.2.2 Aggregated factors affecting rear-end collision risk under fog condition

The logistic model is based on traffic data of each vehicle. However, since most of the available archived traffic and crash data are aggregated, it should be meaningful to aggregate the data over a certain time period and further explore the effects of both traffic parameters and reduced visibility. The data are combined into 5-minute units to obtain the count of the potential rear-end collisions (dangerous car-following statuses), averages of traffic parameters, and visibility level. The count of potential rear-end collisions is a not-negative integer. Count data models such as Poisson and negative binomial models are designed specifically to account for data with such characteristics and have been widely used for traffic crash frequency analysis. The Poisson model is a standard count model assuming that the mean and variance of the distribution are the same. Thus, the Poisson model cannot deal with the over-dispersion (i.e., variance is larger than the mean) issue (Cai et al., 2016). The negative binomial model relaxes the equal mean variance assumption by adding a random term with gamma distribution into the Poisson model. Thus, the negative binomial model is adopted to analyze the count of potential rear-end crashes. The mean the negative binomial can be expressed as follows:

$$\lambda_i = \exp(\boldsymbol{\beta}'\boldsymbol{x}' + \varepsilon_i + \log(5)) \quad (4\text{-}13)$$

where λ_i is the expected number of Poisson distribution for 5-minute unit i, $\boldsymbol{x}'$ is a set of explanatory variables and $\boldsymbol{\beta}'$ is a set of the corresponding coefficients. Usually, $\exp(\varepsilon_i)$ is assumed to be gamma-distributed with mean 1 and variance α so that the variance of the crash frequency distribution becomes $\lambda_i(1 + \alpha\lambda_i)$, which is different from the mean λ_i. In addition, an offset of log(5) is added in the equation since the collisions are aggregated into 5-minute units.

The dependent variable (the potential rear-end crash frequency) and independent variables are summarized in Table 4-3. It is noted that the visibility level was converted to dummy variable similar to the logistic model (dense fog is when the visibility is equal to or less than 200 m and the light fog is when the visibility is larger than 1,000 m). Other independent variables are the volume per lane per five minutes, proportion of trucks, average speed, proportion of vehicles keeping small headway, and proportion of vehicles keeping large headway.

Table 4-3 Summary of statistics of parameters

Variable	Mean	Standard Deviation	Min	Max
Potential rear-end crash frequency	13.192	15.175	0	84
Volume per lane per five minutes	32.596	29.354	1	127
Proportion of trucks	0.257	0.253	0	1
Average speed (mph)	31.848	2.292	21.726	40.099
Proportion of small headway (≤3s)	0.282	0.242	0	1
Proportion of large headway (>10s)	0.390	0.302	0	1
Dense fog (visibility≤200 m)	0.305	0.461	0	1
Light fog (visibility >1000 m)	0.273	0.446	0	1
Time of day	0.456	0.498	0	1

It should be noted that the parameters such as perception reaction time and deceleration rate are assumed fixed in calculating the rear-end collision risk index (RCRI), which could result in the unobserved heterogeneity across different vehicles and drivers. Although the above mentioned logistic and negative binomial models could appropriately account for the data structure, the two models could not directly incorporate the unobserved heterogeneity in the data set. To incorporate the unobserved heterogeneity, the random parameters models were estimated, which could allow for the effect of the independent variables to vary across observation (Anastasopoulos and Mannering, 2011; Barua et al., 2016):

$$\boldsymbol{\beta_i} = \boldsymbol{\beta} + \boldsymbol{\delta_i} \tag{4-14}$$

where subscript i denotes each observation, and δ_i is the random distributed terms which are normally distributed with mean zero. However, due to the structure of the data used in this study, it is suspected that, heterogeneity in the consecutive observations would be relatively insignificant. On the other hand, for the vehicles and drivers observed in the different time periods, there could be significant heterogeneity. Hence, in this study, the random parameters were specified to vary at the hourly level. The formulation for such modeling structure is shown as follows:

$$\boldsymbol{\beta_{ij}} = \boldsymbol{\beta} + \boldsymbol{\delta_i} \tag{4-15}$$

where subscript i denotes each hourly observation, which subscript j indicates each observation in each hourly period, and δ_i is a randomly distributed error term varying at the hourly level.

To validate the benefits of random parameters models, two types of modeling structure were adopted for both logistic and negative binomial models: (1) a random parameters model with hourly observations and (2) a random effects model with hourly observations (with the intercept specified as random to capture the shared unobserved correlation at the hourly level).

As suggested in the previous studies (Cai et al., 2017), Bayesian inference could outperform the traditional maximum likelihood estimation method by incorporating parameter prior information. Hence, all candidate models are estimated in a fully Bayesian estimation using Markov Chain Monte Carlo (MCMC) simulation with the freeware WinBUGS. In the absence of sufficient prior information, non-informative prior are adopted for the parameters (Lee et al., 2017). The models' convergence was evaluated by the Gelman-Rubin statistics, visual examination of the MCMC chains, and the ratios of Monte Carlo errors relative to the respective standard deviations of the estimation. Usually, as a rule of thumb, the ratios should be less than 0.05 (Xu et al., 2017). The 90% Bayesian Credible Interval (BCI) is provided to indicate the significant of examined variables. For the model performance comparisons, measurements including Deviance Information Criteria (DIC), likelihood ratio, and Pseudo R-squared were adopted for both logistic and negative binomial models. In addition, the Area Under the Curve (AUC) was also adopted for the logistic model comparison.

4.5 Results and Discussion

4.5.1 Comparison Results of Rear-End Collision Risk Index (RCRI)

4.5.1.1 Comparison results for vehicles on different lanes

In this section, the six lanes were divided into three lane types including outer lane, middle lane, and inner lane to understand the different impact of reduced visibility on traffic safety in different lanes. As discussed in the previous section, the fog condition was divided into three levels: (1) light fog (visibility distance is greater than 1,000m); (2) moderate fog (visibility distance is greater than 200m and less than or equal to 1,000m); (3) dense fog (visibility distance is less than or equal to 200m). The total sample size and dangerous sample size (samples with potential rear-end crashes) based on the RCRI in different lanes are summarized in Table 4-4. Meanwhile, the results of Chi-square test of difference of RCRI between different fog levels in each lane are presented in Table 4-5.

It can be seen from Tables 4-4 and Table 4-5. The sample sizes of three fog levels are 11,752, 24,237, and 15,089, respectively. In each lane, the reduced visibility under different fog levels has significantly different effects on rear-end collision risk. Besides, the effects of reduced visibility on rear-end collision risk is larger in the middle and outer lanes compared with the inner lane. Specifically, the proportion of dangerous sample size of the inner lane (39.75%) is much higher than the proportion in the outer (12.54%) and middle lanes (25.97%) under light fog conditions. Under the dense fog condition, although the proportion of dangerous sample size in the inner lane is still the highest, the proportions of dangerous sample size in all lanes become comparable. Therefore, it can be concluded that reduced visibility has a significant effect on rear-end crashes for vehicles in all lanes while the effect is larger for the vehicles in the outer and the middle lanes.

Table 4-4 Summary of rear-end collision risk index (RCRI) in different lanes

Fog Levels	Outer Lane		Middle Lane		Inner Lane		All Lane	
	Total sample size	Dangerous sample size	Total sample size	Dangerous sample size	Total sample size	Dangerous sample size	Total sample size	Dangerous sample size
1	2496	313 (12.54%)	4841	1257 (25.97%)	4415	1755 (39.75%)	11752	3325 (28.29%)
2	5131	978 (19.06%)	10058	2874 (28.50%)	9048	4153 (45.90%)	24237	8005 (33.03%)
3	3392	2072 (61.08%)	6436	3715 (57.72%)	5261	3555 (67.57%)	15089	9342 (61.91%)

Table 4-5 Comparison of rear-end collision risk index (RCRI) for vehicles in different lanes

Fog Levels	Outer Lane		Middle Lane		Inner Lane		All Lane	
	Chi-Square	p_Value	Chi-Square	p_Value	Chi-Square	p_Value	Chi-Square	p_Value
1 vs 2	51	<.0001	11	<.0001	46	<.0001	82	<.0001
1 vs 3	1406	<.0001	1130	<.0001	750	<.0001	2996	<.0001
2 vs 3	1569	<.0001	1390	<.0001	629	<.0001	3147	<.0001

4.5.1.2 Comparison results of different types of vehicles

In order to figure out whether the effect of reduced visibility on RCRI varies by different vehicle types, the vehicles were divided into two types: passenger cars and trucks. Thus, the pair of two consecutive vehicles can be divided into four groups: (1) V_L=Car, V_F=Car; (2) V_L=Car, V_F=Truck; (3) V_L=Truck, V_F=Car; and (4) V_L=Truck, V_F=Truck. Here, the V_F is the following vehicle while the V_L denotes the leading vehicle. The dataset used in this section were the same as the above section 5.1.1 and the sample sizes of light fog, moderate fog, and dense fog are also 11,752, 24,237, and 15,089, respectively. The total sample size and dangerous sample size for different vehicle groups are summarized in Table 4-6 and the comparison results of the effect of reduced visibility on each vehicle group by the Chi-square test are provided in Table 4-7.

According to the two tables, the reduced visibility has a significant effect on rear-end collision risks for each vehicle group. When the leading vehicle is a passenger car, the effects of low visibility on the truck is larger compared to the passenger car. Specifically, the proportion of dangerous sample size of Group 2 (29.12%) is lower than that of Group 1 (33.43%) under light fog conditions. However, under dense fog condition, the proportion of dangerous sample size for Group 2 becomes higher than the proportion for Group 1. When the leading vehicle is a truck, the proportion of dangerous sample size for Group 4 (VF=truck) is higher than the proportion for Group 3 (VF=car) under light fog condition. Besides, the increase of the proportion of dangerous sample size of Group 4(52.46%) is more than the increase of the proportion of Group 3 (37.63%). Overall, considering the RCRI, the passenger car drivers are more careful under reduced visibility conditions.

Table 4-6 Summary of rear-end collision risk index (RCRI) for different vehicle types

Fog Levels	Group 1		Group 2		Group 3		Group 4	
	V_L=Car, V_F=Car		V_L=Car, V_F=Truck		V_L=Truck, V_F=Car		V_L=Truck, V_F=Truck	
	Total sample size	Dangerous sample size	Total sample size	Dangerous sample size	Total sample size	Dangerous sample size	Total sample size	Dangerous sample size
1	8240	2755 (33.43%)	1370	399 (29.12%)	1370	66 (4.82%)	772	105 (13.60%)
2	17304	6518 (37.67%)	2710	893 (32.95%)	2708	290 (10.71%)	1515	304 (20.07%)
3	10299	6427 (62.40%)	1785	1360 (76.19%)	1806	763 (42.25%)	1199	792 (66.06%)

Table 4-7 Comparison of rear-end crash index (RCRI) for different vehicle types

Fog Levels	V_F=Car; V_L=Car		V_F=Car; V_L=Truck		V_F=Truck; V_L=Car		V_F=Truck; V_L=Truck	
	chi-Square	p_Value	chi-Square	p_Value	chi-Square	p_Value	chi-Square	p_Value
1 vs 2	43.26	<.0001	39.63	<.0001	6.16	0.01	14.55	0.0001
1 vs 3	1536.81	<.0001	565.85	<.0001	696.03	<.0001	521.05	<.0001
2 vs 3	1586.35	<.0001	602.55	<.0001	804.79	<.0001	587.98	<.0001

4.5.2 Modeling Results Based on Individual Traffic Data

In this section, the logistic model was estimated to explore the impacts of reduced visibility together with the individual traffic data on rear-end collision risk. Before estimating the logistic model, the correlation of all the independent variables was checked and presented in Table 4-8. According to the correlation analysis results, we can see that the correlations between variables are not high.

Table 4-8 Correlation matrix of independent variables for logistic model

	Type of following vehicle	Type of leading vehicle	Speed of following vehicle	Speed of leading vehicle	Headway level	Fog level	Time of day
Type of following vehicle	1	0.232 <.0001	-0.386 <.0001	-0.244 <.0001	0.218 <.0001	0.016 <.0001	-0.111 <0.0001
Type of leading vehicle		1	-0.286 <.0001	-0.386 <.0001	0.139 <.0001	0.018 <.0001	-0.112 <0.0001
Speed of following vehicle			1	0.565 <.0001	-0.115 <.0001	0.112 <.0001	0.053 <.0001
Speed of leading vehicle				1	-0.072 <.0001	0.109 <.0001	-0.291 <.0001
Headway level					1	0.054 <.0001	-0.291 <.0001
Fog level						1	-1.654 <.0001
Time of day							1

The logistic modeling results are shown in Table 4-9. It is shown that the random parameters model could consistently provide better model performance than the random effect model based on different goodness-of-fit measurements. All the significant variables in the random parameters model except the variable 'Light fog vs moderate fog' have significant standard deviation of parameter, which validates the existence of unobserved heterogeneity across the covariates. The two models have same significant variables, which have the same sign of coefficients in the two models.

In both models, the results indicate that following and leading vehicle types are significant for the rear-end collision risk. Compared to the passenger car, the truck could increase the collision risk if it is the following vehicle while the truck could decrease the collision risk if it is the leading vehicle. The results are consistent with the comparison results between different vehicle types. Also, the findings are expected since longer safe stopping distance could be observed for the truck due to the smaller deceleration rate. Both the speed of the following vehicle and the speed of the leading vehicle have significant effect on the rear-end collision risk under fog conditions. The speed of the following vehicle is positively associated with the RCRI, while the speed of the leading vehicle has a negative effect on the RCRI. Also, it is indicated that both the small and large headways are strongly related to higher rear-end collision risk compared to the moderate headways. If a vehicle stays too close to the leading vehicle, the rear-end collision risk is high since the driver of the following vehicle does not have enough time to stop. On the other hand, if the following vehicle stays too far away from the leading vehicle under fog condition, the following vehicle will keep its speed when the leading vehicle takes an emergency brake and the leading vehicle has already stopped when the driver of the following vehicle can see the leading vehicle. Thus, the rear-end collision risk can be higher since the space for the following vehicle to stop becomes smaller. Moreover, compared to the moderate fog condition, the RCRI is higher under dense fog conditions while the RCRI is lower under light fog conditions. Finally, it should be noted that the time of day are not significant in both models. A possible reason is that smaller headway and lighter fog could be observed during the daytime while the effects of the two variables could counteract each other.

Table 4-9 Logistic modeling results with the individual data

Parameter	Random parameters model		Random effect model	
	Estimate	Standard Error	Estimate	Standard Error
Intercept	-6.415	0.097	-5.405	0.149
Standard deviation of parameter	3.934	0.549	0.685	0.093
Type of following vehicle (truck vs passenger car)	1.791	0.102	1.386	0.036
Standard deviation of parameter	0.412	0.106		
Type of leading vehicle (truck vs passenger car)	-1.718	0.187	-1.502	0.035
Standard deviation of parameter	0.933	0.145		
Speed of following vehicle	0.385	0.008	0.338	0.006
Standard deviation of parameter	0.129	0.017		
Speed of leading vehicle	-0.308	0.005	-0.267	0.003
Standard deviation of parameter	0.216	0.025		
Small headway vs moderate headway	4.267	0.276	2.684	0.031
Standard deviation of parameter	1.966	0.267		
Large headway vs moderate headway	1.677	0.386	1.652	0.036
Standard deviation of parameter	0.248	0.050		
Dense fog vs moderate fog	2.775	0.130	1.707	0.029
Standard deviation of parameter	1.342	0.246		
Light fog vs moderate fog	-0.450	0.109	-0.251	0.046
LL(0) (log-likelihood with nothing)	-34471.360		-34471.360	
LL(C) (log-likelihood with constant only)	-33441.400		-33441.400	
LL(b) (log-likelihood with covariates)	-22200.850		-24220.950	
Pseudo R-squared (0)	0.356		0.297	
Pseudo R-squared (C)	0.336		0.276	
Likelihood Ratio (0)	24541.020		20500.820	
Likelihood Ratio (C)	22481.100		18440.900	
DIC	44635.300		48488.900	
ROC	0.873		0.850	

4.5.3 Modeling Results for Aggregated Traffic Data

The correlation results of independent variables for the negative binomial model are provided in Table 4-10. The results indicate that the 'volume per lane' has very high correlation with the proportion of small headways (0.733), the proportion of larger headways (-0.776), and the time of day (0.753). Besides, Strong correlations could be observed between the proportion of small headways and the proportion of large headways (-0.818), between the proportion of small headways and the time of day (0.731), and the proportion of large headway and the time of day (-0.764). Hence, the three variables cannot be employed simultaneously for the model estimation.

Table 4-10 Correlation matrix of independent variables for negative binomial model

	Volume per lane	Proportion of truck	Average speed	Proportion of small headway	Proportion of large headway	Dense fog	Light fog	Time of day
Volume per lane	1	-0.204 <.0001	0.050 0.047	0.733 <.0001	-0.776 <.0001	<.0001 1.000	-0.116 <.0001	0.753 <.0001
Proportion of truck		1	-0.712 <.0001	-0.434 <.0001	0.316 <.0001	0.037 0.143	-0.023 0.355	-0.228 <.0001
Average speed			1	0.251 <.0001	-0.102 <.0001	0.042 0.097	-0.151 <.0001	-0.027 <.0001
Proportion of small headway				1	-0.818 <.0001	-0.113 <.0001	0.089 <..0001	0.731 <.0001
Proportion of large headway					1	0.086 0.001	-0.071 0.005	-0.764 <.0001
Dense fog						1	-0.407 <.0001	-0.140 <.0001
Light fog							1	0.124 <.0001
Time of day								1

Table 4-11 shows the results of the negative binomial model for the potential rear-end crash frequency. Similar to the logistic model, the random parameters model could provide better data fit performance compared to the random effect model based on all the performance measurements. Also, the same variables are found significant in the two models with the same signs of coefficients. Significant standard deviation of all the parameters could be found in the random parameters model, which validates the approach of considering the unobserved heterogeneity of covariates.

Four variables are found significant in the two models. The volume per lane is the traffic exposure and the potential rear-end crash frequency will increase as the volume increases. Under fog conditions, it is found that the average speed has a significant positive relation with the rear-end crash frequency. Further, the rear-end collision risk can increase under dense fog conditions and the risk will decrease if the visibility distance increases. The absolute value of the coefficient for the dense fog is 0.817, which is much larger than the absolute value of the coefficient for the light fog (0.052). Therefore, it can be concluded that the rear-end collision risk will be extremely high under dense fog condition.

Table 4-11 Negative binomial modeling result for the aggregated traffic flow data

	Random parameters model		Random effect model	
Parameter	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**
Intercept	-7.608	0.098	-7.680	0.064
Standard deviation of parameter	0.542	0.175	0.396	0.061
Volume per lane	1.197	0.027	1.178	0.017
Standard deviation of parameter	0.148	0.037	-	-
Average speed	0.090	0.002	0.096	0.003
Standard deviation of parameter	0.017	0.003	-	-
Dense fog (visibility<=200 m)	1.088	0.159	0.690	0.023
Standard deviation of parameter	0.594	0.115	-	-
Light fog (visibility>1000 m)	-0.323	0.118	-0.148	0.039
Standard deviation of parameter	0.318	0.096	-	-
Dispersion	0.016	0.003	0.035	0.004
LL(0) (log-likelihood with nothing)	-34471.360		-34471.360	
LL(C) (log-likelihood with constant only)	-3687.750		-3687.750	
LL(b) (log-likelihood with covariates)	-3477.620		-3553.200	
Pseudo R-squared (0)	0.899		0.897	
Pseudo R-squared (C)	0.057		0.036	
Likelihood Ratio (0)	27516.120		61836.320	
Likelihood Ratio (C)	420.260		269.100	
DIC	7258.710		7520.730	

Hence, based on the random parameters model, the potential rear-end crash frequency can be calculated as:

$$y = \exp(-7.608 + 1.197 * \log(Volume) + 0.090 * \log(Average_{speed}) + 1.088 * (Dense\_fog) - 0.323 * (Light\_fog) + \log(5)) \tag{4-16}$$

4.6 Summary and Conclusions

This study proposed a new algorithm to evaluate the rear-end collision risk under fog conditions. The proposed measure compares the safe stopping distance of the leading vehicle and the following vehicle. According to the relationship between the clearance distance (L) between the leading and following vehicles and the visibility distance (D_v), the vehicle-following statuses were divided into two situations: (1) L <D_v; (2) L $\geq D_v$. For the first situation, the driver of the following vehicle can see the braking light when the leading vehicle starts to brake. On the other hand, the driver of the following vehicle cannot see the braking light until the clearance distance becomes equal to or less than the visibility distance in the second situation. The second situation was divided into two statuses based on the speed of the leading vehicle when the driver of the following vehicle can see the leading vehicle. For different situations, the algorithms to calculate the safe stopping distance were proposed. Based on the proposed algorithms, the potential rear-end collision could be identified by using the individual vehicular traffic and visibility data. Subsequently, vehicles were classified into different types and lanes to examine the different impact of reduced visibility on rear-end collision risk. The random parameters logistic and negative binomial models were estimated based on the individual vehicle data and aggregated traffic flow data to investigate the relation between rear-end collision risk and reduced visibility together with other traffic parameters. Accordingly, several key conclusions can be made.

- The proposed algorithm provides reasonable results in identifying rear-end collision risk under fog conditions. The dynamic movements of two consecutive vehicles when the leading vehicle takes an emergency stop were analyzed in this study and the algorithm to calculate the safe stopping distance was developed. By comparing the safe stopping distance, the potential rear-end collision can be identified.

- The reduced visibility can increase the rear-end collision risk significantly from the light fog condition to the dense fog condition. Overall, the proportion of rear-end collision risk increases from 28.29% to 61.91% when the fog became dense. The reduced visibility has larger impact for the vehicles in the outer and middle lanes compared to the vehicles in the inner lane. Meanwhile, it was revealed that smaller collision risk could be found if the leading vehicle is a truck while the following vehicle is a passenger car.
- The logistic modeling results indicate that the vehicle types of the leading and following vehicles, the speeds of the leading and following vehicles, small and large headways, and dense and light fog indicators have significant relationships with the rear-end collision risk. There would be lower rear-end collision risk if the following vehicle moves more slowly and the leading vehicle drives faster. Interestingly, the rear-end collision risk can increase when the leading vehicle takes an emergency brake if the following vehicle keeps either too small or large headway. Moreover, the rear-end collision risk can become extremely high if the fog gets very dense.
- The negative binomial modeling results suggest that the volume per lane and average speed have positive impact on the potential rear-end crash frequency. Also, the same impact of dense and light fog in the logistic modeling result can be observed.

Due to the lack of accurate real-time visibility and the responding traffic data, few researches have been conducted to explore the impacts of reduced visibility on traffic safety under fog condition. This study developed a new algorithm to investigate the rear-end collision risk under fog condition based on the real-time visibility and traffic data collected by a new detection system. The analysis results indicate that the proposed algorithm can work properly and reasonably in evaluating the rear-end collision risk under fog condition. The proposed algorithm could help understand the changes of traffic safety under fog condition and identify effects of reduced visibility together other traffic parameters on traffic safety. The proposed algorithm could also be used for the hotspot identification for fog-related crashes and treatment evaluation. In addition, it is recommended to integrate the proposed algorithm with the ITS technologies such as Variable Speed Limit (VSL) and Dynamic Message Signs (DMS) can enhance traffic safety under fog condition. Furthermore, the algorithm could be incorporated with the forward collision warning system of connected vehicle in fog conditions. This study focused on the discussion about vehicle-following behavior when the leading vehicle responds to a stimulus by taking an emergency stopping maneuver. An extension of this study to analyze the behavior when the leading vehicle only decelerates but not completely stops is recommended for future research. The car following algorithm developed in this study could be extended to adapt for the advent of Connected Vehicles' systems in Fog conditions.

CHAPTER 5: EFFECTS OF REAL-TIME WARNING SYSTEMS ON DRIVING UNDER FOG CONDITIONS USING AN EMPIRICALLY SUPPORTED SPEED CHOICE MODELING FRAMEWORK

5.1 Introduction

Fog is a weather condition that reduces visibility of the driving scene. Visibility is a critical factor for drivers to perceive roadway information and reduction in visibility due to fog or other factors is a major traffic operation and safety concern. According to the National Highway Transportation Safety Administration's (NHSTA) Fatality Analysis Reporting System (FARS), fog/smoke contributed as a major factor in 3729 fatal crashes that occurred in the United States between 2000 and 2007. Usually, fog is present during the late night and early morning which can increase severe injuries and the possibility of multiple vehicles involved crashes (Al-Ghamdi, 2007). For example, a fog crash with 70-vehicle pileup happened on I-4 in Polk County in January 2008. This crash caused five deaths and many injuries (Hassan and Abdel-Aty, 2011). Efforts to enhance the safety under fog conditions are necessary. The fog warning system serves as an important intelligent transportation system to inform drivers and help them get ready for the upcoming fog. However, little effort has been made to quantify their effects on drivers' speed adjustments. Hence, more detailed analyses are required to describe the speed adjustments within different fog warning systems under different fog conditions.

5.1.1 Driving Behavior under Fog Conditions

The reduced visibility has a significant impact on driving behavior, which needs to be understood to design appropriate mitigation strategies. Various studies have been conducted to explore the drivers' adjustments corresponding to fog such as drivers' speed control, headway maintenance, lane keeping, etc. (Broughton et al., 2007; Ni et al., 2010; Brooks et al., 2011; Hassan and Abdel-Aty, 2011; Hamdar et al., 2016). There have been a number of studies that have focused mainly on car following behavior (Broughton et al., 2007; Kang et al., 2008; Van Der Hulst et al., 1998). However, in most cases, fog would be present in the early morning when the traffic flow is relatively low and the headway distance would be longer. In that case, drivers would be more likely to be under free-flow condition. Then, instead of car-following behaviors, changing speed is the most typical factor (Hamdar et al., 2016). It was revealed that drivers would like to reduce their speed in order to lower the risk in fog conditions (Van der Hulst et al., 1998; Yan et al., 2014; Hamdar et al., 2016; Wu et al., 2017a). Different drivers may have different adjustment of speed under different fog conditions. Mueller and Trick (2012) found that experienced drivers drove faster than novice drivers under clear conditions while at the same speed if they drove under fog conditions, indicating that the experienced drivers reduced their speed more than novice drivers in reduced visibility situations. Based on the real-time traffic data and airport weather data, Wu et al. (2017b) analyzed the traffic flow pattern. It was found that both volume and speed under fog conditions dropped significantly. By proposing a crash risk increase indicator, the authors confirmed the increase of crash risk under fog conditions based on different traffic measures. Trick et al. (2009) examined the age-related differences in speed reduction when driving in fog. The results showed that older drivers reduced their speed substantially while young drivers were less likely to reduce their speed in fog and prone to have more collisions. Yan et al. (2014) conducted a driving simulator experiment and found that the drivers' speed control ability varied at different risk levels. By conducting experiments with three risk levels, different speed control behaviors were observed: basic speed control at a low risk level, dynamic speed adjustment at a medium risk level, and emergent speed responses to pre-crash situation at a high risk level. Although drivers are likely to reduce speed during low visibility conditions, the reduction of speed is found to be insufficient for them to stop within the visibility distance (Sumner et al. 1977), especially when they meet a dangerous situation (Yan et al. 2014).

5.1.2 Fog Warning System

It is necessary to detect any reduction in visibility and develop efficient ways to convey warnings to help drivers get prepared to adjust their speed when they proceed to fog. A typical fog warning system usually includes Dynamic Message Signs (DMSs) or static signs with flashing beacons to convey information to drivers. The signs are typically located before the area where fog is likely to form frequently and would deliver warning messages when the fog is present. Several research efforts have been made to evaluate the effects of fog warning systems on drivers' decisions. Boyle and Mannering (2004) conducted a driving simulator experiment to analyze drivers' speed adjustments under four different advisory-information conditions. The findings of the study suggested that while the warning messages are significant in reducing speeds in the low-visibility area, drivers tended to increase speed in the downstream when such adverse conditions didn't exist. Al-Ghamdi (2007) and MacCarley et al. (2006) found that the fog warning system was significant in reducing the mean speed in fog while it was ineffective in reducing the speed variability. Hassan and Abdel-Aty (2011) conducted self-reported questionnaire survey to explore factors contributing to drivers' compliance and drivers' satisfaction with the fog warning systems. The study concluded drivers' satisfaction with the warning system was the most significant factor that positively affected drivers' compliance with the warning systems. Also, it was revealed that roadway type affected drivers' compliance to the instructions of warning systems under moderate and heavy fog conditions. Williams et al. (2015) examined the effects of different color configuration, brightness levels, and flashing beacons on a DMS on drivers during the day and night under fog conditions. The results indicated that the DMS with black-on-white, white-on-black, and amber-on-black color combinations had longer detection and legibility distances. Meanwhile, the DMSs with high brightness and red-on-black color configurations would make the drivers feel the urgency.

Although several previous studies have paid attention to the effects of warning systems on drivers' speed adjustment maneuvers in the fog condition, most of them have only focused on several particular driving scenarios and only analyzed drivers' speed adjustment when they were already in the fog. There is a lack of systematic analysis of the effects of different fog warning system settings under different conditions. Also, after receiving the fog warning messages, drivers may already adjust their speed before entering the fog area. Actually, drivers should gradually adjust their speed during the process of driving into and out the fog area with the warning system instructions.

5.1.3 Objective of This Study

In this study, a hierarchical driving performance assessment method is proposed to evaluate the effect of the real-time fog warning system on drivers' speed adjustments under different conditions. Then, an empirical experiment study with a driving simulator is conducted to support the proposed modeling framework. The structure of the remainder of this paper is as follows. Section 2 presents the modeling framework and the related speed adjustment indexes. The following section introduces the experimental design and data collection procedures. The model estimation and results are presented in the Section 4. The concluding remarks and the future research directions are presented in the last section.

5.2 Modeling Framework

The objective of this study is to investigate drivers' response to real-time fog warning systems within different fog levels, traffic conditions, and road types. This section introduces a hierarchical assessment concept to capture drivers' decision making and speed adjustment process after perceiving the external information (Figure 5-1). In fact, drivers should adjust their speed based on their current condition such as the visibility levels and the messages obtained from the warning system. In the real world, the warning systems should be installed in the clear area upstream of the fog area. After receiving the warning messages, drivers move from the clear area to the fog area through a transition area (visibility levels are gradually reduced). Hence, drivers' risk perception of the upcoming fog could be classified into three levels at different locations (i.e., clear zone, transition zone, and fog zone) and their corresponding speed adjustments could be also categorized into three levels (i.e., preliminary speed adjustment in the upstream clear zone, medium-term speed adjustment in the transition zone, and final speed adjustment in fog zone). Specially, the analysis of drivers' speed adjustment is to explore how drivers prepare or adapt before entering the fog area with the messages from the warning systems. The analysis for the transition zone corresponds to drivers' speed adjustment when they are proceeding into the fog with the gradually reduced visibility and their perception of the warning messages in the clear zone. The exploration of fog zone is about drivers' final speed choice in the fog area which may be affected by the visibility level and warning messages. This approach involves aspects such as drivers' perception and response for the fog with the messages from the warning system.

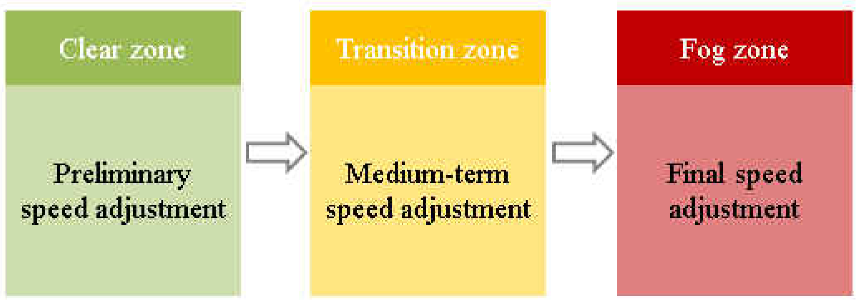


Figure 5-1 Hierarchical speed adjustment behavior assessment concept

5.2.1 Speed Adjustment Indexes

Different speed adjustment indexes are suggested for the proposed modeling framework to characterize drivers' speed adjustment and quantify effects of fog warning systems. During the preliminary speed adjustment process, the drivers are driving in the clear zone and the visibility is not reduced. Thus, the speed adjustment is not affected by the fog levels but the drivers' perception of the upcoming risk based on the warning messages. The ending speed of the clear zone (v_{end}) can reflect the drivers' final speed adjustment to see how drivers' get prepared for the downstream fog condition. When driving in the transition zone, the visibility level gets reduced gradually and drivers should adjust their speed dynamically with the impacts of the warning message and reduced visibility. Improper speed adjustment may result in a crash especially a rear-end crash. In the previous literature, the maximum deceleration rate was usually employed to explore drivers' risky driving behaviors (Andrew et al., 2012; Haque and Washington, 2015; Li et al., 2015; Wu et al., 2017c; Zhang et al., 2015). For example, Haque and Washington (2015) used the maximum deceleration rate to evaluate the effects of mobile phone distraction on drivers' braking behaviors. It was indicated that braking would be more aggressive if the maximum deceleration rate was larger. Li et al (2015) used the maximum deceleration rate to evaluate safety when drivers entered the curve under the fog condition. When drivers entered the transition zone with gradually reduced visibility, most of drivers would reduce their speed. Hence, the maximum deceleration rate (a_{max}) is adopted as an index of drivers' aggressiveness in the transition zone. In the fog zone, the visibility won't change and the speed should become stable after drivers adjust their speed in the clear zone and transition zone. Considering the fact that drivers may have different speed preferences corresponding to the reduced visibility and warning system, the average speed reduction proportion in the fog zone compared with the clear zone ($Proportion_{red}$) is employed to evaluate the final changes. The proportion of average speed reduction is calculated as follows:

$$Proportion_{red} = \frac{v_{clear} - v_{fog}}{v_{clear}} \tag{5-1}$$

where, v_{fog} is the average speed in fog zone and v_{clear} is the average speed in clear zone. It should be noted that sometimes drivers may not reduce speed in the fog zone while increase or keep their speed instead. In that case, the $Proportion_{red}$ can be a negative or zero value. Meanwhile, the positive proportion of average speed reduction should be on the interval (0,1), given the nature of the proportion variable.

5.2.2 Statistical Models

Three different speed adjustment indexes are proposed to explore drivers' adjustments and quantify the effects of fog warning systems including ending speed in the clear zone (v_{end}), maximum deceleration rate in the transition zone (a_{max}), and the average speed reduction proportion ($Proportion_{red}$) in the fog zone compared with the clear zone.

5.2.2.1 Linear Model

Since the ending speed and maximum deceleration rate are continuous variables, a linear model with random effects is adopted to analyze the effects of warning systems on drivers' speed adjustment in the clear and transition zones. The model can be represented by:

$$y_{ij} = \boldsymbol{\beta x} + \varepsilon_{ij} \tag{5-2}$$

$$\varepsilon_{ij} \sim N(0, \sigma^2) \tag{5-3}$$

where, y_{ij} is the dependent variable of experiment j by participant i. $\boldsymbol{x}$ represents independent variables and the $\boldsymbol{\beta}$ is the corresponding parameters. In addition, the ε_{ij} is the random effects for participant i with normal distribution. In this model, a log transformation, which can reduce the variance and minimize the heteroscedasticity, is applied for the dependent variable.

5.2.2.2 Hurdle Beta Model

As discussed above, the proportions of average speed reduction in fog zone compared with clear zone should be continuous numbers on the interval (0, 1) if drivers reduce their speeds in fog zone. However, the proportions of average speed reduction could be negative or zero if drivers intend to increase or keep their speeds in fog zones. Hence, the proportions of average speed should follow a mixed distribution in which a continuous nonnegative random proportion variable mixed with a probability mass truncated at zero. An alternative approach for modeling such mixed distributions is the hurdle model (Cai *et al.* 2016; Boucher *et al.* 2010; Ma and Yan, 2015; Ma *et al.* 2016), which could introduce a hurdle between positive and non-positive outcomes. Hurdle models have been adopted for modeling the mixed distributions in the previous traffic crash studies. For example, Boucher and Santolino (2010) applied the hurdle model to analyze the disability score data and suggested that an advantage of hurdle models is that the zero score process could be modeled separately. Ma *et al* (2015) proposed a hurdle regression framework to analyze traffic crash rates of road segments and extended the modeling structure to model the equivalent property damage only crash rate (Ma *et al.* 2016). The two studies consistently illustrated that the hurdle models' superior modeling performance in comparison to the Tobit model for the censored crash data. Further, Cai *et al* (2016) applied the hurdle negative binomial models for pedestrian and bicycle crashes based on traffic analysis zones. The authors also indicated that the dual-state model outperforms the conventional single-state model. These studies suggested that the hurdle model is highly flexible to deal with such mixed distributions. Hence, the hurdle modeling structure was adopted to analyze the proportion of average speed reduction.

The hurdle model, proposed by Mullahy (1986), is composed of two components. The first component is a binary model dealing with whether the response crosses the "hurdle", while the second component is a truncated-at-hurdle regression model.

Assume that the first truncated part is governed by function f_1 and the second model process follows a truncated-at-hurdle functionf_2. Then the Hurdle model can be specified as follows if we set the hurdle as 0 (Cai *et al*. 2016):

$$f(p_{ij}) = \begin{cases} f_1(\leq 0) = p_{ij}, & p \leq 0 \\ (1 - f_1(\leq 0)) \dfrac{f_2}{1 - f_2(\leq 0)}, & p > 0 \end{cases} \tag{5-4}$$

The logistic regression model is employed to estimate p_{ij},

$$p_{ij} = \frac{\exp(\boldsymbol{\beta}'\boldsymbol{x} + \varepsilon'_{ij})}{1 + \exp(\boldsymbol{\beta}'\boldsymbol{x} + \varepsilon'_{ij})} \tag{5-5}$$

$$\varepsilon'_{ij} \sim N(0, \sigma'^2) \tag{5-6}$$

where, $\boldsymbol{\beta}'$ is the parameter explanatory variables. As for the function f_2, several alternate approaches have been taken to model proportions. These alternatives include Tobit regression, fractional logit, and beta regression models. The previous studies have suggested that the beta regression model is the most preferred approach for modeling proportion data (Ospina and Ferrari, 2012, Moeller, 2013, Meaney and Moineddin, 2014). Hence, the beta regression model was adopted to analyze the positive proportion of speed reduction.

Within a logit link function, the model is given by:

$$Proportion_{ij} \sim B(u_{ij}, \phi_{ij}) \tag{5-7}$$

$$logit(u_{ij}) = \boldsymbol{\beta}''\boldsymbol{x} + \varepsilon''_{ij} \tag{5-8}$$

$$logit(u_{ij}) = \boldsymbol{\beta}''\boldsymbol{x} + \varepsilon''_{ij} \tag{5-9}$$

where, $Proportion_{ij}$ is observed proportion of experiment *j* by participant i, u_{ij} is the distribution mean and ϕ_{ij} plays the role of a precision parameter. $\boldsymbol{x}$ is the set of explanatory variables, $\boldsymbol{\beta}'$is the corresponding parameters. The density function can be specified as

$$f(p, u, \varphi) = \frac{\Gamma(\phi)}{\Gamma(u\phi)\Gamma((1-u)\phi)} p^{u\phi-1}(1-y)^{(1-u)\phi-1}, p \in (0,1) \tag{5-10}$$

Thus, the hurdle beta model can be specified.

While the linear and hurdle beta models could appropriately account for the data structure, another concern is that the effects of certain parameters may vary across drivers due to the unobserved heterogeneity. If the unobserved heterogeneity is ignored, the model would be misspecified and the estimated parameters could be biased and inefficient (Mannering *et al.* 2016). To address this issue, random parameters can be estimated, allowing for the effect of explanatory variables to vary across participants (Anastasopoulos and Mannering, 2011, Barua *et al.* 2016). The random parameters for the linear regression model can be specified as follows:

$$\boldsymbol{\beta_i} = \boldsymbol{\beta} + \boldsymbol{\delta_i} \tag{5-11}$$

where $\boldsymbol{\beta_i}$ is the vector of participant-specific parameters and $\boldsymbol{\delta_i}$ is the random distributed terms which are normally distributed with mean zero. In addition, the random parameters of hurdle beta model can be specified with the same approach.

As suggested in the previous studies (Cai et al., 2017; Huang and Abdel-Aty, 2010; Washington et al., 2005), Bayesian inference outperforms the traditional maximum likelihood estimation method by incorporating parameter prior information. The freeware WinBUGS has been widely used to estimate models in a fully Bayesian inference using Markov Chain Monte Carlo (MCMC) simulation. Hence, all the candidate models are programmed, estimated, and evaluated in WinBUGS. In the absence of sufficient prior information, non-informative prior are specified for the parameters (Lee et al., 2017; Zeng et al., 2017).

The models' convergence was evaluated by the Gelman-Rubin statistics, visual examination of the MCMC chains, and the ratios of Monte Carlo errors relative to the respective standard deviations of the estimate. As a rule of thumb, the ratios should be less than 0.05(Xu *et al.* 2017). The 90% Bayesian credible interval (BCI) is provided to indicate the significance of examined variables. The Deviance Information Criteria (DIC) was used for the model performance comparisons.

$$DIC = \mathrm{D}(\bar{\theta}) + 2p\mathrm{D} \tag{5-12}$$

Where $\mathrm{D}(\bar{\theta})$ is the deviance at the posterior mean of the parameters and pD is the effective number of the model. Roughly, differences of more than 10 in the value of the DIC would rule out the model with the higher DIC (Zeng et al., 2017).

5.3 Experimental design

Once the hierarchical concept to characterize the drivers' adjustments with the impact of fog warning systems is proposed, an experimental study is required to support the proposed framework. A host of circumstances including fog levels, traffic conditions, and road types are of interest. Hence, a driving simulator which could provide the necessary controls to explore all possible scenarios, should be an appropriate and cost-effective alternative compared with field tests. The driving simulator can give drivers the impression that they are driving a vehicle in the real word by simulating the real driving environment and fog warning systems through the feedback in the form of visual, motion, and audio cues (Hamdar et al., 2016). Hence, drivers can operate the simulator according to the circumstances and the warning messages. By simulating vehicle motion according to drivers' operations, the vehicle kinematic data can be generated and used to analyze drivers' decisions. The procedure of the driving simulator experiment design is introduced in this section.

5.3.1 Participants

In order to better consider the effects of drivers' characteristics on the speed adjustment, the quasi-induced exposure method was adopted to recruit participants. The quasi-induced exposure method derives the population distribution from the distribution of not-at-fault drivers in two-vehicle crashes since the crashes could be reasonably attributed to only the at-fault drivers (Stamatiadis and Deacon, 1997). The key assumption of the method is that the distribution of not-at-fault drivers closely represents the distribution of all drivers exposed to accident hazards (Abdel-Aty et al., 1998; Abdel-Aty et al., 2009; Yan et al., 2008). In this study, seventy-two participants (thirty-eight males and thirty-four females) were included, who ranged from 18 to 70 years. Two years' crash data (2013 and 2014) at a Freeway in Florida were collected from Crash Analysis Reporting System (CARS), while at-fault drivers' information was excluded. The not-at-fault drivers in two-vehicle crashes represent the age and gender distribution of the actual driver population (quasi-induced exposure methodology). The previous studies suggested that age and gender could have significant effects on drivers' risk perception (Borowsky et al., 2010; Ma and Yan, 2014). In this study, three age groups were classified as young (18-24), middle-age (25-59), old (>60). Such classification has been widely used in the previous studies (Abdel-Aty et al., 2009; Yan et al., 2008). The Chi-Square statistical test (($\chi2$=4.665, d.f.=7, p=0.701)) suggested that there was no significant difference between the age and gender distributions of participants and that of not-at-fault drivers. Each participant held a valid driver's license with at least 1 year of driving experience and none of the participants had a prior experience with the driving simulator. The experiment was reviewed and approved by the University of Central Florida Institutional Review Board (IRB).

5.3.2 Apparatus

The National Advanced Driving Simulator (NADS) MiniSim driving simulator was used to conduct the experiment and collect the data, as shown in Figure 5-2. The simulator has three screens 22.5 inches high and 40.1 inches wide) with a 110 degrees front field of view and left, middle, and right rear-view mirror. Participants interacted with the simulator by a control interface with steering wheel, pedals, and speedometer. All data were collected at 60 HZ.

Figure 5-2 NADS MiniSim at UCF

5.3.3 Scenario Design

The experimental road in this study was based on the northbound sections on I-75 and SR441 approximately 10 miles south of Gainesville, Florida. The selected sections are located in a high fog crash risk area where 11 people were killed in a multi-vehicle involved crash in January, 2012 (Ahmed et al. 2014). I-75 is a six-lane freeway with 70 mph speed limit, while SR441 is a four-lane arterial with 65 mph speed limit. For each road section, the total length was about 8 mile consisting of three zones: (1) clear zone (4-5 miles), (2) transition zone (0.5 mile), and (3) fog zone (2.5 miles) (Figure 5-3). The start point of the clear zone is just near the start point of the selected sections. The length of clear zone was determined to ensure sufficient distance to allocate multiple warning systems. In the clear zone, two types of fog warning systems were applied at different locations under light fog, moderate fog, and heavy fog. The transition zone was designed with gradually reduced visibility to avoid a sudden visibility change. It was assumed that drivers could get used to the reduced visibility with the 0.5-mile distance. Further, drivers should drive in the fog zone around 90 seconds with a 2.5-mile distance. Hence, the speeds could finally become stable in the fog zone. As shown in Figure 5-4, the visibility in the fog scenarios was 500 ft., 300 ft., and 150 ft. respectively.

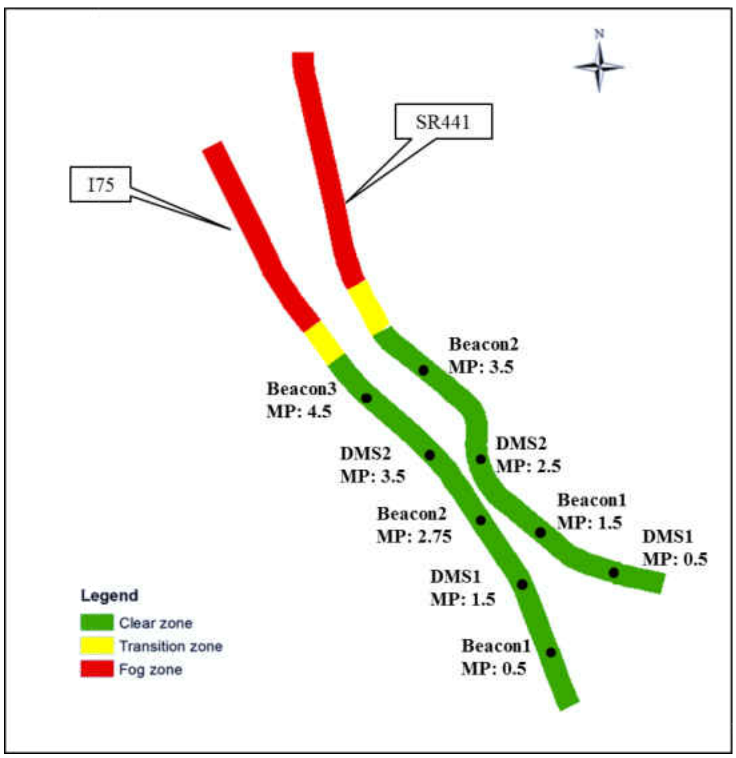


Figure 5-3 Layout of experiment road (MP: mile post)

Light Fog | Moderate Fog | Heavy Fog

Figure 5-4 Three fog levels

Fog warning system: two typical types of warning systems were applied in the experiments: DMS and static sign with beacon. As for the DMS, warning messages and advisory messages were considered. The DMS with warning messages simply indicates the upcoming fog condition to attempt to make drivers be cautious (Figure 5-5a). Meanwhile, the DMS with advisory messages delivers alerts of upcoming fog and also provides a recommendation for the drivers to reduce speed (Figure 5-5b). As shown in Fig. 4c, the static sign with beacon which will flash when fog is present attempts to make drivers pay attention for the upcoming fog.

(a) DMS with Warning Message

(b) DMS with Advisory Message

(c) Beacon

Figure 5-5 DMS and beacon

Summary of scenarios: in total, 6 variables are considered in this experiment, which includes roadway type, visibility level, number of DMS signs, type of DMS, traffic flow setting, and whether there are flashing beacons (Table 5-1). Although totally 216 scenarios would be obtained based on the 6 variables, only 24 scenarios were considered through the fractional factorial design

(Wu and Hamada, 2011). Each participant was assigned to 3 different scenarios with a block design. This design was selected to accommodate the limited time of each participant and to reduce the probability of motion sickness. With this arrangement, each experiment had at least 9 participants.

Table 5-1 Scenario variable levels

Attribute	Description	Attribute Levels
Roadway type	Roadway types for simulation	Freeway (I-75) Arterial (SR441)
Visibility level	Fog intensity based on visibility	Low, 500ft Moderate, 300 ft High, 150 ft
No. of DMS	Number of DMS used for warning	0 sign 1 sign 2 signs
Type of DMS	Message displayed on DMS	Null Warning Advisory
Traffic flow setting	Traffic conditions	Low Volume High Volume
Flashing beacons	Presence of flashing beacons along road	No Yes

The speed limit of I-75 is 70 mph, while the speed limit of SR441 is 65 mph. The traffic setting was based on field traffic data that was collected on a similar road segment on a Freeway in Florida, where both weather sensors and traffic sensors were deployed at the site as part of this study. Since fog usually forms during the early morning hours (Abdel-Aty et al., 2010), the real-time traffic data between 6:00 am and 8:30 am under fog conditions were collected to set the surroundings of the simulated vehicle. The traffic volumes during the period were not congested, which is consistent with the previous studies (Abdel-Aty et al., 2010; Wu et al., 2017b; Moore and Cooper, 1972) that the amount of traffic would decrease under fog condition. Usually, the morning peak hour of traffic volume is usually after 7:00 am and before 9:00 am (Geroliminis and Sun, 2011;

Shi and Abdel-Aty, 2015). Hence, based on the collected data and the previous studies, low traffic volume could be collected between 6:00 am and 7:00 am (non-peak hour) which has an average headway of 20 seconds, while high traffic volume occurred between 7:30 am and 8:30 am (peak hour) with the average headway of 10 seconds. However, traffic volumes during the two periods were not congested. In addition, the average speeds of surrounding vehicles under clear conditions are 72 mph (S.D=6.5 mph) on I-75 and 67 mph (S.D=6.2 mph) on SR441 in the scenarios. Meanwhile, the average speeds under fog conditions will decrease by about 2 mph with the increase of each fog level.

5.3.4 Experimental Procedure

Upon arrival at the laboratory, each participant signed a consent form and filled in a background information questionnaire. Once the participants get familiar with the apparatus in the driver's seat, an instruction for the experiment were given. The instruction didn't include any information about the details of experiments which may potentially influence driving behavior. Participants were instructed to drive as normally as they usually do in a real car. Then two test scenarios were provided to let drivers get familiarized with operating the simulator. The first test scenario would be followed by a 5-min rest period, and participants would continue the next test scenario if they didn't feel any negative effects of driving. Also, the participant could repeat the test scenarios as many times as necessary until he or she felt comfortable with driving the simulator.

During each trial, the participants were instructed to pull over and stop after they had driven through the data collection segments. Each trial would take about 6 minutes and participants could have at least 5 minutes to rest between trials. The entire experimented lasted about 30 minutes.

5.3.5 Data Collection and Overall Analysis

During the experiment, 216 (72*3) trials were conducted and 2 trials were dropped because the participants had motion sickness during driving. After the experiment, seven scenarios related explanatory variables and five variables related to the participants' characteristics were collected and shown in Table 5-2. As discussed above, drivers' speed adjustment is hierarchical and there exist correlations among the three speed adjustment indexes, including the ending speed of clear zone, the maximum deceleration rate in the transition zone, and the speed reduction proportion in the fog zone compared with the clear zone. Hence, the output of a previous step was also used as the input for the next step in the modeling estimation. Specifically, the ending speed of the clear zone (v_{end}) was used as an explanatory variable for the maximum deceleration rate (a_{max}) in for transition zone. Meanwhile, the two variables v_{end} and a_{max} were employed as two explanatory variables for the speed reduction proportion in the fog zone compared with the clear zone ($Proportion_{red}$).

Table 5-2 Descriptive Statistics of Dependent Variables

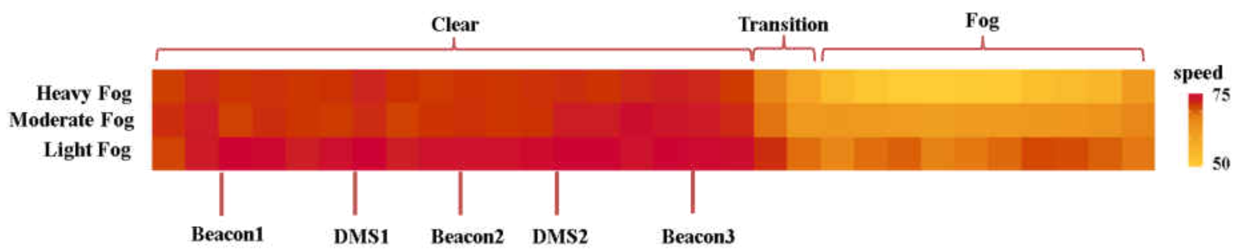
Name	Description	Unit	Mean	Standard Deviation
v_{end}	The ending speed of the clear zone	MPH	71	7.45
a_{max}	The maximum deceleration rate in the transition zone	$Feet/s^2$	0.67	0.28
$Proportion$	The positive average speed reduction proportion in fog zone compared with clear zone (N=195)	-	0.19	0.15
	The average speed reduction proportion in fog zone compared with clear zone (negative value, N=19)	-	-	-

Table 5-3 Descriptive Statistics of Variables

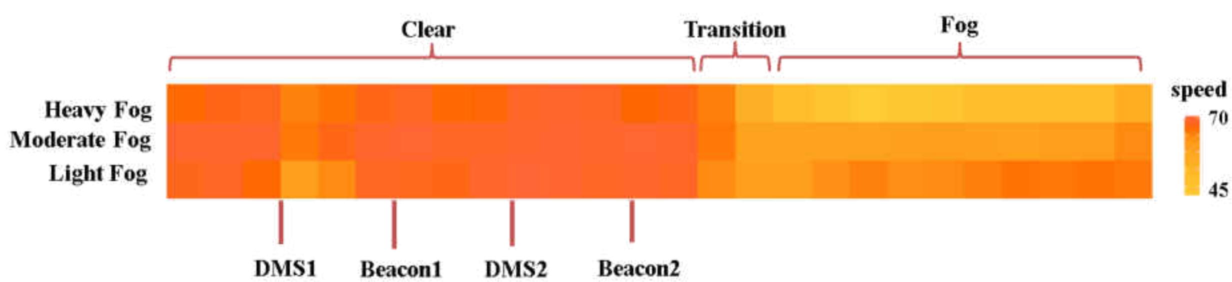
Name	Description	Input value	Count	Percentage (%)
Scenarios related variables				
RD_TYPE	Roadway types	Freeway=1	106	49.53
		Arterial=0	108	50.47
LIGHT_FOG	Light fog	Yes=1	36	16.82
		No=0	178	83.18
HEAVY_FOG	Heavy Fog	Yes=1	88	41.12
		No=0	126	58.88
N_DMS_0	Number of DMS is zero	No sign=0	54	25.23
		Others=1	160	74.77
N_DMS_1	Number of DMS is one	One sign=1	90	42.06
		Others=2	124	32.71
WARN_DMS	DMS with warning message only	Yes=1	80	37.38
		No=0	134	62.62
ADVISE_DMS	DMS with warning message and advised speed	Yes=1	80	37.38
		No=0	134	62.62
BEACON	Beacon	Yes=1	125	58.41
		No=0	89	41.59
VOLUME	Traffic volume	High=1	106	49.53
		Low=0	108	50.47
Participants related variables				
YOUNG	Young participants (age between 18 to 24)	Yes=1	69	32.24
		No=0	145	67.76
OLD	Old participants (age >60)	Yes=1	12	5.61
		No=0	202	94.39
GENDER	Gender	male=1	113	52.8
		Female=0	101	47.2
EDU	Education levels	Graduate and above=1	136	36.45
		Undergraduate=0	78	63.55
LICENSE	Whether the first driver license (learning driving skills) in Florida	Yes=1	131	61.21
		No=0	83	38.79

5.4 Model Estimation

Figure 5-6 displays the average speed in the three zones under different fog levels on freeway and arterial. It is clearly shown that the average speed is consistently reduced from the clear zone to fog zone, indicating that participants would gradually adjust their speed with the warning system instructions. Also, it is revealed that participants would lower their speed in the fog zone when the fog was denser. In the following sections, participants' speed adjustment in different zones will be analyzed in detail.



(a) Average speed on freeway



(b) Average speed on arterial

Figure 5-6 Average speed under different scenarios

Clear zone: Table 5-3 shows the linear regression modeling results for the variable ending speed of clear zone. Two scenarios related variables (roadway type, flashing beacon) and three participants-related variables (indication of young participants, indication of old participants, and FL license) are significant based on a 90% significance level. Besides, significant heterogeneity could be found for significant heterogeneity could be found for three variables including 'RD_TYPE', 'YOUND', and 'LICENSE'..

As for the scenarios related variables, the ending speed will be higher on the freeway, which should be related to the speed limit. As for the fog warning system, the drivers would reduce their speed before entering the transition zone if a beacon is present. However, the effects of the DMS warning systems on the speed reduction before entering the transition zone are not significant.

As for the participant related variables, young drivers tend to maintain higher speed before entering the fog zone compared to old drivers. This indicates that young drivers are more aggressive and the old drivers are more careful in fog situations. It is as expected since old drivers are generally more experienced and they have more accurate understanding of the risk involved in fog (Borowsky et al. 2009). Also, if the drivers learned driving in Florida, they are more familiar with the fog condition. Thus, it is expected that they are more likely to be prepared before they enter into fog by reducing their speed.

Table 5-4 Modeling results of ending speed in clear zone

Variable	Mean	Standard Error
Constant	4.229**	0.014
Standard Deviation of Parameter Distribution	0.047**	0.008
Scenarios related variables		
RD_TYPE	0.069**	0.010
Standard Deviation of Parameter Distribution	0.029**	0.008
BEACON	-0.016*	0.009
Participants related variables		
Young	0.077**	0.025
Standard Deviation of Parameter Distribution	0.065**	0.022
Old	-0.055*	0.033
License	-0.034**	0.020
Standard Deviation of Parameter Distribution	0.032**	0.010
$\boldsymbol{\sigma^2}$	0.060**	0.004
D($\bar{\theta}$)	-596.007	
DIC	-521.930	
*Significant at the 90% confidence level		
**Significant at the 95% confidence level		

Transition zone: The modeling results of maximum deceleration rate in transition zone are presented in Table 5-4. Similar to the clear zone, all significant variables except 'YOUNG' have significant heterogeneity in the random parameters model. The results indicate that drivers would make larger deceleration rate in the transition zone if they drive in dense fog. Although the effects of DMS are not significant for the ending speed, both the DMS with advisory speed and DMS with warning message have positive effects on the drivers' deceleration rate selection. Meanwhile, the DMS with advisory speed has larger effect on drivers since this warning system provides more straightforward and helpful information. Furthermore, it is found that the young drivers are less sensitive to the fog condition in the transition zone. It indicates that the young drivers are more aggressive and less likely to make adjustment for the fog situation.

Table 5-5 Modeling results of maximum deceleration rate in transition zone

Variable	Mean	Standard Error
Constant	-0.648**	0.071
Standard Deviation of Parameter Distribution	0.065**	0.035
Scenarios related variables		
HEAVY_FOG	0.164**	0.066
Standard Deviation of Parameter Distribution	0.067**	0.035
ADVISE_DMS	0.195**	0.084
Standard Deviation of Parameter Distribution	0.070**	0.039
WARN_DMS	0.175**	0.084
Standard Deviation of Parameter Distribution	0.099**	0.063
Participants related variables		
Young	-0.273*	0.164
$\boldsymbol{\sigma^2}$	0.437**	0.024
D($\bar{\theta}$)	252.879	
DIC	290.220	
*Significant at the 90% confidence level		
**Significant at the 95% confidence level		

Fog zone: Table 5-5 displays the hurdle beta regression modeling results of average speed reduction proportion in the fog zone compared with clear zone. Still, heterogeneous effects of all significant variables except the 'LIGHT_FOG' are significant in the random parameters model. The modeling results have two parts: logistic regression part and beta regression part. The results of the logistic regression part indicate whether drivers are willing to maintain a lower speed in fog and the results from the beta regression part reveals the levels of speed reduction if the driver chooses to reduce speed in fog.

In the two parts, it is shown that the warning systems have no effect for the drivers' speed selection in the fog zone since they have driven in the fog for a while. As for the logistic regression part, it is revealed that drivers are more likely to reduce their speed when the fog is heavy. Also, drivers are more sensitive to the fog condition if they drive on the freeway.

As for the beta regression part, fog level and roadway type are significant in the model. As expected, the two variables have positive impact on the speed reduction level. The result also reveals that even if the young driver reduces his/her speed in fog, their speed reduction is smaller compared with the other age groups. It is worth mentioning that neither beacon nor DMS is significant in the hurdle beta regression model. Interestingly, the maximum deceleration rate in the transition zone has a positive effect on the speed reduction. The result is expected since drivers should be more sensitive to the reduced visibility and would select lower speed in the fog if he/she takes larger maximum deceleration rate.

Table 5-6 Modeling results of average speed reduction proportion in fog zone

Variable	Mean	Standard Error
Logistic regression part		
Constant	1.687**	0.765
Standard Deviation of Parameter Distribution	0.781**	0.748
Scenario related variable		
HEAVY_FOG	4.529**	2.234
Standard Deviation of Parameter Distribution	0.987 **	1.250
RD_TYPE	1.379 **	0.675
Standard Deviation of Parameter Distribution	0.352**	0.363
σ_1^2	0.333**	0.261
Beta regression part		
Constant	-1.968**	0.121
Standard Deviation of Parameter Distribution	0.649**	0.072
Scenario related variable		
LIGHT_FOG	-0.510**	0.142
HEAVY_FOG	0.825**	0.077
Standard Deviation of Parameter Distribution	0.139**	0.079
RD_TYPE	0.264**	0.072
Standard Deviation of Parameter Distribution	0.126**	0.062
Participants related variable		
Young	-0.412**	0.178
Standard Deviation of Parameter Distribution	0.151**	0.130
a_{max}	0.191*	0.115
Standard Deviation of Parameter Distribution	0.113**	0.096
σ_2^2	0.079**	0.044
$D(\bar{\theta})$	-550.500	
DIC	-352.708	

*Significant at the 90% confidence level
**Significant at the 95% confidence level

5.5 Conclusion and Discussion

Driving in fog is a potentially dangerous activity especially when the fog suddenly appears. Fog warning systems can deliver warning messages to drivers and help them improve their decisions for the reduced visibility condition. Studies have been conducted to evaluate the effect of different fog warning systems. However, most of them only focus on the drivers' response in a particular situation and only analyze drivers' speed when they are already in the fog zone. There is a lack of a systematic analysis of driving performance, especially drivers' speed adjustment with the instructions of warning systems. This study aims to quantify the effects of fog warning systems by exploring driving reaction to two real-time fog warning devices. A hierarchical assessment concept was proposed to characterize drivers' speed adjustments after receiving warning messages in different zones with different visibility levels (i.e., clear zone, transition zone, and fog zone). For the three zones, three different safety indexes, which are ending speed in the clear zone, maximum deceleration rate in the transition zone, and average speed reduction proportion in the fog zone were evaluated in the analysis. Specially, the ending speed in clear zone represents whether drivers prepare for the upcoming fog, the maximum deceleration rate in the transition zone indicates the drivers' aggressiveness of speed adjustment for the gradually reduced visibility, and the average speed reduction proportion denotes their final speed choice for the fog. Two linear models with random effects and one Hurdle beta regression model were estimated for the three indexes to determine the significant contributing factors. Also, the three models were modified by allowing the parameters to vary across the participants to account for the unobserved heterogeneity. Both scenarios related variables and participants' characteristics were considered for the model estimation. An empirical driving simulator study was undertaken to test the proposed analysis framework. To specify, twenty-four driving simulator experiments with two types of warning systems (i.e., beacon and dynamic message sign (DMS)) were designed and carried out using the National Advanced Driving Simulator (NADS) MiniSim driving simulator. Throughout the experiment, 216 effective results conducted by 72 participants were collected. Based on the modeling results, the effects on fog warning systems along with other external factors including the roadway types, visibility levels, traffic flow, and drivers' characteristics were discussed in detail.

The results of the driving simulator experiment are in accordance with the real-world observations, indicating the reasonableness of the proposed modeling framework and the experiment. According to the modeling results, it appears that there could be a benefit from installing a beacon in term of the speed reduction before entering the transition zone. DMS may affect drivers' brake decision at the beginning section of reduced visibility. However, neither DMSs nor beacons were observed to lead to considerable influence on the speed reduction proportion in the fog zone. Also, the study found that drivers' speed adjustments was also affected by the visibility levels. Drivers are more likely to reduce their speeds or brake harder when the fog gets heavier. Meanwhile, drivers are prone to be more sensitive to visibility reduction if they are driving on a freeway.

Regarding the effects of drivers' demographic characteristics, younger drivers are less likely to decrease their speeds and also they are not willing to have a harder brake in the transition zone. One possible reason for this phenomenon is that young drivers are more confident in their driving skills and they should drive more aggressively. Also, if the drivers get their first driver license in Florida, they are more likely to be familiar and prepared before they enter into fog and would select lower ending speed in clear zone. The results also revealed that male drivers are prone to have lower maximum deceleration rate in the transition zone.

This study quantifies the effect of the fog warning system on drivers' speed adjustments. The results revealed that installing beacons before fog areas may help drivers be better prepared before entering into fog. In addition, DMSs have influence on the drivers' deceleration decision in fog while the advisory message may have stronger effect than the warning message. It was found that drivers' age and gender also had significant effects on the measurements. However, only "young" drivers exhibit significant differences in contrast to drivers in the other age groups for the maximum deceleration rate and proportion of speed reduction. It would be interesting to further explore the effect of age on the risk perception with other categorizations of the age variable.

With a better understanding of drivers' speed adjustments responding to the fog warning system, more appropriate fog warning systems can be suggested to enhance traffic safety when fog is present. In addition to the empirical, the proposed analysis framework could be further validated with the naturalistic driving data under fog conditions. Also, in the future, the connected-vehicle technology can make the proposed modeling framework more applicable with a warning system is inside the car. The use of the connected vehicle can also further decrease crash risk by incorporating drivers' personal characteristics in the warning systems, and fulfil the goal of improving traffic safety in fog conditions.

CHAPTER 6: EFFECTS OF CONNECTED-VEHICLE WARNING SYSTEMS ON REAR-END CRASH AVOIDANCE BEHAVIOR UNDER FOG CONDITIONS

6.1 Introduction

Fog is an inclement weather with reduced visibility and has a significant impact on driver behavior, traffic flow characteristic, and traffic safety. Compared to the crashes under clear conditions, fog-related crashes are prone to be more severe and involve multiple vehicles (Abdel-Aty *et al.* 2011, Naik *et al.* 2016). According to fatal crash statistics from the National Highway Transportation Safety Administration (NHSTA), fog contributed as a major factor to 7,070 fatal crashes that have occurred in the United States from 2000 to 2015. In 2008, a fog-related crash with 70-vehicle pileup happened in Florida, causing five deaths and many injuries (Hassan and Abdel-Aty, 2011).

In the previous studies, a number of researches have investigated the change of driver behavior under fog conditions. Broughton et al. (2007) observed reduced headway distance under fog conditions. It was suggested that drivers may reduce their headway distances to seek visible cues in fog. Based on the real-time traffic data and airport weather data, Wu *et al.* (2017b) analyzed the traffic flow pattern and found that both volume and speed under fog conditions dropped significantly. By proposing a crash risk increase indicator, the authors confirmed the increase of crash risks under fog conditions based on traffic measurements. Mueller and Trick (2012) compared experienced and novice driver's behavioral compensation in fog. The authors suggested that changing speed is the most typical change among all the driving behavioral adjustments corresponding to fog. The study also showed that experienced drivers would reduce their speeds more than novice drivers. Wu *et al.* (2017c) investigated the impacts of fog warning systems (beacons and variable message signs) on driver's speed adjustments for fog conditions using a driving simulator study. The authors found that the warning system could significantly affect driver's speed adjustments before they drove into the fog area, but could not sufficiently change driver's final speed after entering into the fog area.

Since some drivers tend to reduce their headway distance during fog, they may not be able to have enough response time to react to imminent events even if they had reduced their speeds, which results in an increase of the rear-end crash risk (Shi and Tan, 2013). A driving simulator study conducted by Yan *et al.* (2014) further confirmed that driver's speed compensation in fog conditions could not sufficiently reduce the rear-end crash risk at the medium and high crash risk levels. Meanwhile, although some drivers would keep longer headway distances, rear-end crashes may still happen since they may not be able to see the braking lights of the front vehicle (Wu *et al*. 2017a).

In recent years, connected-vehicle Crash Warning Systems (CWS) technologies are gaining increasing acceptance in traffic safety, which displays a vista for enhancing traffic safety under fog conditions. Previously, CWS technologies were based on radars or cameras. However, bad weather could reduce the systems' accuracy. Connected vehicles could further improve the performance of CWS by deploying Vehicle-to-Vehicle (V2V) communications or Vehicle-to-Infrastructure (V2I) communications (Li *et al.* 2014a). The V2V communications can provide the real-time position and speed of the lead vehicle. Thus, the CWS can detect the sudden slow down or stop of the lead vehicle and timely alert the drivers of the following vehicle with an in-vehicle warning message (Benedetto *et al.* 2015).

In general, the warning type is one of the important attributes of a warning system, which can significantly affect the effectiveness of warning information (Xiang *et al.* 2016). Currently, the warning type can be categorized into three types: visual CWS, tactile CWS, and audio CWS. The visual CWS usually presents warning messages in an instrument cluster or in a Head-up Display (HUD) (Wege *et al.* 2013). The audio warning system can be further divided into two types, i.e., nonverbal and verbal information. Nonverbal warning system usually provides a repetitive sound, such as a "bi-bi" beep sound, while verbal warning system delivers information by synthesized voice which imitates human voice (Chang *et al.* 2009). The nonverbal warning system is usually utilized to alert drivers to brake under emergency situations, especially during high rear-end crash risk situations (Spence and Ho, 2008, Mohebbi *et al.* 2009). Compared with the audio CWS, the visual CWS could help drivers observe risk faster (Wege *et al*. 2013). The tactile CWS can direct drivers' attention to a specific direction or location through the localized vibrations of spatial tactile displays (Xiang *et al.* 2016). Compared with tactile CWS, the visual and audio CWS can provide additional information about the details of the warning events (Haas and Van Erp, 2014)rp, 2014). Furthermore, the previous studies also demonstrated that the multimodal CWS which integrated visual and audio CWS could be more effective than visual CWS alone in enhancing driver's performance.

The safety benefits of CWS have been evaluated in the previous literature and many studies have indicated that the warning systems could effectively help reduce rear-end crash risks (Fildes *et al.* 2015). However, there is lack of studies on the safety effectiveness of CWS on rear-end crashes under fog conditions. Therefore, the current study aims to examine the effects of CWS on driver's rear-end crash avoidance behavior under fog conditions based on a driving simulator experiment. Specifically, the objective of this study is to investigate whether warning systems (visual only vs.

visual & audio) have significant effects on driver's read-end crash avoidance performance, when the lead vehicle makes an emergency stop.

6.2 Experiment

6.2.1 Participants

Fifty-four participants were recruited for this study. The average age of the participants was 38.4 years old, ranging from 18 to 75 years old. Each participant held a valid driver license and had at least 1 year of driving experience. The experiment lasted for about 30 min in total for each participant. IRB approval was obtained before starting the experiments.

6.2.2 Apparatus

The National Advanced Driving Simulator (NADS MiniSim) was used for this experiment. NADS MiniSim provided a 130-degree horizontal by a 24-degree vertical field of view in front of the seated participants with three screens (22.5 inches high and 40.1 inches wide each). Two speakers were installed in the front to mimic the sound of the passenger car as well as deliver the audio warning messages, and a third speaker was mounted below the driver's seat to simulate roadway vibrations. The text warning messages were presented through a HUD interface at the bottom of the middle screen (Figure 6-1a), which was set up to be transparent and would not obstruct the participants' view. The simulator was equipped with a four-channel video capture system, and collected driving data at a rate of 60 Hz.

(a) NADS MiniSim driving simulator with HUD interface

(b) Moderate fog

(c) Dense fog

Figure 6-1 Driving simulator and the studied fog levels

6.2.3 Scenario Designs

The experiment was designed as a $3\times 2 \times 3$ mixed factorial design with warning types (no warning, HUD warning only, HUD & Audio warning) as a within-subject variable, and age (young: 18-24 years old, working age: 25-54 years old, old: 55-75 years old) as well as fog level (moderate and dense) as between-subject variables. As shown in Figure 1b and 1c, the visibility distances in the moderate and dense fog scenarios were 300 ft and 100 ft, respectively. Each fog level had 27 participants with 9 participants in each age group and each participant performed the experiment under three warning conditions: no warning, HUD warning only, and HUD & audio warning.

The participants resumed driving on the outer lane of a two-lane straight roadway segment under the clear conditions. A lead vehicle was placed in front of the test vehicle with a speed of 50 mph (73.33 ft/s). The 50 mph speed is the driver's average speed under fog conditions observed in the authors' previous driving simulator study (Wu *et al.* 2017c). The drivers were asked to drive from the clear conditions to the fog conditions, and not overtake the lead vehicle. A risky scenario was introduced in order to test the participants' performance under the hazardous condition: the lead vehicle was triggered to make an emergency stop with a high deceleration rate of 16 ft/s2 after driving for about 1 mile under the fog conditions.

Two types of warning strategies ("HUD only" and "HUD & Audio") were explored to compare with no warning conditions. These warning strategies can be implemented in both V2I and V2V environment. Fog can be detected by weather sensors, and information would be delivered to drivers by V2I communications. Meanwhile, V2V communications could be applied to inform drivers with hazardous situations. During the experiment, after the lead vehicle started to decelerate, the warning message would be delivered based on the headway distance between the test vehicle and lead vehicle. To avoid the "cry-wolf" effects of premature warning message, the headway distance for delivering the warning message was carefully determined. The driver's reaction time and deceleration rate was set to be 1.5 s and 11.15 ft/s2, respectively (Highway and Officials, 2011). When the participants received the warning message, as suggested by Wu *et al*. (2017a), the lead vehicle could have three different statuses: (1) start to decelerate; (2) was decelerating; and (3) stop. For the three different statuses, the minimum stopping distance for the test vehicle would range from 110 ft to 351 ft. Detailed calculation process could be found in Wu *et al.* (2017a). Hence, in this study, the warning message was delivered when the headway distance between two vehicles was less than 400 ft. Also, such design could ensure that the participants would receive the warning message before they saw the brake light of the lead vehicle. Once the warning system was triggered, the HUD only warning would display the words of “Slow Vehicle Ahead” for about 1 s. The HUD & Audio warning delivered a beep sound along with the HUD message. It should be noted that the purpose of the study is to investigate the effects of rear-end crash avoidance warning system under fog conditions, while the technological requirements to realize such system in the real world are beyond the scope of this paper.

Procedure: upon arriving at the laboratory, each participant was briefly introduced to the requirements of the experiment and all participants were required to read and sign a consent form. Participants were notified that they could quit the experiment at any time in case of motion sickness. Before the formal experiments, the participants had at least 10 minutes to get trained and familiarize themselves with the operation of the driving simulator. Then, they performed the formal driving experiments under either moderate or dense fog with three different warning conditions in a random sequence. It should be noted that the gender of participants was also carefully considered when assigning the fog levels. Between each trial, participants could have at least 5 minutes to rest. After the experiment, the participants were required to finish a survey about their experience with the scenarios. More than 90% of the participants thought the driving simulator had a high level of realism and the HUD was helpful, while only 60% of the participants thought the audio warning sound was helpful.

Dependent variables: Figure 6-2 shows an example of the curves of vehicles’ speeds and the sequence of events when the participants encountered the braking lead vehicle. Based on the key time moment shown in the figure, several critical measurements were defined and extracted to evaluate the participants' driving performance. These measurements are explained as follows:

- Throttle Release Time

Time to initial throttle release ($t_{initial}$): the time between the onset of lead vehicle's braking and the moment when the participant begins to release the throttle pedal.

Time to final throttle release ($\mathrm{t}_{\mathrm{Release}}$): the time between the moment when the participant begins to release the throttle pedal and the moment at which the participant completely release the throttle pedal.

Time to initial brake ($\mathrm{t}_{\mathrm{brake}}$): the time between the moment when the participant completely release the throttle pedal and the moment at which the participant begins to press the brake pedal.

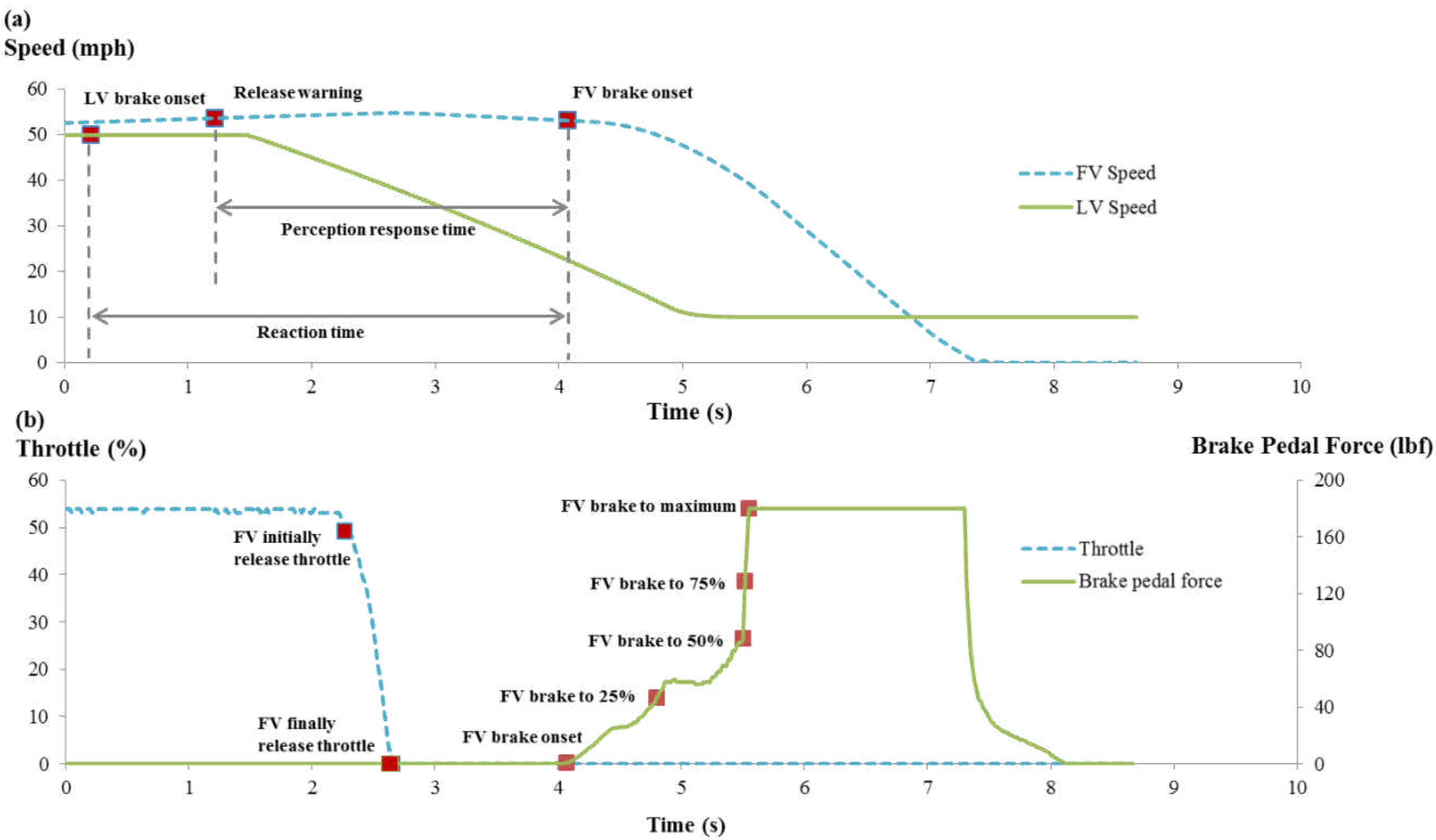


Figure 6-2 Rear-End crash avoidance behavior

Note: LV lead vehicle; FV following vehicle.

➢ Brake Transition Time

Time to 25% brake ($t_{25\%brake}$): the time between the moment of the initiation of pressure on the brake pedal and the time when the test vehicle pedal pressure reached 25% of the maximum pedal force that each participant would reach. The maximum brake pedal force limit of the test vehicle is 180 lbf.

Time to 50% brake ($t_{50\%brake}$): the time between the moment of the initiation of pressure on the brake pedal and the time when the test vehicle pedal pressure reached 50% of the maximum pedal force that each participant would reach.

Time to 75% brake ($t_{75\%brake}$): the time between the moment of the initiation of pressure on the brake pedal and the time when the test vehicle pedal pressure reached 75% of the maximum pedal force that each participant would reach.

Time to maximum brake ($t_{maxbrake}$): the time between the moment of the initiation of pressure on the brake pedal and the time when the test vehicle pedal pressure reached the maximum brake pedal force.

➢ Response Time

Perception Response Time (PRT): the time between the moment when the participants is able to realize the brake of the lead vehicle and the time when the driver of the test vehicle starts to brake. When the headway distance is shorter than the visibility distance, the driver can realize the brake of the lead vehicle through seeing the braking light of the lead vehicle. Otherwise, the driver will be notified of the brake of the lead vehicle when the warning information is provided.

Brake Reaction Time (BRT): the time between the lead vehicle brake onset and the time when the participant begins to brake.

It should be noted that the brake reaction time is different with the perception response time. Instead, the reaction time includes the perception response time and the time from the moment when the lead vehicle starts to brake to the moment at which the driver realizes the lead vehicle's brake (see Figure 2a). Perception response time is utilized to describe how quick the participant can respond after receiving stimulation, while brake reaction time is used to describe how fast the participant is able to response after risky situation is present.

- Minimum Time-to-Collision

Minimum time-to-collision ($MTTC$): the time it would take for the test vehicle to hit the lead vehicle given that their current speeds are maintained. The minimum value is selected from the time interval between the moment when the lead vehicle starts to brake and the time when the driver brakes to stop behind the lead vehicle.

- Maximum Brake Pedal Pressure

Maximum brake pedal pressure ($Brake_{max}$): the maximum value of brake pedal pressure observed during the braking event, which should be less than or equal 180 lbf.

6.3 Results

Although 54 participants were recruited in the experiment, only the data of forty-eight participants were collected for the analysis since 6 old participants (4 old females and 2 old males) could not finish the experiment due to motion sickness. In the completed 144 trials ((54-6) ×3), seven trials were excluded, because some participants chose the steering wheel to maneuver around the lead vehicle instead of braking to avoid hitting the lead vehicle and some participants drove too slow and were not able to follow the front vehicle. Hence, a dataset containing information for 137 (144-7) trials was created for the analysis.

For the measurements of the participants' rear-end crash avoidance behavior, the repeated measures multivariate analyses of variance (MANOVA) was conducted for throttle release time measurements and brake transition time measurements, in which high correlations were expected. Repeated measures analyses of variance (ANOVA) were then conducted on the significant factors revealed by the MANOVA analysis. For the significant factors with more than two groups, a set of post-hoc analyses were conducted to further compare the difference. For the other measurements including response time, MTTC, and $\mathrm{Brake}_{\mathrm{max}}$, only repeated measure ANOVA and post-hoc analyses were performed. The statistical significance level was set to be alpha=0.1.

6.3.1 Throttle Release Time

Three measurements were employed to assess the participants' throttle release time including time to initial throttle release ($t_{initial}$), time to final throttle release ($t_{Release}$), and time to initial brake

(t_{brake}). The repeated measures MANOVA analysis suggested that only the warning type (F=6.18, p=0.003) had significant effect on driver's throttle release time.

The ANOVA results indicated that the time to initial throttle release (F=5.97, p<0.01) and the time to final throttle release (F=4.09, p=0.02) contributed to the multivariate effects. Post-hoc tests, shown in Table 6-1, suggested that participants under no warning condition need more time to start and finish the throttle releasing maneuver. However, there was no significant difference between "HUD only" warning and "HUD & Audio" warning, which indicated that adding audio warning system could not significantly affect participants' awareness of impending accidents and hence could not shorten the throttle release time.

Table 6-1 Post hoc test of the effects of warning type for $t_{initial}$ and $t_{Release}$

Paired Condition	Dependent Variables	
	Time to initial throttle release	Time to final throttle release
No warning vs HUD only	1.08**	0.35**
No warning vs HUD & Audio	1.44**	0.36**
HUD only vs HUD & Audio	0.36	0.01

** indicates significant at an alpha level of 0.05, * indicates significant at an alpha level of 0.1

6.3.2 Brake Time

Participants' brake transition time were examined by four measurements, i.e., time to 25% brake ($t_{25\%brake}$), time to 50% brake ($t_{50\%brake}$), time to 75% brake ($t_{75\%brake}$), and time to maximum brake ($t_{maxbrake}$). The MANOVA test revealed significant effects of warning type (F=3.06, p=0.05) and age (F=2.69, p=0.07). However, there was no significant difference between male and female participants (F=0.02, p=0.89) or between moderate and dense fog conditions (F=0.02, p=0.89) in terms of brake transition time.

The subsequent repeated measures ANOVA analysis showed that warning type has significant main effect on both $t_{75\%brake}$ (F= 2.66, p=0.07) and $t_{maxbrake}$ (F=2.79, p=0.06). As shown in Table 6-2, the post hoc test indicated that the time to 75% brake and maximum brake became longer under the no warning condition compared with the "HUD & Audio" warning conditions. No significant difference could be observed between the two different warning types.

In addition, the ANOVA test results of age illustrated significant impact on $t_{75\%brake}$ (F= 2.45, p=0.09) and $t_{maxbrake}$ (F=5.96, p<0.01). The post-hoc test suggested that young drivers tended to spend longer time to reach 75% and maximum pedal force compared with working age and old drivers. However, no significant difference was found between working age and old drivers.

Table 6-2 Post-hoc test of the effects of warning types and age for $t_{75\%brake}$ and $t_{maxbrake}$

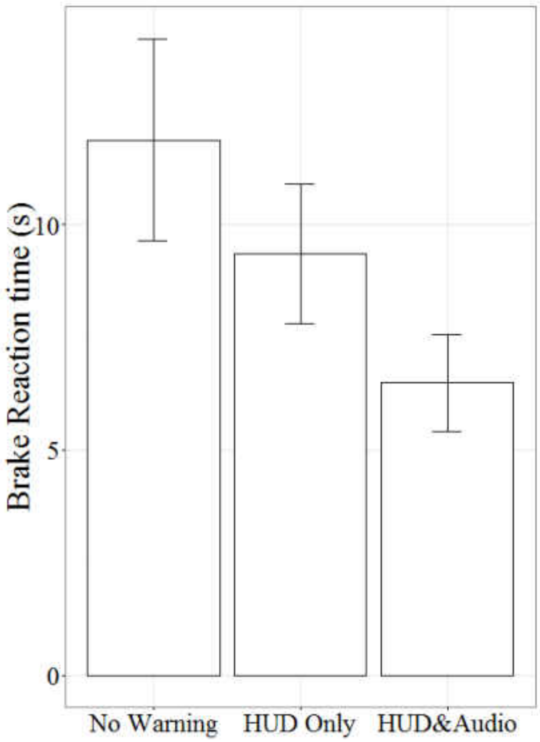
Paired Condition		Dependent variables	
		Time to 75% brake	Time to maximum brake
Warning type	No warning vs HUD only	-0.30*	-0.28*
	No warning vs HUD-Audio	-0.35*	-0.49*
	HUD only vs HUD-Audio	-0.05	-0.21
Age	Young vs Working age	0.28*	0.44*
	Young vs Old	0.32*	0.73**
	Working age vs Old	0.03	-0.21

** indicates significant at an alpha level of 0.05, * indicates significant at an alpha level of 0.1

6.3.3 Response Time

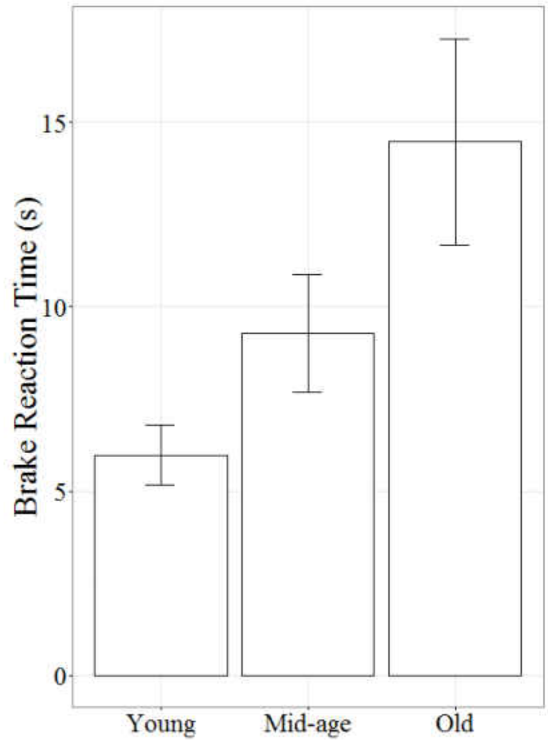
The repeated measures ANOVA revealed that warning type, fog level, gender, and age did not have significant impact on the perception response time. Participants, on average, reported a perception response time of 2.21s, a result similar with previous studies (Yan *et al.* 2015, Wang *et al.* 2016).

The influences of warning type, fog level, gender, and age on brake reaction time were examined through similar repeated measures ANOVA tests. The effects of warning type (F=3.56, p=0.03) and age (F=3.68, p=0.03) were significant. However, fog level (F=2.11, p=0.15) and gender (F=0.83, p=0.37) did not have significant impact on the brake reaction time. Figure 3 presents the mean brake reaction time for different warning types and different age groups, as well as the post-hoc test results for the two significant factors. From the results, there was significant difference of brake reaction time between the no warning condition and the “HUD & Audio” condition. Compared with no warning condition, “HUD & Audio” condition had less brake reaction time (see Figure 6-3a). It was also useful to note that no significant difference could be observed between the “HUD only” condition and the other two conditions. Regarding the effect of age, the brake reaction time was the largest in the old age group, which indicated that old drivers need more time to respond to the emergency event (see Figure 6-3b). However, the difference between young drivers and working age drivers was not significant.



Post hoc test	
Comparison Groups	**Difference**
No Warning vs HUD Only	2.52
No Warning vs HUD & Audio	5.38*
HUD Only vs HUD & Audio	2.86

(a) Warning type



Post hoc test	
Comparison Groups	**Difference**
Young vs Mid-age	-2.33
Young vs Old	-7.92**
Mid-age vs Old	-5.59*

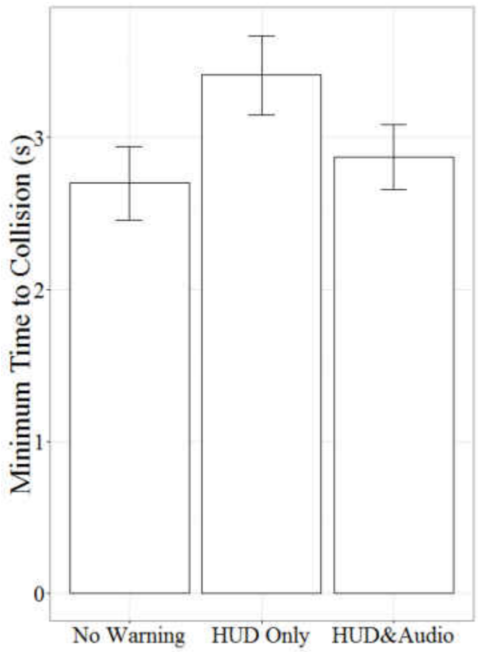
(b) Age

** indicates significant at an alpha level of 0.05, * indicates significant at an alpha level of 0.1

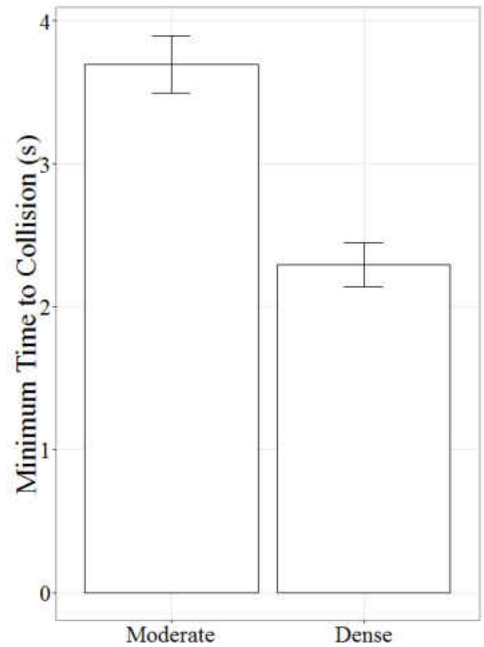
Figure 6-3 Mean brake reaction time under different warning types and age groups

6.3.4 Minimum Time to Collision (MTTC)

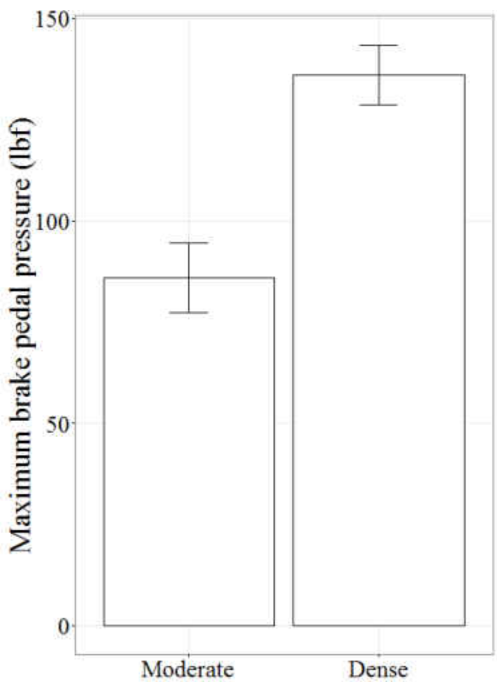
The minimum time to collision (MTTC) is an essential surrogate measure to evaluate the rear-end crash risk under fog conditions (Wu *et al.* 2017a). The ANOVA analyses suggested that the effects of warning type (F=3.89, p=0.02) and fog level (F=20.98, p<0.01) on MTTC are significant while the effects of gender (F=0.13, p=0.72) and age (F=0.07, p=0.93) are not significant. The mean MTTCs of different warning types and different fog levels were presented in Figure 6-4.



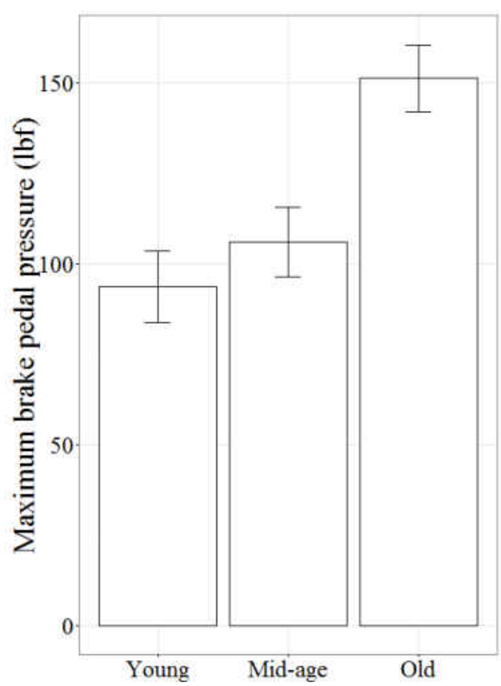
(a) Warning type for MTTC



(b) Fog level for MTTC



(c) Fog level for $Brake_{max}$



(d) Age for $Brake_{max}$

Figure 6-4 Minimum time to collision under different warning types and fog levels

The post hoc analysis indicated that the MTTC under no warning condition (M=2.70 s, S.D.=1.65 s) was significantly lower than that under "HUD only" condition (M=3.41 s, S.D.=1.75 s) (see Figure 4a). Although the no warning condition also had lower MTTC compared with "HUD & Audio" condition, the difference was not significant, presumably owing to the random effect. Meanwhile, no significant difference could be observed between the two warning types.

Figure 4b suggests that smaller MTTC could be found under dense fog conditions (M=2.30 s, S.D.=1.28 s), compared with the moderate fog conditions (M=3.69 s, S.D.= 1.66 s). The finding indicates that rear-end crash risk would increase when visibility distance decreased, which is consistent with previous studies (Underwood *et al.* 2002, Peng *et al.* 2017, Wu *et al.* 2017a).

6.3.5 Maximum Brake Pedal Pressure ($Brake_{max}$)

The ANOVA analyses revealed significant effects of fog level (F=13.01, p<0.01) and age (F=6.12, p<0.01) on the maximum brake pedal pressure. However, warning type (F=1.42, p=0.25) and gender (F=0.13, p=0.72) did not significantly affect the maximum brake pedal pressure. The result of warning type indicated that the warning message would not affect participants' employment of the maximum brake pedal pressure if the participants had realized the risky situations through either seeing the braking light of lead vehicle or noticing by the warning message. The mean maximum brake pedal pressures for different fog levels and different age groups are illustrated in Figure 6-4c and 6-4d.

Figure 4c indicates that drivers would employ a larger brake pedal pressure under the dense fog conditions (M=136.04 lbf, S.D.=61.46 lbf) compared with the moderate fog conditions (M=86.81 lbf, S.D.=69.62 lbf).

As for the effects of age, old drivers (M=152.19 lbf, S.D.=50.01 lbf) tend to have larger maximum brake pedal pressure compared with the other two age groups, and there is no significant difference of the brake pedal pressure between young drivers (M=92.72 lbf, S.D.=69.22 lbf) and working age drivers (M=106.01 lbf, S.D.=71.88 lbf) (see Figure 4d).

6.4 Discussions

This study investigated the effectiveness of connected-vehicle crash warning system (CWS) on participants' performance during the process of rear-end crash avoidance under fog conditions. Scenarios were specifically designed for rear-end crashes caused by the emergency stop of the lead vehicle. These experiments were designed to test different warning types along with different fog levels, participants' age and gender groups. Table 6-3 summarizes the effects of the tested factors on the participants' rear-end crash avoidance behavior. Participants' throttle release time ($t_{Release}$, t_{brake}) is only affected by the warning type while participants' brake transition time ($t_{75\%brake}$, $t_{\max brake}$) could be affected by both warning type and age. As for the two types of response time, BRT could be affected by warning type and participants' age while no factor has significant effects on PRT. In addition, $MTTC$ is affected by the warning type and fog level, while $Brake_{max}$ could be affected by fog level and age.

Table 6-3 Summary of effects of factors

Factors		Warning type	Fog Level	Age	Gender
Throttle Release Time	$t_{initial}$				
	$t_{Release}$	**			
	t_{brake}	**			
Brake Transition Time	$t_{25\%brake}$				
	$t_{50\%brake}$				
	$t_{75\%brake}$	*		*	
	$t_{\max brake}$	*		**	
Response Time	PRT				
	BRT	**		**	
Minimum Time to Collision	$MTTC$	**	**		
Maximum Brake Pedal Pressure	$Brake_{max}$		**	**	

Note: ** indicates significant at an alpha level of 0.05, * indicates significant at an alpha level of 0.1

6.4.1 Effects of Crash Warning System

Previous studies suggested that drivers could have better decisions if they get prepared for the subsequent road conditions (Underwood *et al.* 2002). Whether drivers could successfully avoid the read-end crashes would depend on how quickly the drivers can identify the impending crashes and execute crash avoidance actions. In this study, both shorter throttle release time and shorter brake reaction time could be found with the presence of warning systems, which indicates the advantage of the warning systems. Meanwhile, drivers braking process could be smoother (smaller $t_{75\%brake}$ and $t_{\max brake}$) with the warning systems. In addition, drivers could have greater MTTCs with warning systems, which confirmed the benefits of crash warning systems under fog conditions.

Although previous studies showed that a warning message could lower driver's perception response time and increase the maximum braking pedal pressure (Ho *et al.* 2006), there were no significant difference identified in the perception response time and maximum braking pedal pressure. In this study, both the start moment of warning message and the moment when participants see the brake light of the lead vehicle could be regarded as stimulus, and the response to the stimuluses of each driver under the emergency situation is relatively similar (Xiang *et al.* 2016). Hence, drivers would have similar perception reaction time and similar maximum braking pressure. Meanwhile, previous studies suggested that multimodal CWS (e.g., visual & audio warning) could further improve driver's rear-end crash avoidance performance (Haas and Van Erp, 2014). However, no significant difference was identified in the participants' throttle release time, brake transition time, or other performance measurements between "HUD only" CWS and "HUD & Audio" CWS in this study.

6.4.2 Effects of Fog Level

Car-following driving behavior in fog is a complex task since participants need to consider the interactions between their speeds and the lead vehicles' speeds. Previous studies have confirmed that participants tend to adopt safer driving maneuvers under fog conditions, such as reducing speed and getting less distracted, to avoid potential crash arising from the reduced visibility (Li *et al.* 2015). In this study, no significant effect of fog levels was observed for the participants' throttle release time, brake transition time, and response time, while participants would press brake pedal harder in dense fog. However, relatively smaller minimum time-to-collision was found under dense fog conditions, which indicated that the increased brake pedal pressure was still not sufficient to compensate for the increase of risk caused by reducing visibility distance. When fog become dense, participants in the test vehicle could not see the braking lights of the lead vehicle, resulting in higher rear-end crash risk (Sullivan and Flannagan, 2003, Wu *et al.* 2017d).

6.4.3 Effects of age and gender

There was no significant difference between different age groups in the perception reaction time. However, old participants had significantly longer brake reaction times because they need more time to make mental calculations (Makishita and Matsunaga, 2008). Also, it should be noted that working age drivers also need longer brake reaction time compared with young drivers, although the difference is not significant. In addition, young participants spent longer time to reach 75% and maximum brake force, which means their braking processes could be smoother than other participants (Highway and Officials, 2011). Meanwhile, since old drivers started braking relatively late and they were more sensitive to the potential risk (Cai *et al.* 2017), they had to make harder brake to avoid crashes.

Although some of the previous studies found that male drivers are more likely to engage in risky driving behavior (Butters *et al.* 2012), no significant gender effect was found in this study, a result in line with other previous fog-related driving behavior studies (Mueller and Trick, 2012, Yan *et al.* 2014). Thus, it can be reasoned that, when driving in fog, males' risky driving behavior might be counteracted by the speed or other compensation behavior in fog.

6.5 Conclusions

In the present study, we investigated the effects of crash warning systems (CWS) in the context of connected vehicles on driver's rear-end crash avoidance performance when the lead vehicle made an emergency brake under fog conditions. Response time (i.e., perception response time and brake reaction time), minimum time-to-collision, and maximum brake pedal pressures are important variables indicating driver's safety conditions. The experiment results indicated the positive effects of crash warning system on safety. It was found that the warning system can significantly reduce driver's brake response time and minimum time-to-collision. Nevertheless, no significant additional effect of audio warning could be found. Additionally, the decrease of visibility distance could increase the crash risk, and old drivers are more vulnerable road users under fog conditions. No significant gender effect could be identified in this study.

This study contributed a simulator-based experiment in examining the influence of CWS during fog. Results showed that drivers tend to adjust their braking behavior with the presence of CWS. Earlier responses and smoother braking process were observed under the connected-vehicle (CV) warning environment.

Overall, greater safety benefits and better driving performance could be achieved by providing CWS under CV environment during fog. Because the V2V and V2I communications are not affected by the reduced visibility, more accurate information could be provided to drivers. Thus, the effectiveness of the CWS could be enhanced by CV technologies. The findings of this study are relevant to the incorporation of warning and V2V&V2I applications of CV during inclement weather conditions. Such applications could help drivers avoid rear-end crashes under reduced visibility conditions. Future research could investigate the effects of different delivery time of warning message under fog conditions and different designs of the Head-up Display (HUD).

CHAPTER 7: COMBINED CONNECTED VEHICLES AND VARIABLE SPEED LIMIT STRATEGY TO REDUCE CRASH RISK UNDER FOG CONDITIONS

7.1 Introduction

The effect of fog on both crash occurrence and severity is a major concern in the traffic safety field. Previous research pointed out that fog can increase crash severity and multi-vehicle involved crash risk (Al-Ghamdi, 2007, Wu *et al.* 2017b, Wu *et al.* 2017d). The reduced visibility conditions that are caused by fog result in a shorter sight distance and a longer stopping sight distance (Wu *et al.* 2017a). When a crash happens, approaching vehicles may not be able to observe the downstream slow traffic in time and lead to secondary crashes (Li *et al.* 2014b), and potentially multi vehicles multi fatalities pile up as in recent experiences in Florida.

One of the possible methods to improve safety under fog conditions is implementing Variable Speed Limits (VSL). By restricting speeds, VSLs enable drivers have better preparation before they entering into the adverse weather area, and decrease the crash risks under the adverse weather conditions (Wu *et al.* 2017d).

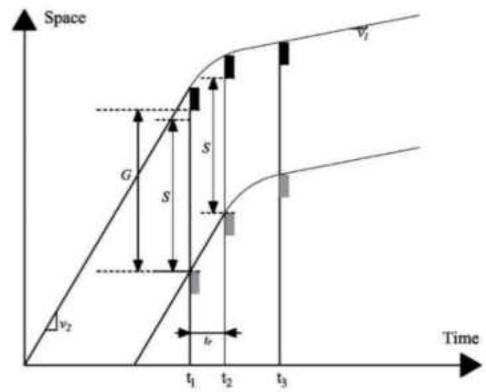
VSL may improve safety and mobility under adverse conditions (Li *et al.* 2014b) In the US, VSL has been deployed under inclement weather conditions, such as fog, precipitation, wind, etc..

However, VSL strategies require Variable Message Signs (VMSs) to deliver information, which are placed discretely, and the deployment of VMSs can be expensive. This disadvantage could be improved by using connected-vehicle (CV) technologies, which include Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication (Wang *et al.* 2015b). With the CV technologies, vehicles could have more information about the current traffic status, and better traffic control commands could be made. Meanwhile, some crashes may be prevented by the systems based on CV technologies, such as forward collision warning system, blind spot warning system, etc. This paper aims to investigate the feasibility of the proposed VSL control strategy and CV to decrease crash risks under fog conditions.

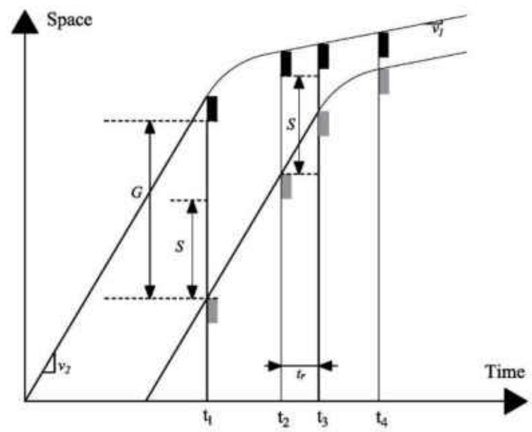
7.2 Methodology

7.2.1 VSL Optimization

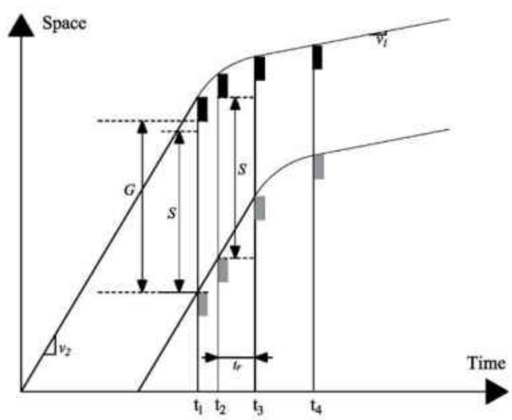
During fog conditions, traffic congestion may be formed due to the occurrence of crashes. For two consecutive vehicles, if the front vehicle decreases its speed due to congestion, rear-end crashes may happen when the following vehicle keeps small headway or responds late. Meanwhile, since fog reduce the sight distance, drivers may not be able to respond in time, which may lead to higher crash risk during fog (Wu *et al.* 2017a). Figure 7-1(a) shows the trajectories of the vehicles when the leading vehicle's speed decreases from v_2 to v_1, and the gap between the vehicles (G) is smaller than the sight distance (S).



(a) when $S > G$



(b) when $G > \frac{(v_2-v_1)^2}{2a} + S$



(c) when $s \leq G \leq \frac{(v_2-v_1)^2}{2a} + S$

Figure 7-1 Trajectories of two vehicle

Thus, under the abovementioned situation, a rear-end crash occurs if:

$$\frac{v_2^2 - v_1^2}{2a} + v_1 t_r + G < v_2 t_r + \frac{v_2^2 - v_1^2}{2a} \tag{7-1}$$

So,

$$v_2 > v_1 + \frac{G}{t_r} \tag{7-2}$$

where t_r is the reaction time, which equals 1.5 s in this study; a is the deceleration rate, which equals 2.8 m/s^2 in this study.

As it is shown in Figure 7-1(b) & Figure 7-1(c), there are two different situations when gap is greater than or equal to visibility ($G \geq S$): (1) when the following vehicle is able to see the front vehicle, the front vehicle's speed has been decreased to v_1 ($G > \frac{(v_2-v_1)^2}{2a} + S$) (Figure 2(b)); (2) when the following vehicle is able to see the front vehicle, the front vehicle is still decreasing its speed ($s \leq G \leq \frac{(v_2-v_1)^2}{2a} + S$) (Figure 2(c)).

Based on Figure 2(b), when $G > \frac{(v_2-v_1)^2}{2a} + S$, a rear-end crash occurs if:

$$v_1(t_r + \frac{v_2-v_1}{a}) + \mathrm{S} < v_2 t_r + \frac{v_2^2-v_1^2}{2a} \tag{7-3}$$

$$v_2 > v_1 + (2as + a^2 {t_r}^2)^{1/2} - a t_r \tag{7-4}$$

Otherwise, a rear-end crash occurs (Figure 2(c)) if:

$$\frac{v_2^2 - v_1^2}{2a} + v_1\left(t_r + \frac{v_2 - v_1}{a} - \frac{v_2' - v_1}{a}\right) + G < v_2(\Delta t + t_r) + \frac{v_2^2 - v_1^2}{2a} \quad (7\text{-}5)$$

because $v_2\Delta t - \frac{1}{2}a\Delta t^2 + G = v_2\Delta t + S$, $\Delta t = t_2 - t_1$, and $v_2' = v_2 - (2a(G - S))^{1/2}$

$$=> \ v_2 > \frac{v_1(t_r + \left(\frac{2(G - S)}{a}\right)^{\frac{1}{2}}) + G}{(\frac{2(G - S)}{a})^{1/2} + t_r} \quad (7\text{-}6)$$

where $v_2'$is the front vehicle's speed when the following vehicle see the front vehicle.

Moreover, the aggregated Microwave radar data could be used to approximate individual vehicle data as follows (Li *et al.* 2014b):

$$v = \frac{1}{N\sum_{n=1}^{N} v} = \overline{\mathrm{V}}[t, t + \Delta t] \quad (7\text{-}7)$$

$$G = \frac{\bar{L}(1 - \bar{O}_u[t, t + \Delta t])}{\bar{O}_u[t, t + \Delta t]} \quad (7\text{-}8)$$

where Δt is loop detectors' updating period; $\overline{\mathrm{V}}[t, t + \Delta t]$ is average speed at loop detector during $[t, t + \Delta t]$; $\bar{O}_u[t, t + \Delta t]$ is average occupancy at the upstream detector during $[t, t + \Delta t]$; $\bar{L}$ is average vehicle length, which is 15 ft in this study.

7.2.2 Development of VSL Strategy

Previous studies found that VSL could reduce crash risks by decreasing speed variations of different roadway segments (Hossain and Muromachi, 2010, Wang *et al.* 2017a). In this study, the real-time data was obtained from radar detectors, while weather data was collected from weather sensors. Based on the above analysis, the optimized speed limit of VSL (V_{opt}) is calculated by:

$$V_{opt}(t+\Delta t) = \begin{cases} V_D + \dfrac{G}{t_r} \; if \; G \leq S \\ V_D + (2aS + a^2 {t_r}^2)^{1/2} - at_r \; if \; G > \dfrac{(v_U - v_D)^2}{2a} + S \\ \dfrac{V_D\left(t_r + \left(\frac{2(G-S)}{a}\right)^{\frac{1}{2}}\right) + G}{\left(\frac{2(G-S)}{a}\right)^{\frac{1}{2}} + t_r} \; otherwise \end{cases} \tag{7-9}$$

Where V_D is the average speed of the downstream detector.

Meanwhile, the posted speed limit of VSL ($VSL(t + \Delta t)$) is adjusted based on the relationship between speed of real-time traffic ($V_D(t)$) and posted speed limit at time t ($VSL(t)$).

$$VSL(t + \Delta t) = (1 + \alpha) * \mathrm{V_{opt}}(t + \Delta t) \tag{7-10}$$

where α is real-time traffic compliance level indicator, which is calculated by $\frac{V_D(t) - VSL\,(t)}{VSL\,(t)}$.

In addition, constraints are setup with the consideration of traffic operation and safety:

(1) constraint of travel time: $VSL\;(t + \Delta t)\; \geq VSL(t)\frac{1}{1+t_m}$, where t_m is the average travel time increase rate. In this study, the value of t_m is 0.05;

(2) the maximum difference between the posted speeds of two neighboring detectors is 10 mph;

(3) the maximum difference between the post speeds of two consecutive time steps is 10 mph.

7.2.3 Connected Vehicle

Different methods have been utilized in order to reflect the effects of CV on driver behavior. Currently, one of the common models is the Intelligent Driver Model (IDM) (Kesting *et al.* 2008, Kesting *et al.* 2010, Milanés and Shladover, 2014, Khondaker and Kattan, 2015, Shladover *et al.* 2015, Talebpour and Mahmassani, 2015, Songchitruksa *et al.* 2016). The IDM acceleration function is as follows:

$$\mathrm{a}_{IDM} = a[1 - \left(\frac{v}{v_0}\right)^{\delta} - \left(\frac{s^*}{s}\right)^2] \tag{7-11}$$

$$s^* = \mathrm{s}_0 + \mathrm{T}v + \frac{\mathrm{v}\Delta\mathrm{v}}{2\sqrt{ab}} \tag{7-12}$$

where v_0 is the desired speed; v is the vehicle's speed; s is the gap between consecutive vehicles.

The values of the parameters were determined based on previous studies (Kesting *et al.* 2010, Milanés and Shladover, 2014, Li *et al.* 2017): Minimum distance in congested traffic (s_0) = 2 m (6.6 ft); desired time gap (T) =0.6 s; maximum acceleration (a) =1 m/s^2 (3.3 ft/s^2); desired deceleration (b) =2 m/s^2 (6.6 ft/s^2); Free acceleration exponent (δ) =4. It worth mentioning that the maximum communication distance for CVs is 300 m (984.3 ft) during the simulation.

7.3 Experiment Design

A freeway section (westbound of I-4) in Florida is utilized to test the abovementioned VSL algorithm and CV technologies, where a severe multi vehicles fog-related crash had happened (Hassan *et al.* 2011). There are three lanes in each direction, and the weather data was collected from a Fog Monitoring System (FMS) at the roadside (Abdel-Aty *et al.* 2016). Figure 7-2 shows the layout of the studied roadway segment. Since the distances between detector #1 & #2 and detector #5 & #6 are relatively small, no VSL sign was placed close to Detector #2 or #5. Thus, three VSL signs and six detectors were implemented in VISSIM. At the beginning of the simulation, a crash is assumed to happen between Detector #5 and Detector #6, and 2 lanes were blocked due to the crash. The VSL algorithm was fulfilled by the Component Object Model (COM) interface, which is used to program and regulate vehicle movements, and the CV behavior was regulated by the external driver behavior model in VISSIM, and it was based on Intelligent Driver Module (IDM) and was developed with a C++ program (Wang *et al.* 2017b). In-field traffic data under fog conditions was collected for calibration and validation.

Figure 7-2 Simulation network

A week day with heavy fog duration (6:15 am to 8:15 am, visibility level: 45 m to 88 m) on February 2nd, 2016 was chosen as the simulation periods. The simulation network was calibrated by traffic volume at 15-min intervals, and was validated by average speeds at 15-min intervals. Geoffrey E. Heavers (GEH) statistics was calculated by traffic volume from both in-field detectors and simulation at 15-min intervals.

$$GEH = \sqrt{\frac{(E-V)^2}{(E+V)^2}} \tag{7-13}$$

where E is the simulated volume (vehicle/hour), and V is the field volume (vehicle/hour).

In this VISSIM network, 91.25% of the GEH values are within the error of 5, and 92.50% of l speed difference between the in-field data and the simulation data is within 5 mph at the detectors' locations. These results demonstrate that the VISSIM model is validated.

Moreover, a Remote Traffic Microwave Sensor (RTMS) augmented with a device to collect vehicle-based data was installed within the studied roadway segments to collect traffic data. The RTMS was augmented with a Click 514 device to capture the headways between each vehicle on each lane in addition to the regular traffic parameters. Thus, driver behavior parameters during fog conditions in VISSIM were further calibrated by a sensitivity analysis based on in-field headway data.

This experiment aims to reduce secondary crash risks under fog condition. The secondary crash occurrence conditions are analyzed first. Then, safety benefits of the VSL control/CV are evaluated through the microscopic traffic simulation VISSIM. Finally, concluding remarks and limitation are discussed.

The main objective of this paper is to evaluate the proposed VSL strategy, and understand the impact of the VSL strategy together with CV technologies on traffic safety. Thus, in order simplify the experiment, only 0% CV penetration rate and 100% CV penetration rate were tested in this study. Three variables were considered: traffic volume (low and high), penetration rates of CV (0% and 100%), and VSL compliance rates (0%, 30%, 60, and 100%). In total, 12 scenarios were included during the experiment (Table 7-1), and the scenarios can be divided into four types: base (no VSL or CV), VSL only, CV only, and implementing VSL under CV environment (VSL&CV). The values of high volume were set to be triple of the values of low volume, which is based on the field traffic data. Ten runs were carried out with different random seed values for each scenario. Each simulation lasted 2 hours, and the first 30 minutes are considered the warm-up period.

Table 7-1 Simulation scenarios for experiment

Scenario Number	VSL Compliance rate	CV Penetration rate	Volume
1	0%	0%	Low
2	0%	0%	High
3	0%	100%	Low
4	0%	100%	High
5	30%	0%	Low
6	60%	0%	Low
7	100%	0%	Low
8	30%	0%	High
9	60%	0%	High
10	100%	0%	High
11	100%	100%	Low
12	100%	100%	High

7.4 Evaluation Measurement

Traffic safety effects are quantified by speed homogeneity and Time-to-Collision at braking (TTC_{brake}). Speed homogeneity is defined as the standard deviation of speed (van Nes *et al.* 2010), and it was found to have significant relationship with crash frequency and crash severity (Yu and Abdel-Aty, 2014a, b). Furthermore, two types of TTC are usually utilized in traffic safety analysis: TTC1 and TTC2. TTC1 assumes the front vehicle maintains its speed, while TTC2 describes situations when the leading vehicle stops suddenly, which is also called TTC at braking (Peng *et al.* 2017). During the simulation, traffic data was collected at six detectors in the VISSIM network, and few small TTC1 was observed during the simulation. Moreover, one of the major concerns of fog-related rear-end crashes is that the following vehicles may not be able to respond in time when the front vehicle has a sudden stop because of the reduced visibility (Li *et al.* 2014b). Thus, TTC at braking (TTC2) during fog is employed in this study to evaluate traffic safety in different situations. It is worth noting that if the headway distance between two CVs is greater than their maximum communication distance (300 m), although they are not able to communicate with each other, no rear-end risky situation could be observed due to the large headway distance. In this study, the definition of the TTC at braking (TTC_{brake}) is as follows (Peng *et al.* 2017):

$$TTC_{brake} = \begin{cases} \dfrac{G}{v} & \textit{If both the leading vehicle and the following vehicle are connected vehicle} \\ \dfrac{\min(visibility, G)}{v} & \textit{otherwise} \end{cases} \tag{7-14}$$

where v is the speed of the following vehicle.

In addition, the dangerous TTC_{brake} percentage is calculated as follows. The threshold of TTC was set to be 2 seconds in this study.

$$TTC_{brake_{\%}} = \frac{\text{No. of TTC} < \text{Threshold TTC}}{Total\ number\ of\ recorded\ TTC} \tag{7-15}$$

Previous research found that VSL may increase travel time, since relative smaller speed limits are applied. In order to evaluate the effects of VSL and CV on traffic efficiency, the Total Travel Time (*TTT*) is calculated as follows:

$$TTT = \sum_{i=1}^{N} T_i \tag{7-16}$$

where T_i is the travel time of vehicle i, N is the total number of vehicles during the simulation.

7.5 Results and Discussion

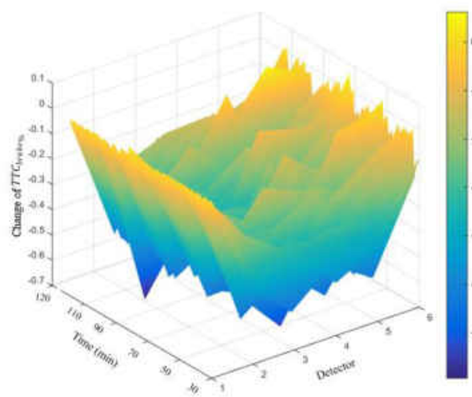
7.5.1 Effects of Variable Speed Limit

The effects of the VSL control with various driver compliance rates are summarized in Table 7-2. Negative values of the change of $TTC_{brake\%}$ mean enhanced traffic safety, and negative values of the change of TTT indicate improved traffic efficiency with the proposed VSL strategy. The results indicate that the VSL can reduce crash risks significantly, especially during low volume conditions (-29.4%). The crash risks were also decreased with the increase of the VSL compliance rates. The difference in crash risks under three different compliance rates confirmed the conclusion that VSL's impacts on safety varies by driver's compliance levels (Hellinga and Mandelzys, 2011). Meanwhile, TTTs increased by 26.9% and 3.5% during low volume condition and high volume condition, respectively. Compared to the reduction of crash risks, we could conclude that the proposed VSL strategy may reduce the crash risks without having large impact on traffic efficiency. Furthermore, the average speed homogeneity improvement is 0.5% for low volume scenarios and 24.0% for the high volume scenarios, which shows that the proposed VSL strategy could improve speed homogeneity, especially during high volume conditions.

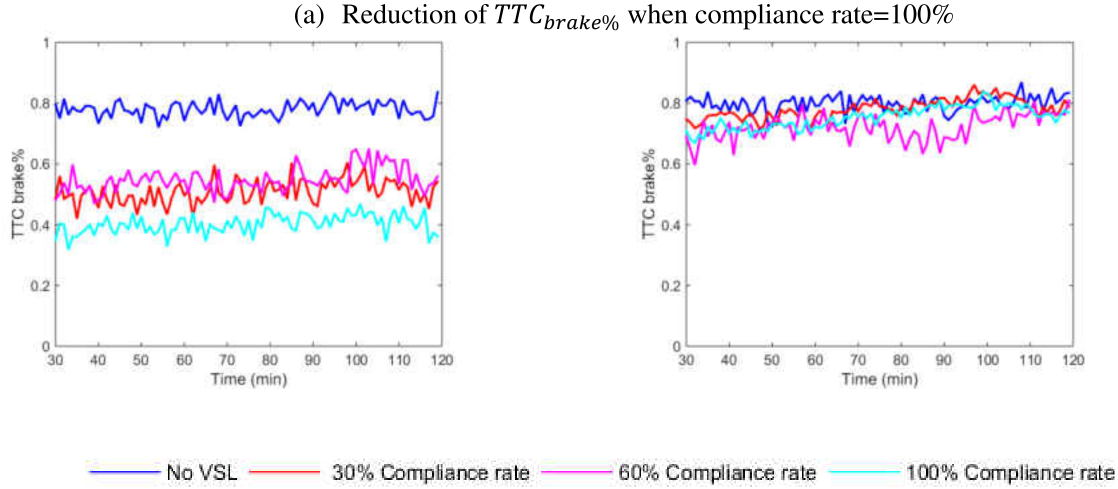
Table 7-2 Effects of the VSL control strategy

		Compliance rate		
		30%	60%	100%
Change of $TTC_{brake\%}$	Low volume (%)	-11.5	-23.1	-29.4
	High volume (%)	0	-1.3	-10
Change of TTT	Low volume (%)	+1.9	+13.8	+26.9
	High volume (%)	+3.9	+3.8	+3.5

The change of $TTC_{brake\%}$ when compliance rate equals 100%, and $TTC_{brake\%}$ curves for Non-VSL scenarios and VSL scenarios under three compliance rates are shown in Figure 7-3. In general, the VSL strategy successfully reduced the $TTC_{brake\%}$ value during almost all the VSL implemented periods. It is worth mentioning that since more severe traffic congestion was formed and vehicles' speeds decreased due to congestion in high volume conditions, the performance of the proposed strategy is better under low volume conditions, which is consistent with previous research (Abdel-Aty *et al.* 2006, Abdel-Aty *et al.* 2008).



(a) Reduction of $TTC_{brake\%}$ when compliance rate=100%



(b) Low volume

(c) High volume

Figure 7-3 $TTC_{brake\%}$ by time

7.5.2 Effects of connected vehicles

Table 7-3 shows the crash risk difference and *TTT* difference of the CV cases compared to the Non-CV cases. During low volume conditions, larger gaps and higher speeds were observed. Since CV could communicate with nearby vehicles and make them informed of dangerous situations, CV's effects are more significant in low volume scenarios when drivers are less likely to observe nearby vehicles without CV technologies. Meanwhile, CV is prone to have smaller gaps because drivers could be more confident about their driving due to the information provided by CV technologies. Thus, smaller *TTT*s were observed under the CV environment, which illustrates that the CV could effectively improve traffic efficiency, especially under high volume conditions. Moreover, the results also reveal that CV technologies have significant benefits on speed homogeneity, while the improvement of speed homogeneity is 8.6% and 62.5% for low and high volume condition, respectively.

Table 7-3 Effects of CV

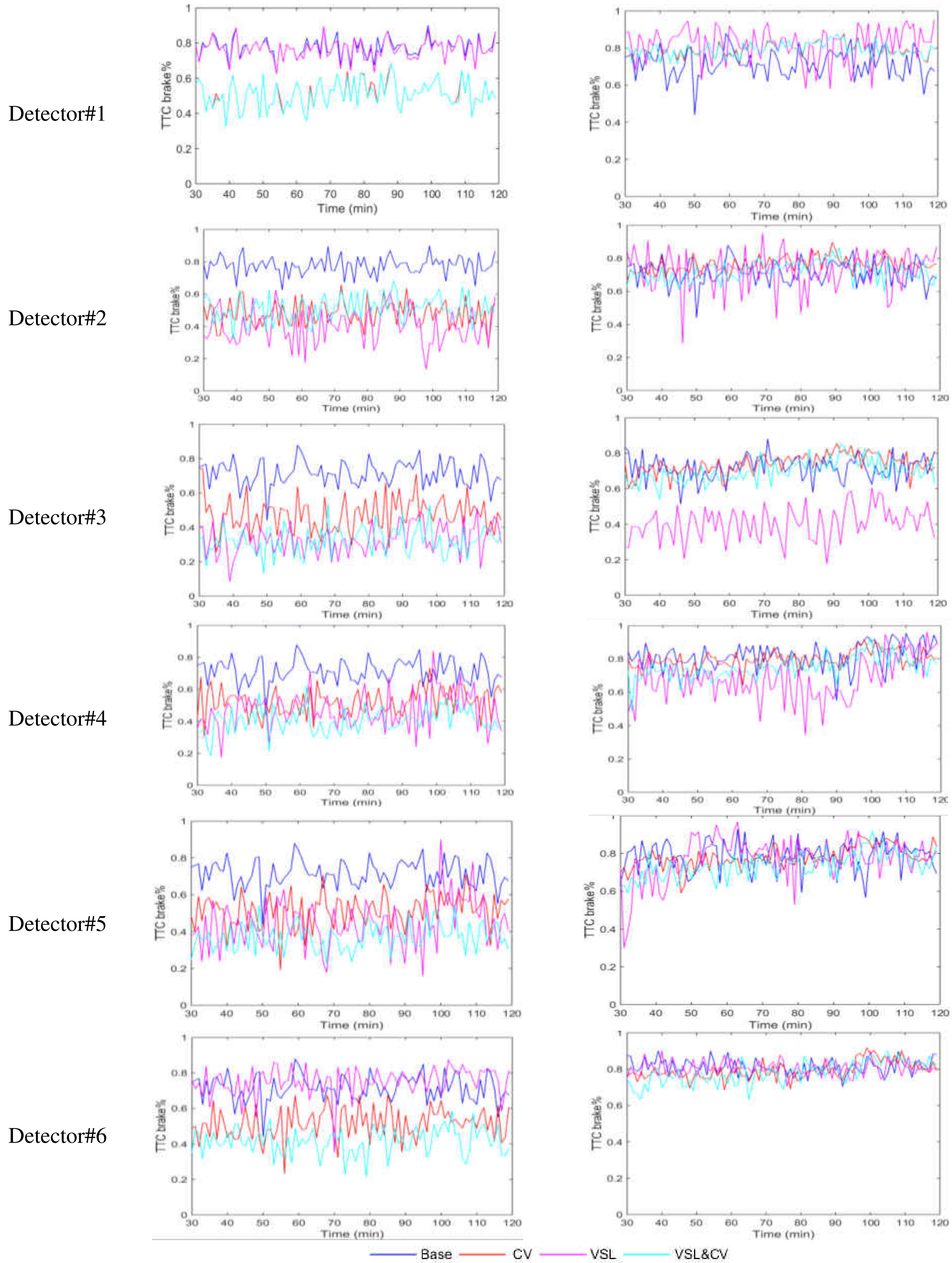
	Low Volume	High Volume
Change of $TTC_{brake\%}$ (%)	-34.6	-2.5
Change of *TTT* (%)	-3.8	-64.3

Effects of Variable Speed Limit under Connected Vehicle environment (VSL&CV): table 7-4 provides the comparison of the effects of VSL only, CV only, and VSL&CV. Negative values of the change of $TTC_{brake\%}$ or the change of TTT indicate reduced crash risks or improved traffic efficiency, while positive values of speed homogeneity improvement mean enhanced speed homogeneity with the proposed VSL strategy. The results illustrate that both VSL and CV have significant effects on traffic safety, while CV could diminish the increase of travel time caused by the VSL strategy, a result in line with other similar investigations (Lee and Park, 2013, Khondaker and Kattan, 2015). Moreover, CV successfully improved traffic efficiency under high volume conditions. However, the VSL strategy performed better when the traffic volume is low.

Table 7-4 Effects of VSL/CV under different conditions

	Low Volume			High Volume		
	VSL	CV	VSL & CV	VSL	CV	VSL & CV
Change of $TTC_{brake\%}$ (%)	-29.4	-34.6	-48.7	-10.0	-2.5	-5.0
Change of *TTT* (%)	+26.9	-3.8	+22.8	+3.5	-64.3	-55.2
Speed homogeneity improvement (%)	+0.5	+8.6	+2.8	+22.5	+62.3	+56.0

In order to further confirm the effects of VSL and CV, $TTC_{brake\%}$ is plotted by each detector in Figure 7-4. It can be observed that the VSL strategy and CV have no negative effects for the entire roadway section. It is worth mentioning that since CVs may prone to have higher speeds and smaller gaps, the reduction on $TTC_{brake\%}$ of during VSL&CV scenarios may not be higher than VSL only scenarios during high volume conditions.



(a) Low volume (b) High volume

Figure 7-4 $TTC_{brake\%}$ for different locations.

7.6 Conclusions

This study proposed a VSL control strategy that considered real-time traffic conditions and weather conditions to reduce secondary crash risks under fog conditions (or downstream reduction in capacity in general). Based on the car-following analysis under fog conditions, a dynamic speed limit strategy was developed and fulfilled by VISSIM COM interface. Meanwhile, Intelligent Driver Model (IDM) that was coded by C++ was included in the connected-vehicle (CV) related VISSIM scenarios to represent the change of driver behavior under CV environment.

The VISSIM model that was employed in this study was carefully calibrated and validated based on field traffic data and weather data at a foggy duration on February 2nd, 2016 (6:15 am – 8:15 am). A 10-mile roadway section of I-4 westbound that has experienced a severe fog-related crash was coded in the micro-simulation software VISSIM. A total of 12 scenarios were investigated, and the results were quantified as change of TTC at braking ($TTC_{brake\%}$), change of speed homogeneity, and change of total travel time (TTT) across ten runs.

From the results, it can be concluded that the proposed VSL strategy effectively enhanced safety, while slightly decreased traffic efficiency. Meanwhile, the improvement of speed homogeneity was more significant under high volume conditions. The performance of VSL is better with a higher driver's compliance level. The results also demonstrate that CV could also improve traffic safety and traffic efficiency. Implementing VSL under CV environment (VSL&CV) could further enhance safety, while CV could diminish the increase of travel time that was caused by the speed limit reduction. Moreover, crash risk migration was not observed during the simulation when the VSL was implemented.

Moreover, although the results show the impacts of the proposed VSL strategy and CV on traffic safety, limitation do exist in this study. Different CV penetration rates could be tested in order to fully investigate the effects of CV in the future. In addition, this research use the real-time traffic data under fog conditions to calibrate and validate the simulation network. Since drivers may adjust their car-following behaviors under fog conditions, these adjustments could also be considered in the future simulation studies.

CHAPTER 8: CONCLUSIONS

8.1 Summary

This dissertation mainly focused on understanding the effects of reduced visibility on traffic safety, and evaluate different countermeasures to improve traffic safety. Real-time traffic data (aggregated traffic data & disaggregated traffic data) and real-time weather data have been employed to investigate traffic safety conditions under reduced visibility conditions. In addition to the real-time data, different simulation experiments were utilized to analyze the impact of fog countermeasures.

Traffic characteristics may change under reduced visibility conditions. It was found that the average volume and the average speed become lower under fog conditions. A Crash Risk Increase Indicator (CRII) was defined, in order to use real-time traffic data to estimate crash risks during fog. The CRII includes two parts: 1) CRII for local traffic flow characteristics; 2) CRII for traffic flow relationships. Speed, speed standard deviation, and occupancy were introduced for the local traffic flow characteristics CRII analysis.

Crash risk analysis based on CRII value was conducted based on a logistic model. For crash risk under fog conditions, locations at ramp vicinities and locations with heavier traffic are prone to have crash risk increased during fog. The innermost lane with heavier traffic is more likely to experience an increase of crash risk during fog.

Moreover, disaggregate traffic data could also be employed to evaluate traffic conditions under fog. A surrogate safety measurement for fog conditions was proposed to evaluate the impact of reduced visibility on traffic safety. The measurement compared the minimum stopping distance of the leading vehicle and the following vehicle. According to the proposed algorithms, individual vehicular traffic and visibility data could be utilized to identify potential rear-end crashes events.

The effects of reduced visibility on rear-end crash risk were examined by different vehicle type and lanes. It was found that the reduced visibility could increase the rear-end crash risk significantly during fog. For the fog impact on different lanes, the reduced visibility was found to have a larger impact for the vehicles in the outer and middle lanes. Meanwhile, greater impact were observed for trucks compared with passenger cars. Meanwhile, the study utilized traffic flow conditions to evaluate rear-end crash risks under fog conditions. The results indicated that the speed of the following vehicle, the speed of leading vehicle, headway, volume per lane, average speed, and fog level were related to rear-end crash risk.

Fog warning systems could be deployed to help drivers improve their decisions for the reduced visibility condition. Two types of simulation were employed to analyze the effect of fog warning systems, which includes driving simulator and Micro-simulation VISSIM.

First, the effects of fog warning systems was evaluated by exploring driving reaction to Variable Speed Limits (VSLs) and beacons through a driving simulator experiment. Driver's speed adjustments after receiving warning messages were observed based on a hierarchical assessment concept. From the modeling aspect, the random parameters models consistently provided better data fit, and significant heterogeneity could be found for all significant variables.

For the fog systems, installing beacons would be beneficial to speed reduction behavior before entering into fog. When drivers driving from clear zone to the fog zone, VMSs may have effects on driver's brake decisions, while the advisory message may have stronger effect than the warning message. However, no significant effects on speed reduction proportion was found when VMSs or beacon presented. Compare to driving on arterials, drivers are more sensitive to visibility reduction when they are driving on a freeway, and drivers are more likely to brake harder or reduce speed when driving in dense fog. Additionally, drivers who received their first driver licenses in Florida are prone to reduce their speeds before entering into fog zone. When driving into fog area, female drivers are prone to have larger maximum deceleration rate, while younger drivers are less likely to reduce their speeds or have a harder brake.

Second, another simulator-based experiment was conducted to examine the influence of crash warning system (CWS) when fog present. It was found that providing CWS under Connected-Vehicle (CV) environment during fog could help drivers improve their driving performance and safety, since earlier responses and smoother braking process were observed under CV environment. However, no further benefits were observed when adding audio warning to the CWS, while crash risk could increase with the decrease of visibility distance. For the effects of driver's demographic characteristics, old drivers are more vulnerable to visibility decrease, and no significant gender effect could be identified.

Moreover, reduction in capacity may present during inclement weather conditions. In order to improve traffic safety when downstream experiences capacity reduction under fog conditions, a VSL control algorithm was proposed. The VSL strategy was based on a car-following analysis under fog conditions, while both real-time traffic conditions and weather conditions were taken into consideration. A dynamic speed limit strategy was developed according to the strategy.

In order to test the proposed VSL control algorithm, a roadway section of I-4 westbound that has experienced a severe fog-related crash was coded in the micro-simulation software VISSIM. Traffic data at a foggy duration on February 2nd, 2016 (from 6:15 am to 8:15 am) was selected for calibration and validation in VISSIM. According to the simulation results, the proposed VSL strategy successfully improved safety. However, slightly reduction in traffic efficiency was observed. In addition, the VSL performance was better when driver's have higher compliance level. Further improvement was found with CV technologies. The simulation results showed that CV could benefit both traffic safety and efficiency, while implementing VSL under CV environment (VSL&CV) could diminish the increase of travel time that was caused by the speed limit reduction.

8.2 Implications

Chapter 3 proposed a Crash Risk Increase Indicator (CRII), which was used for evaluating traffic safety conditions during fog. The results from Chapter 3 indicate that the proposed method works properly to designate the potential increase of crash risk under fog conditions, while important contributing factors were considered for CRII value. Based on the results, it was recommended that ramp meters could be deployed at the locations that are identified by the proposed indicator at fog durations to control the traffic volume and improve traffic safety near ramp areas. Meanwhile, Dynamic Message Signs (DMS) or beacons could be utilized to notify drivers about the potential risk during fog.

Chapter 4 developed a new algorithm to estimate the rear-end crash risk for fog conditions. The algorithm was discussed about driver behavior when the leading vehicle responds to a stimulus by taking an emergency stopping maneuver, and the analysis results revealed that the proposed algorithm could work properly to evaluate the rear-end crash risk when fog present. This algorithm provided a better understanding of the changes of crash risk during fog, and revealed the impact of reduced visibility on traffic safety. It was suggested that this algorithm could be extended to Active Traffic Management (ATM) under fog conditions, and Variable Speed Limit (VSL) could be employed through DMS to enhance traffic safety during fog. It is worth mentioning that although the algorithm was proposed for fog conditions, it could also be employed for rain or other inclement weather conditions, which could decrease visibility distances.

Chapter 5 has important implications for both researchers and practitioners about driver's speed adjustments responding to fog system systems. To specify, the effects of DMS and beacon were explored in Chapter 5. Potential safety benefits were observed when deploying beacon or DMS in the driving simulator scenarios, and more appropriate fog warning systems could be suggested to enhance the traffic safety when fog presents. Moreover, CV technologies could be utilized together with the DMS and beacon. The use of CV technologies may further decrease crash risk and fulfill the goal of traffic safety improvement.

Further driving simulator experiment was conducted to evaluate the effects of CV under fog conditions. In Chapter 6, a Forward Collision Warning (FCW) was tested when the leading vehicle make an emergency stop under fog condition. The results indicated that providing warning to drivers under CV environment could help improve driving performance and enhance traffic safety. The study in Chapter 6 is related to incorporation of warning and V2V&V2I applications under inclement weather conditions. It was suggested that such applications could be deployed to help drivers prevent crashes during fog, and ATM could be deployed together with CV technologies to further enhance traffic safety.

Chapter 7 also provides some essential implications for traffic safety researchers. A VSL strategy under fog conditions was proposed based on the algorithm proposed in Chapter 4. From the results of VISSIM simulation, the proposed VSL strategy could effectively improve traffic safety. However, due to the reduction of speed limits, traffic efficiency was slightly decreased during fog. Moreover, implementing VSL under CV environment could enhance both traffic safety and efficiency, since more accurate information could be provided to drivers by CV technologies. It was also found that CV could diminish the decrease of traffic efficiency that was caused by the speed limit reduction.

APPENDIX A: PROTOCOL AND STUDY MATERIALS FOR DRIVING SIMULATOR EXPERIMENT #1

Evaluating Toll Plazas and Visibility Conditions Using Driving Simulation

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1. PROTOCOL TITLE

Evaluating Toll Plazas and Visibility Conditions Using Driving Simulation

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3. OBJECTIVE

There are two main objectives for this driving simulator experiment. The first is to determine driver behavior in varying fog conditions and whether the presence of a Dynamic Message Sign (DMS) plays a significant impact on driving. The second is to study driver behavior while driving through a hybrid toll plaza. To do this, subjects will run through different scenarios on a NADS MiniSim driving simulator provided for the research. Variables of interest for the experiment will also be collected from the subjects, which will be observed with the results of the simulations to see if there is any correlation with these variables and the results from the scenarios. These variables will be collected confidentially and include the subject's age, gender, driving experience and frequency, highest education level, accomplished income level, or zip code, and whether they have been in an accident in the last 3 years. Questions will also be given to the subjects in written form before, during, and after the experiment in order to collect additional information that may provide an impact in the results. Feedback will also be collected from the subjects at the end of the simulation which will be used to make improvements to future simulation research projects.

Source: Mini Sim Driving Simulator (http://sonify.psych.gatech.edu/research/driving/index.html)

(4)

Questions asked prior to the simulation testing involve determining the subjects driving history and experience, as well as familiarity in fog conditions and toll plazas, as well as variable collection. These questions also allow us to get a better understanding of individuals driving habits and whether they will experience any sort of motion sickness during the testing. Between each simulation scenario, subjects will be asked addition questions in regards to the scenario they just ran. These questions include how the subject performed in the given scenario, what they observed, how they reacted, and how they felt about the situation. The subjects will also be asked how they are feeling and whether they need a few minutes to rest between these scenarios as well. Finally, at the end of the entire simulation test, subjects will again be asked if they are feeling well enough to leave and feedback will be collected from the subject on what they thought of the simulation experiment. By using this feedback, we have the opportunity to improve future simulation studies. (Samples of these questions that will be asked can be found on the attached questionnaire.)

Once the simulations have been completed and the required data has been collected, we will then analyze the results to see how people react in fog and dynamic message sign conditions, as well as toll plazas. From our research, we hope to find ways to improve the safety of our roadways by determining potential benefits from the tested environments.

4. BACKGROUND

Studying driving behavior in a real world scenario can be extremely challenging and dangerous, especially when these situations involve adverse conditions, such as fog. Due to unpredictability, it is hard to create fixed or constant environmental factors along the physical roadways. Interference from other drivers can also complicate data and also pose potential safety hazards when trying to conduct studies with volunteers. Simulations allow us to test specific scenarios under user specific conditions, allowing for more control over the environment and consistency between each subjects tests. Using simulation software also allows a cheaper alternative to testing driving behaviors compared to bigger more advanced systems such as Virginia Tech's "Smart Road." Although the simulation scenario is not as realistic as a 'real world' setting, we can validate the data in many different ways, one of which, stated by Dr. Kathy Broughton, Dr. Fred Switzer, and Dr. Dan Scott in their "Car Following Decisions" paper, would be to simply compare it to results from 'real world' studies and see if the trends are comparable (1-2). This is an absolute possibility for this research, as a sensor will be placed at the location the fog scenarios are based off of. Ultimately it was determined from the investigation that driving simulation studies were much safer and more economic than a real world setting.

Currently, there have been many research and study topics involving the analysis of driver behavior in fog conditions using driving simulation. However, many focus on simply how varying fog levels compare to collision, driving behavior, or sight distance. For this study, we will be focusing on whether the presence of a Dynamic Message Sign (DMS) effects an individual's driving behavior in fog conditions, and in what way it impacts this behavior. Validation in this regard will be fairly simple as well thanks in part to the previous fog simulation studies. Again, many of these past studies have focused on purely driving behavior, and many of which drew similar conclusions and results based on their studies. It was found that there is much consistency in driving behavior (acceleration or deceleration in fog, braking, speed, ect.) in fog conditions (3), meaning that it could be possible to validate the results based on other simulation findings if the data is consistent.

Aside from fog, dynamic message signs will play a very important role in this research as it is our overall goal to determine their impacts in driving behavior, especially when considering them for early detection warning devices. Dynamic message signs (DMS), as they sound, are signs capable of displaying different data such as warnings, directions, speed limits, and much more. In today's technology advanced age, DMS messages are becoming more and more used due to their convenience and ability to relay messages rapidly and readily. Due to this, more studies have been created to examine their potential in transportation engineering and safety. For one, it has been well researched that DMS brightness and color pattern plays an influential role in driver response to them, as well as the presence of beacons. Although this topic does not directly impact this simulations specific focus, these findings do provide significant information that could be used or considered when creating the DMS messages in the simulation software.

Very little research has been done to evaluate the safety and behavior of drivers traveling through toll plazas. This is especially true for the new tolling systems. However, toll roads have become very popular and along with this popularity research has started growing on the subject in order to make toll plazas safer. According to the literature, there are three most common toll collection systems (6). These systems are the Traditional Mainline Toll Plaza (TMTP), the Hybrid Mainline Toll Plaza (HMTP), and the All-Electronic Toll Collection (AETC). The Hybrid Mainline Toll Plaza will be the only type of toll system that will be focused on in this experiment. The HMTP is a mixture of both the Traditional Mainline Toll Plaza and All-Electronic Toll Collection. This system contains either the express Open Road Tolling (ORT) lanes on the mainline and the traditional toll collection to either side or traditional toll collection on the mainline and the separate ORT lanes on the sides. The ORT lanes and traditional toll collection are separated by barriers so that the driver must decide which lane he or she will use well before the toll collection occurs. Signs must be adequate enough to ensure that the driver can decide where to go in a safe and timely manner.

It has been found by the U.S. National Traffic Safety Board (NTSB) that toll plazas are the most dangerous locations on highways as of April 2006 (5). Using a simulator will benefit in researching these areas to allow us to examine driver behavior and to determine where exactly the problems are in toll plazas. In his "Traffic Safety Evaluation and Modeling of Toll Collection Systems", Dr. Muamer Abuzwidah compared multiple scenarios of toll plazas including a comparison between diverge-and-merge areas. Sixty hybrid mainline toll plazas were used to compare the areas. He noted that "since the lengths are different between the (diverge-and-merge) areas, the frequency of crashes were controlled by the segments' lengths." It was found that more crashes occurred within the diverge area than within the merge area (6). This is understandable and will be further analyzed in our research so that we can determine what can be done to lessen the chance of crashes.

A big problem that will need to be dealt with is the fact that the diverge area of the Dean toll plaza, which our simulator is based on, is very close to the on ramp that is located upstream of the plaza. Therefore, not only is the driver concentrating on merging onto the highway, but also on diverging into the hybrid toll plaza. Even though there is a lane in the toll plaza which is designated solely to E-Pass users, many E-Pass users who come from the on ramp on the right of the highway change lanes across the highway to the left side in order to use the ORT lanes. We can assume that this could mainly be due to poor signage. This research will expand further upon the problems caused within the diverge-and-merge areas of toll plazas.

5. SETTING OF RESEARCH

The simulation study will be conducted at the University of Central Florida, in one of our available offices in Engineering building II. The office itself is large enough to accommodate the testing equipment and personnel, and is easily accessible by the research assistants. Since the research location is conducted within the UCF engineering building, many accommodations and equipment are readily available in case of any issue. Restrooms and water fountains are accessible to subjects and personnel, and first-aid kits, fire extinguishers, and so on are also ready to use.

6. RESOURCES AVAILABLE TO CONDUCT HUMAN RESEARCH

Since we plan on recruiting many of the subjects for this study through friends, family, and the University itself, many recruitment options are available to us. Friends, family, and even possibly campus faculty can be easily contacted and requested for participation either in person or by other means of communication. However, recruiting students for the study will require a bit more work to accomplish. The current plan is to advertise the study by word of mouth in classrooms, clubs, and around campus to recruit potential volunteers for the short study.

Overall, the simulation study should only take around one hour to complete, making time commitment not a huge problem. This hour block includes pre-simulation procedures, such as going over the disclaimer and allowing the subject time to practice to become more acquainted with the simulator. Three questionnaires will be given to the subjects throughout the study. One before driving the simulator, one after each scenario, and one after the study. Following these preliminary procedures, each subject will then run through 8 scenarios chosen at random from a pool of created scenarios. The scenarios chosen will vary between the toll plaza and fog related scenarios. Assuming each scenario lasts 3-5 minutes, there should be plenty of time to familiarize the subject, run the tests, and even allow some time in between tests for the subject to rest if he or she needs it.

A majority of the research group involved in the research have a few years of transportation safety research experience, a few already obtained PhD’s in the field. We are also working with other universities in the country. These include the University of Massachusetts, University of Iowa, the University of Puerto Rico, and the University of Wisconsin who have current experience in simulation research. The other universities will have no access to the data that we will collect. The only collaboration we will have and have had with these universities is guidance with simulation research, since they have more experience in the field. Furthermore, we will only share our results and findings with them in order to expand this research further. They are not involved in the data or experiments.

As previously stated, the simulation will be conducted in a private office inside Engineering Building II on UCF campus. Access to the room is approved, and only a select few research staff have access to the room and simulator. Amenities, such as water fountains and restrooms are readily available, as well as seating if someone needed to rest. While the simulation is being conducted, subjects will be with at least one staff member at all times to monitor them and walk them through the procedure.

7. STUDY DESIGN

7a) Recruitment

For this experiment, a maximum of 72 subjects will be needed to run the simulation and be tested. The subjects will ideally range from ages 18 to late 60's, and each will be a Florida resident. Since most of the variables of interest in this study are based on the subjects' demographics, a nice even distribution will need to be met to assure unbiased results. To meet this, we will recruit a variety of subjects with varying age, gender, education, ethnicities, and backgrounds. Subjects will run the simulations through voluntary means, and will be recruited through UCF clubs and classes, friends or relatives, and possibly other local students who are interested in the research. No matter how they are recruited, each subject is expected to run through the scenarios presented in the MiniSim as if they were, or as close as possible to, driving in a real life scenario.

Subjects will be recruited during the months of May, June, and possibly July. The family and friends of the researchers be recruited by word of mouth or by e-mail. Likewise, faculty and staff will also be recruited by word of mouth or by e-mail. A description will be given to explain the basis of the research and will be sent out through these e-mails.

Identifying potential subjects will not be a difficult task for this research because the only requirements are as follows: The subject must be in the age range of 18 to late 60's, must have a driver's license, and must not have a history of motion sickness. Being in a college environment, it should be possible to find many potential subjects. As stated previously, 72 subjects will be needed to complete this research study.

7b) Compensation

Since this experiment will only last one hour and it is being ran strictly through voluntary subjects, no compensation is planned on being offered.

7c) Inclusion and Exclusion Criteria

In order to be eligible for this research experiment, subjects must fit within a predefined demographic determined by the research group. The demographic of interest includes both male and female Florida residents ages 18 to late 60's. The subjects must have a valid driver's license and have no history of extreme motion sickness or other medical conditions that can be caused by disorientation such as seizures or strokes. Subjects must also be physically capable of concentrating at a computer screen for at least one hour without having any complications.

Each person who partakes in the simulation testing will have general information about themselves questioned and or recorded. These include age, gender, ethnicity, driving experience and history, approximate income, and a few other general variables that could prove to be significant in the final analysis. Assuming the subject meets the required criteria and performs the simulation, additional variables and information will be gathered from the subject including data from their scenario performance and info on the driver's reaction based on their answers to the post simulation questions. The data that we are most interested in for this experiment is primarily the driving behavior, including speed, acceleration or deceleration rates, brake usage, lane changing, and vehicle distancing just to name a few. With the addition of the questionnaire we can also gain information in regards to how the subject reacted to the given scenarios. Information such as; were the sign(s) encountered easy to read or understand, how confusing the scenario was, or even how they reacted to a specific event can provide valuable research information in terms of driver reactions.

Again, 72 subjects are expected to be needed for the study; the results from each subject are expected to be used. The only situation where data results will be ignored or not used is if a situation occurs that results in an early withdraw of the subject or an error occurred during the simulation. Since the experiment requires the subjects to have a drivers license and must be at least 18 years or older, no children or teenagers will be considered for this research.

7d) Study Endpoints

N/A

7e) Study Timelines

The duration of the participation of a subject will be approximately one hour. This includes the explanation of what will be needed of them during the study, the scenarios the subject will be tested on, and breaks in between scenarios, as needed. It is estimated that testing will take 3 to 4 months. The primary analyses should be completed by August 2015.

7f) Procedure

The overall procedure for running the simulation should not take more than one hour for each subject, and each run will aim to be as consistent as possible. Before the simulation is started, each subject will be given a consent form that goes over what is expected of them and any possible health advisories. This consent form must be read by any subject before any testing can begin so each subject knows what to expect. Once this is done, the subject will be given preliminary questions in written form, including questions on the variables of interest (age, gender, ect.), and then will be given a test simulation to get them more acquainted and comfortable with the hardware. This portion of the procedure should take approximately 10 minutes where ideally the subject gets 5 minutes of test driving in the simulator.

Following this initial practice, the subject will be given short rest if needed and then the actual study scenarios will be provided. Prior to starting the group of scenarios, the subject will be reminded of what their task is in the simulation; and following the scenarios, each subject will be questioned in regards to the scenarios they just ran. Between each scenario group, the subject will also be given the option to take a rest if they are feeling motion sick or ill, and if they are unable to continue the test will be concluded.

Since this simulation study is looking at both Visibility DMS and Toll plaza conditions, the scenarios that the subjects will run involve completely different conditions. To keep things more in order and consistent, the groups of scenarios will each be based on one study. For the first group, both a freeway and arterial road will be generated and along them will contain a random fog and sign condition. In order to create a valid experiment, a pool of many different scenarios with varying conditions will be created, but only a few will be used randomly on each subject. The same applies for the toll plaza as multiple conditions could be present and needs to be tested.

The simulated toll plaza has been designed to represent the Dean Road toll plaza in Orlando, Florida. There are many conditions that will be tested for the toll plaza scenario as stated previously. One group of conditions includes using signs that the driver looks at to help them decided which lane they should be in as well as the location of these signs. The Dean Road toll plaza is located close to on and off ramps. Therefore, another group of conditions is the different lengths between the ramps and the plaza. These conditions can help determine what will make the road more efficient and safe when drivers diverge and merge to and from toll plazas. Ideally five random scenarios will be chosen for both the fog and toll plaza simulations, each taking around 2 to 4 minutes.

These scenarios will also include other computer controlled vehicles that could encourage the subject to change lanes or provide roadway obstacles that the subject must watch out for. Additional signage will also be included apart from the dynamic message signs, such as speed limit signs and exit signs. The DMS themselves will have varying messages depending on the scenario; these include a “recommended speed” message, a “slow down or reduce speed” message, or even a “fog warning” message. After all this simulation data is collected, analysis will begin to determine correlation between driving conditions and subject data.

There are four recording devices that are used by this simulator. One device is pointed directly at the subject’s feet and will record only their feet. One is directed towards their face and another towards their hands. The last recording device will be located behind the subject, recording the monitors and where they direct the simulated vehicle. It is necessary to note that the researchers will be the only people that will access these videos and they will be deleted immediately after the necessary data is collected. The videos will be stored in a locked, safe place. The data collected from these videos include, but are not limited to, eye movements, gas and brake pedal usage, and head movements. There is very minimal risk when using the MiniSim. The only risk the subjects have in using the simulator is motion sickness. In this case, the subject would be provided water and a cool place to sit. The motion sickness will be monitored by the research assistants who will watch for signs of uneasiness. There will be questionnaires for each subject before and after the scenarios. Attached is a copy of each questionnaire used.

Data collected during the experiment range from how the subject uses there pedals to how often they switch lanes to swerving. Data will also be collected using the questionnaires. This data includes age, gender, years of driving experience, years of driving experience in Florida, how often a person uses toll roads or roads susceptible to fog, occupation, range of income, highest level of education, how realistic the person thought the scenarios were, etc.

For the visibility related scenarios, the subject will drive through freeways and arterial lanes with varying fog and DMS conditions. These scenarios will be based in Paynes Prairie, Gainesville; a location that has seen severe crashes in the past due to visibility issues. By basing our study on this location, we gain the added benefit of using data collected from the actual site to compare and validate the simulator results. As previously stated, multiple scenarios will be made for different situations including fog density, DMS presence and number, and DMS message presented. Normally each scenario will begin under clear or slight fog conditions and as the driver proceeds down the courses, the set conditions will begin to change. From this pool of scenarios, roughly 3 or 4 will be randomly selected for each subject to run.

The toll plaza simulation will be based on the toll plaza at Dean Road in Orlando, Florida. It is very closely located in between on- and off- ramps from both Dean Road. The on-ramp from Dean Road westbound is extremely close to the toll plaza and gives a driver very little time to decide which lane they would like to use. Because of this, there will be multiple scenarios of how different distances between the on-ramp and the toll plaza affect the behavior of a driver. There will also be different signs located at different locations and distances from the toll plaza. In the simulation, the driver will be told in what form he or she will be paying with for the toll so that they can decide which lane to choose. More scenarios will include whether the subject will start on the on-ramp and go through the plaza with cash or E-Pass and then continue on the mainline. Others will be starting on the mainline, going through the plaza, and then exiting on the off-ramp after the plaza. Other drivers will start on the mainline and continue through on the mainline.

7g) Data Specimen Management

N/A

7h) Provisions To Monitor

N/A

7i) Withdrawal

If subjects show continuous or extreme signs of motion sickness, he or she will be withdrawn from the simulation test. Once withdrawn, the subject will be given a place to rest and water until they feel well enough to leave.

In a situation where a subject was withdrawn from a test, the data collected will most likely be invalidated and will not be used. However, if the subject completes a specific scenario prior to the issues causing the withdrawal to occur, then the data for those scenarios might still be usable.

8. RISKS

The main risk that is encountered while driving in the simulation is motion sickness, or any other form of motion related ailments. If a subject begins to feel any uneasiness or needs a break, they will be free to do so. Once out of the simulator, the sickness should subside momentarily. At the end of the test, subject will also be questioned to give them time to relax and will be offered a place to rest if they need some time before they leave. Also, were any serious problem occur, a researcher will be with the subject at all times so subjects should never be along for long periods of time.

9. POTENTIAL BENEFITS

Overall there is no real direct benefit towards subjects in this study other than compensation or learning something about the transportation engineering field and simulation research. The subject will also be contributing to research for safer and more efficient roadways.

10. PROVISIONS TO PROTECT PRIVACY OF SUBJECT

The simulation tests will be conducted behind closed doors with only the research assistants and subject present. The data collected from the subject will be completely confidential, where no information collected from the subject will be related to a name or identity. If subjects are not comfortable answering a question, such as income or crash history, a value range will be provided to choose from or the subject has the right to not answer. The data collected will be strictly used for academic purposes and will only be accessible to those involved in the research group.

11. PROVISIONS TO MAINTAIN CONFIDENTIALITY

In order to maintain confidentiality of the data, as well as the subjects, all data collected will be kept secure where only research staff will be able to access and look at it. Subject names will also not be used, recorded, or related to the data collected from the subjects in order to assist in creating anonymous data. The data is also going to be restricted to limited use, not only by who can access it but also where it can be accessed. The data will be stored for at least five years after the research study has been completed, per UCF IRB Policies and Procedures.

12. MEDICAL CARE AND COMPENSATION FOR INJURY

N/A

13. COSTS TO SUBJECTS

Subjects may incur a cost for parking, if this occurs, they will be reimbursed.

14. CONSENT PROCESS

All consent will be taken care of at the very start of the study, prior to any simulation testing on the subject. Each subject will be given an informed consent form that they are to go over before any testing can begin. While the subject does this, the available staff at the time will go over the form with them, ideally in the first 10 minutes, covering the most important parts of the document and check with the subject to ensure that they understand what is being discussed. This means that before any testing has begun, the subject will have been given a verbal form of consent for both what is expected of the simulation as well as understanding. The potential subjects will be asked if they have had a seizure or if they have a history of seizures. They will be excluded from partaking in the study if they answer “yes” to this question. Also, since the subject if free to withdraw from the simulation at any time, a person’s willingness to continue shows adequate ongoing consent.

Since all the subjects expected to take part in this experiment are Florida residents, we can assume that practically all of the subjects will have English as a primary language or at least have a firm grasp the language. This will be the only language spoken during the study and we will not be able to recruit subjects that do not know English.

15. CONSENT DOCUMENTATION

A written consent form will be provided prior to any testing, and will be gone over by the tester to ensure the subject understands everything. Before the simulation is started, each subject will be given a consent form that goes over what is expected of them and any possible health advisories. This consent form must be read by any subject before any testing can begin so each subject knows what to expect. The assistant conducting the research will also be available to answer any questions the subject may have and go over the consent form with them. Once this is done, the subject will be given preliminary questions, including questions on the variables of interest (age, gender, etc.).

16. VULNERABLE POPULATIONS

N/A

17. DRUGS AND DEVICES

N/A

18. MULTI-SITE HUMAN RESEARCH

N/A

19. SHARING RESULTS WITH SUBJECTS

N/A

SUMMARY

Through observation of the results of these simulation scenarios, we hope to use the findings to determine more efficient ways to use dynamic message signs for adverse weather conditions, as well as improve efficiencies at toll plazas. The work done and data collected also provides a base for other research projects and studies to read the data or do further testing on the results. As far as fog research, these studies can include closer analysis on the type of DMS used, additional signal data such as beacons, and even possibly more focus on the DMS message presented. These toll plaza studies will comprise of determining how to make the signs more understandable for drivers and where to place them in order to help them drive through toll plazas safely. Again, one of the biggest issues with simulation studies is validation of the simulation environment to accurately reflect real world data. Luckily, this will not be too big of an issue due to having access to traffic data collected from the sites of interest.

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Evaluating Toll Plazas and Visibility Conditions Using Driving Simulation

Informed Consent

Principal Investigator:	Mohamed Abdel-Aty, PhD. P.E.
Co-Investigator(s):	Kali Carroll Ryan Selby
Sub-Investigator(s):	Qi Shi, PhD Muamer Abuzwidah, PhD Qing Cai, PhD Candidate Yina Wu, PhD Candidate
Sponsor:	Florida Department of Transportation National Center for Transportation Systems Productivity and Management UTC SAFER-SIM UTC
Investigational Site(s):	University of Central Florida, Department of Civil, Environmental, and Construction Engineering

Introduction: Researchers at the University of Central Florida (UCF) study many topics. To do this we need the help of people who agree to take part in a research study. You are being invited to take part in a research study which will include about 60 people from around the Orlando area as well as faculty, staff, and students at UCF. You have been asked to take part in this research study because you are within the age range of 18-65 and have driver's license. You must be 18 years of age or older to be included in the research study.

The people conducting this research are Kali Carroll and Ryan Selby of UCF department of Civl, Environmental, and Construction Engineering. Qi Shi, Muamer Abuzwidah, Yina Wu, and Qing Cai will also be helping with this research. The researchers are collaborating with Dr. Michael Knodler and Dr. Donald Fisher the from the University of Massachussetts Amherst, as well as graduate students from the University of Puerto Rico in Mayaguez. Because the researchers are graduate students, they are being guided by Mohamed Abdel-Aty, PhD P.E., a UCF faculty advisor in the department of Civil, Environmental, and Construction Engineering.

What you should know about a research study:

- Someone will explain this research study to you.
- A research study is something you volunteer for.
- Whether or not you take part is up to you.
- You should take part in this study only because you want to.
- You can choose not to take part in the research study.
- You can agree to take part now and later change your mind.
- Whatever you decide it will not be held against you.
- Feel free to ask all the questions you want before you decide.

Purpose of the research study: The purpose of this study is to Evaluate driver behavior (1) in varying fog visibility conditions along a roadway with or without dynamic message sign presence and (2) in a hybrid toll plaza under different operating conditions.

What you will be asked to do in the study: The laboratory assistant, with whom you will interact, will give you a questionnaire to fill out before and after the experiment has been completed. This questionnaire will be kept confidential. You do not have to answer every question or complete every task. You will not lose any benefits if you skip questions or tasks. The laboratory assistant will then have you sit in the driver's seat of the simulator, which contains a steering wheel, gas and brake pedals, buttons that will be explained, three monitors that display the simulation world you will drive in, and another small monitor that displays the car's dashboard information. Before starting the actual testing scenarios, the laboratory assistant will execute a practice simulation, which involves a simple roadway and intersection. This practice scenario can be used to better acquaint you with the displays and how the vehicle operates.

Once you feel comfortable enough with the simulator, you will have a short break if needed and then continue on to the experiment. The experiment will consist of six different and random scenarios that will last about 5-7 minutes each. You will also have a 5 minute break in between each scenario if needed. The entire session should last a maximum of 70 minutes.

Location: As noted previously, the study will be done using a driving simulator. The simulator will be located on the main campus of the University of Central Florida. It is in the Engineering 2 building, room 325A.

Time required: We expect that you will be in this research study for, at the very most, 70 minutes.

Audio or video taping: You will only be video taped during this study. If you do not want to be video taped, you will still be able to be in the study. Discuss this with the researcher or a research team member. If you are video taped, the tape will be kept completely confidential in a locked, safe place. The tape will be erased or destroyed immediately after we process the data. There are four recording devices that are used by this simulator. One device is pointed directly at your feet and will record only your feet. One is directed towards your face and another towards your hands. The last recording device will be located behind you, recording the monitors and where you direct the simulated vehicle. It is necessary to note that the videos will be kept confidential and only the researchers will be the only people that will access these videos. The data collected from these videos include, but are not limited to, eye movements, gas and brake pedal usage, and head movements.

Funding for this study: This research study is being paid for by the Florida Department of Transportation, National Center for Transportation Systems Productivity and Management UTC, and SAFER-SIM UTC.

Risks: Side effects of VE (virtual environment) use may include stomach discomfort, headaches, sleepiness, dizziness and decreased balance. However, these risks are no greater than the sickness risks you may be exposed to if youwere to visit an amusement park such as Disney Quest (Disney Quest is a VE based theme park), Disney World or Universal Studios parks and ride attractions such as roller coasters. You will be given 5-minute breaks during the exercise, if necessary, to lessen the chance that you will feel sick. If you experience any of the symptoms mentioned, please tell the researcher and remain seated until the symptoms disappear. Water will also be provided to you if needed. Please let the researcher know if you have had a seizure or have a history of seizures.

Benefits: The benefits of this experiment will include contributing to the safety of future roadway designs and help researchers better understand driving habits in various driving conditions. There is no actual compensation or other payment to you for taking part in this study.

Confidentiality: All personal data collected from this experiment, both documented and filmed, will be kept strictly confidential and will only be assessable to personel directly involved in the research. Absolute confidentiality cannot be guaranteed, however data collected will be made as anonymous as possible and will only be used for research purposes. Aside from the research team, IRB will also have access to any recorded information as well for review purposes.

Study contact for questions about the study or to report a problem: If you have questions, concerns, or complaints, or think the research has hurt you, talk to Kali Carroll, Graduate Student, Transportation Engineering Program, College of Civil, Environmental, and Construction Engineering, by email at kcarroll@knights.ucf.edu or Ryan Selby, Graduate Student, Transportation Engineering Program, College of Civil, Environmental, and Construction Engineering, by email at ryans1298@knights.ucf.edu or Dr. Mohamed Abdel-Aty, Faculty Supervisor, Department of Civil, Environemental, and Construction Engineering at by email at m.aty@ucf.edu.

IRB contact about your rights in the study or to report a complaint: Research at the University of Central Florida involving human subjects is carried out under the oversight of the Institutional Review Board (UCF IRB). This research has been reviewed and approved by the IRB. For information about the rights of people who take part in research, please contact: Institutional Review Board, University of Central Florida, Office of Research & Commercialization, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901. You may also talk to them for any of the following:

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

SIMULATOR QUESTIONNAIRE

Before scenarios

1. Do you have a history of severe motion sickness or seizures?
   a. Yes
   b. No

2. How long have you had a Florida driver's license?
   a. Less than 5 years
   b. 5-10
   c.11-15
   d.16-20
   e.21+

3. How often do you use toll plazas?
   a. One to two times per year
   b. One to two times per month
   c. One to two times per week
   d. One to two times per day
   e. Three or more times per day

4. What type of toll plaza are you most familiar with?
   a. Traditional Mainline Toll Plaza
   b. All-Electronic Toll Collection System
   c. Hybrid Mainline Toll plaza

5. Do you own a SunPass?
   a. Yes
   b. No

6. Have you driven in any fog conditions in the past year?
   a. Yes

b. No

7. Are you familiar with dynamic message signs?
   a. Yes
   b. No

8. How old are you?
   a. 18-24
   b. 25-35
   c. 36-50
   d. 51-60
   e. 60+

9. Did you learn how to drive in another state?
   a. Yes
   b. No

   If yes, please explain:

10. How often do you typically drive?
    a. 1-5 trips per week
    b. 1-2 trips per day
    c. 3-5 trips per day
    d. 5+ trips per day

    If never, please explain:

11. What is your highest level of education?
    a. Some high school
    b. High school
    c. Some College
    d. Bachelor's Degree
    e. Grad. School

12. What is your range of income?
    a. 0 – 10,000
    b. 10,000 – 25,000
    c. 25,000 – 40,000
    d. 40,000 – 55,000
    e. 55,000 – 70,000
    f. 70,000+

13. Have you been in any vehicular accidents in the last 3 years?
    a. Yes
    b. No

    If so, what was the crash type (e.g. sideswipe, rear-end, head-on, etc.)? How many cars were involved? Where did the crash occur (e.g. intersection, highway, toll plaza, etc.)?

14. What vehicle do you normally drive?
    a. Sedan
    b. Pickup Truck or Van
    c. Motorcycle or Moped
    d. Professional Vehicle (Large Truck or Taxi)
    e. Other

15. Are you a professional driver / Does your job involve driving?
    a. Yes
    b. No

SIMULATOR QUESTIONNAIRE

Between scenarios

1. Do you feel sick or nauseous and need a rest?
   a. Yes
   b. No

2. Were you able to understand the signs?
   a. Yes
   b. No

   Please, explain:

3. Did you have trouble navigating/understanding the course?
   a. Yes
   b. No

   Please, explain:

<u>FOG SCENARIOS</u>

1. How did you react to the change in visibility?

2. How much more difficult would you say it was driving in the fog compared to the clear condition? How difficult was it to see other vehicles or signs?
    a. Extremely Difficult
    b. Very Difficult
    c. Somewhat Difficult
    d. No Difference

3. Did the DMS sign make driving in the fog condition easier or less stressful or was it a distraction or unhelpful?
    a. Helpful
    b. Unhelpful

4. Was the DMS sign easy to read and understand?
    a. Yes
    b. No

5. How did you feel while driving in the fog condition?
    a. Very Nervous
    b. Slightly Nervous
    c. Indifferent
    d. Slightly Confident
    e. Very Confident

6. How many DMS did you notice during your drive?
    a. 0
    b. 1
    c. 2
    d. 3

7. (If applicable) Did the beacons better prepare you for the fog condition?
    a. Yes
    b. No

<u>TOLL PLAZA SCENARIOS</u>

1. Did you have more trouble diverging into the separate toll plaza lanes and merging back on after the toll plaza?
    a. Yes
    b. No

Please, explain:

2. Do you think the signs were placed in proper locations and contained helpful information?
    a. Yes
    b. No

Please, explain:

3. Do you think you had a sufficient amount of time to decide which lane to get in and stay in to go through the appropriate toll collection area?
    a. Yes
    b. No

Please, explain:

SIMULATOR QUESTIONNAIRE

Between scenarios

4. Do you feel sick or nauseous and need a rest?
    c. Yes
    d. No

5. Were you able to understand the signs?
    c. Yes
    d. No

Please, explain:

6. Did you have trouble navigating/understanding the course?
   c. Yes
   d. No

Please, explain:

<u>FOG SCENARIOS</u>

8. How did you react to the change in visibility?

9. How much more difficult would you say it was driving in the fog compared to the clear condition? How difficult was it to see other vehicles or signs?
   a. Extremely Difficult
   b. Very Difficult
   c. Somewhat Difficult
   d. No Difference

10. Did the DMS sign make driving in the fog condition easier or less stressful or was it a distraction or unhelpful?
    a. Helpful
    b. Unhelpful

11. Was the DMS sign easy to read and understand?
    a. Yes
    b. No

12. How did you feel while driving in the fog condition?
    a. Very Nervous
    b. Slightly Nervous
    c. Indifferent
    d. Slightly Confident
    e. Very Confident

13. How many DMS did you notice during your drive?
    a. 0
    b. 1
    c. 2
    d. 3

14. (If applicable) Did the beacons better prepare you for the fog condition?
    a. Yes
    b. No

TOLL PLAZA SCENARIOS

4. Did you have more trouble diverging into the separate toll plaza lanes and merging back on after the toll plaza?
   a. Yes
   b. No

Please, explain:

5. Do you think the signs were placed in proper locations and contained helpful information?
   a. Yes
   b. No

Please, explain:

6. Do you think you had a sufficient amount of time to decide which lane to get in and stay in to go through the appropriate toll collection area?
   a. Yes
   b. No

Please, explain:

SIMULATOR QUESTIONNAIRE

Between scenarios

7. Do you feel sick or nauseous and need a rest?
   e. Yes
   f. No

8. Were you able to understand the signs?
   e. Yes
   f. No

   Please, explain:

9. Did you have trouble navigating/understanding the course?
   e. Yes
   f. No

   Please, explain:

<u>FOG SCENARIOS</u>

15. How did you react to the change in visibility?

16. How much more difficult would you say it was driving in the fog compared to the clear condition? How difficult was it to see other vehicles or signs?
    a. Extremely Difficult
    b. Very Difficult
    c. Somewhat Difficult
    d. No Difference

17. Did the DMS sign make driving in the fog condition easier or less stressful or was it a distraction or unhelpful?
    a. Helpful
    b. Unhelpful

18. Was the DMS sign easy to read and understand?
    a. Yes
    b. No

19. How did you feel while driving in the fog condition?
    a. Very Nervous
    b. Slightly Nervous
    c. Indifferent
    d. Slightly Confident
    e. Very Confident

20. How many DMS did you notice during your drive?
    a. 0
    b. 1

c. 2
d. 3

21. (If applicable) Did the beacons better prepare you for the fog condition?
    a. Yes
    b. No

TOLL PLAZA SCENARIOS

7. Did you have more trouble diverging into the separate toll plaza lanes and merging back on after the toll plaza?
    a. Yes
    b. No

Please, explain:

8. Do you think the signs were placed in proper locations and contained helpful information?
    a. Yes
    b. No

Please, explain:

9. Do you think you had a sufficient amount of time to decide which lane to get in and stay in to go through the appropriate toll collection area?
    a. Yes
    b. No

Please, explain:

SIMULATOR QUESTIONNAIRE

After scenarios

1. How do you feel? Are you capable of leaving or need some time to rest?

2. Do you have any suggestions or feedback on how to improve the simulation or have any complaints in regards to the scenarios you ran?

3. Do you think the scenarios were logical and true to a real life situation?

4. What did you like and dislike about the simulation?

5. What did you think was the most beneficial towards your ability to navigate the courses?

APPENDIX B: PROTOCOL AND STUDY MATERIALS FOR DRIVING SIMULATOR EXPERIMENT #2

Evaluating Managed Lane and Fog Systems Conditions Using Driving Simulation

Mohamed Abdel-Aty, Ph.D., P.E.

Yina Wu, Ph.D. Candidate

Qing Cai, Ph.D. Candidate

Jaeyoung Lee, PhD

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February 2017

1. PROTOCOL TITLE

Evaluating Managed Lane and Fog Systems Conditions Using Driving Simulation

2. PRINCIPAL INVESTIGATOR

Mohamed Abdel-Aty, Ph.D., P.E.

3. OBJECTIVE

There are two main objectives for this driving simulator experiment. The first is to determine driver behavior in varying fog conditions and explore the impacts of different fog warning systems on driver behavior. The second is to study driver behavior while driving from general purpose lane to managed lane. To do this, participants will run through different scenarios on a NADS MiniSim driving simulator provided for the research. Variables of interest for the experiment will also be collected from the participants, which will be observed with the results of the simulations to see if there is any correlation with these variables and the results from the scenarios. These variables will be collected anonymously and include the participant's age, gender, driving experience and frequency, highest education level, accomplished income level, or zip code, and whether they have been in an accident in the last 3 years. Questions will also be given to the participants in written form before, during, and after the experiment in order to collect additional information that may provide an impact in the results. Feedback will also be collected from the participants at the end of the simulation which will be used to make improvements to future simulation research projects. Further, a questionnaire survey will be also conducted to investigate users' preference on HUD design under fog condition.

Source: Mini Sim Driving Simulator (http://sonify.psych.gatech.edu/research/driving/index.html)

(4)

Questions asked prior to the simulation testing involve determining the participants driving history and experience, as well as familiarity in fog conditions and managed lane, as well as variable collection. These questions also allow us to get a better understanding of individuals driving habits and whether they will experience any sort of motion sickness during the testing. At the end of the entire simulation test, subjects will again be asked if they are feeling well enough to leave and feedback will be collected from the participant on what they thought of the simulation experiment. By using this feedback, we have the opportunity to improve future simulation studies. (Samples of these questions that will be asked can be found on the attached questionnaire.)

Once the simulations have been completed and the required data has been collected, we will then analyze the results to see how people react in fog and warning systems, as well as managed lane. From our research, we hope to find ways to improve the safety of our roadways by determining potential benefits from the tested environments.

4. BACKGROUND

Studying driving behavior in a real world scenario can be extremely challenging and dangerous, especially when these situations involve adverse conditions, such as fog. Due to unpredictability, it is hard to create fixed or constant environmental factors along the physical roadways. Interference from other drivers can also complicate data and also pose potential safety hazards when trying to conduct studies with volunteers. Simulations allow us to test specific scenarios under user specific conditions, allowing for more control over the environment and consistency between each participants tests. Using simulation software also allows a cheaper alternative to testing driving behaviors compared to bigger more advanced systems such as Virginia Tech's "Smart Road." Although the simulation scenario is not as realistic as a 'real world' setting, we can validate the data in many different ways, one of which, stated by Dr. Kathy Broughton, Dr. Fred Switzer, and Dr. Dan Scott in their "Car Following Decisions" paper, would be to simply compare it to results from 'real world' studies and see if the trends are comparable (1-2). This is an absolute possibility for this research, as a sensor will be placed at the location the fog scenarios are based off of. Ultimately it was determined from the investigation that driving simulation studies were much safer and more economic than a real world setting.

Currently, there have been many research and study topics involving the analysis of driver behavior in fog conditions using driving simulation. However, many focus on simply how varying fog levels compare to collision, driving behavior, or sight distance. For this study, we will be focusing on whether the presence of a warning system effects an individual's driving behavior in fog conditions, and in what way it impacts this behavior. Validation in this regard will be fairly simple as well thanks in part to the previous fog simulation studies. Again, many of these past studies have focused on purely driving behavior, and many of which drew similar conclusions and results based on their studies. It was found that there is much consistency in driving behavior (acceleration or deceleration in fog, braking, speed, ect.) in fog conditions (3), meaning that it could be possible to validate the results based on other simulation findings if the data is consistent.

Besides, the research team will investigate the effectiveness of warning strategies on low visibility conditions utilizing driving simulator. Various low visibility warning systems will be tested for different combinations of scenarios to assistant drivers' decisions or avoid certain type of crashes. Based on the tested results of driver behaviors, we can examine which warning types are the most safety effective among the various types such as messages (e.g., sentence, pictogram, etc.), sound, and vibration. It is expected that appropriate warning systems can be suggested to enhance safety in fog condition based on our driving simulator experiment.

Besides the fog conditions, the managed lane is also studied in our experiment. Managed Lanes are designated lanes where the flow of traffic is managed by limiting vehicle eligibility, restricting facility access, or variable price tolls. The managed lanes have emerged as an effective dynamic traffic management strategy. In recent years, several major cities in the United States have introduced managed lane systems such as ETLs (Express Toll Lanes), HOT (High-Occupancy Toll) lanes, or HOV (High Occupancy Vehicle) lanes.

In order to efficiently and safely operate the managed lane system, it is necessary to determine the safe length and location of weave access zones nearby on- or off- ramps. Although many managed lanes have been built and various safe length has been recommended (4-5), most of studies were based on microsimulation. In our driving simulator experiment, we aim to test drivers' lane changing behavior and investigate whether the length is sufficient for the drivers to merge into or out from the managed lane. Drivers require enough time (distance) to decide to use (leave) the managed lane. This decision-making process should take more time compared to general lane changing, merging or diverging, since they need to reasonably think if they have a willingness to pay the current toll rate in improve mobility (e.g., reduced travel time). Thus, there are two major cases we need to consider: fist, a distance from an upstream managed lane exit to the next downstream off-ramp; second, a minimum distance from an upstream on-ramp to the next downstream managed lane entrance.

5. SETTING OF RESEARCH

The simulation study will be conducted at the University of Central Florida, in one of our available offices in Engineering building II. The office itself is large enough to accommodate the testing equipment and personnel, and is easily accessible by the research assistants. Since the research location is conducted within the UCF engineering building, many accommodations and equipment are readily available in case of any issue. Restrooms and water fountains are accessible to participants and personnel, and first-aid kits, fire extinguishers, and so on are also ready to use.

6. RESOURCES AVAILABLE TO CONDUCT HUMAN RESEARCH

Since we plan on recruiting many of the participants for this study through friends, family, and the University itself, many recruitment options are available to us. Friends, family, and even possibly campus faculty can be easily contacted and requested for participation either in person or by other means of communication. However, recruiting students for the study will require a bit more work to accomplish. The current plan is to advertise the study by word of mouth in classrooms, clubs, and around campus to recruit potential volunteers for the short study.

Overall, the simulation study should only take around one hour to complete, making time commitment not a huge problem. This hour block includes pre-simulation procedures, such as going over the disclaimer and allowing the participant time to practice to become more acquainted with the simulator. Three questionnaires will be given to the participants throughout the study. One is before driving the simulator, and two are after the experiment. Following these preliminary procedures, each subject will then run through 7 scenarios chosen at a random order from a pool of created scenarios. The scenarios chosen will vary between the managed lane and fog related scenarios. Assuming each scenario lasts 4-6 minutes, there should be plenty of time to familiarize the participant, run the tests, and even allow some time in between tests for the participant to rest if he or she needs it.

A majority of the research group involved in the research have a few years of transportation safety research experience, a few already obtained PhD's in the field. We are also working with other universities in the country. These include the University of Massachusetts Amherst and the University of Puerto Rico who have current experience in simulation research. The other universities will have no access to the data that we will collect. The only collaboration we will have and have had with these universities is guidance with simulation research, since they have more experience in the field. Furthermore, we will only share our results and findings with them in order to expand this research further. They are not involved in the data or experiments.

As previously stated, the simulation will be conducted in a private office inside Engineering Building II on UCF campus. Access to the room is approved, and only a select few research staff have access to the room and simulator. Amenities, such as water fountains and restrooms are readily available, as well as seating if someone needed to rest. While the simulation is being conducted, participants will be with at least one staff member at all times to monitor them and walk them through the procedure.

7. STUDY DESIGN

7a) Recruitment

For this experiment, a maximum of 54 subjects will be needed to run the simulation and be tested. The subjects will ideally range from ages 18 to late 60's, and each will be a Florida resident. Since most of the variables of interested in this study are based on the participants' demographics, a nice even distribution will need to be met to assure unbiased results. To meet this, we will recruit a variety of subjects with varying age, gender, education, ethnicities, and backgrounds. Participants will run the simulations through voluntary means, and will be recruited through UCF clubs and classes, friends or relatives, and possibly other local students who are interested in the research. No matter how they are recruited, each participant is expected to run through the scenarios presented in the MiniSim as if they were, or as close as possible to, driving in a real life scenario.

Participants will be recruited during the months of February, March, and possibly April. The family and friends of the researchers be recruited by word of mouth or by e-mail. Likewise, faculty and staff will also be recruited by word of mouth or by e-mail. A description will be given to explain the basis of the research and will be sent out through these e-mails.

Identifying potential participants will not be a difficult task for this research because the only requirements are as follows: The participant must be in the age range of 18 to late 60's, must have a driver's license, and must not have a history of motion sickness. Being in a college environment, it should be possible to find many potential participants. As stated previously, 54 subjects will be needed to complete this research study.

7b) Compensation

Since this experiment will only last one hour in total and it is being ran strictly through voluntary participants, no compensation is planned on being offered.

7c) Inclusion and Exclusion Criteria

In order to be eligible for this research experiment, participants must fit within a predefined demographic determined by the research group. The demographic of interest includes both male and female Florida residents ages 18 to late 60's. The participants must have a valid driver's license and have no history of extreme motion sickness or other medical conditions that can be caused by disorientation such as seizures or strokes. Subjects must also be physically capable of concentrating at a computer screen for at least half one hour without having any complications.

Each person who partakes in the simulation testing will have general information about themselves questioned and or recorded. These include age, gender, ethnicity, driving experience and history, approximate income, and a few other general variables that could prove to be significant in the final analysis. Assuming the participant meets the required criteria and performs the simulation, additional variables and information will be gathered from the participant including data from their scenario performance and info on the driver's reaction based on their answers to the post simulation questions. The data that we are most interested in for this experiment is primarily the driving behavior, including speed, acceleration or deceleration rates, brake usage, lane changing, and vehicle distancing just to name a few. With the addition of the questionnaire we can also gain information in regards to how the participant reacted to the given scenarios. Information such as; were the sign(s) encountered easy to read or understand, how confusing the scenario was, or even how they reacted to a specific event can provide valuable research information in terms of driver reactions.

Again, 54 participants are expected to be needed for the study; the results from each subject are expected to be used. The only situation where data results will be ignored or not used is if a situation occurs that results in an early withdraw of the participant or an error occurred during the simulation. Since the experiment requires the participants to have a driver license and must be at least 18 years or older, no children or teenagers will be considered for this research.

7d) Study Endpoints

N/A

7e) Study Timelines

The participants are expected to come to do the experiment twice, at the very most, 30 minutes for each time. This includes the explanation of what will be needed of them during the study, the scenarios the subject will be tested on, and breaks in between scenarios, as needed. It is estimated that testing will take 3 to 4 months. The primary analyses should be completed by May 2017.

7f) Procedure

The overall procedure for running the simulation should not take more than one hour for each participant, and each run will aim to be as consistent as possible. Before the simulation is started, each participant will be given a consent form that goes over what is expected of them and any possible health advisories. This consent form must be read and sign by any participant before any testing can begin so each participant knows what to expect. Once this is done, the subject will be given preliminary questions in written form, including questions on the variables of interest (age, gender, etc.), and then will be given a test simulation to get them more acquainted and comfortable with the hardware. This portion of the procedure should take approximately 10 minutes where ideally the participant gets 5 minutes of test driving in the simulator.

Following this initial practice, the participant will be given short rest if needed and then the actual study scenarios will be provided. Prior to starting the group of scenarios, the participant will be reminded of what their task is in the simulation. Between each scenario group, the participant will also be given the option to take a rest if they are feeling motion sick or ill, and if they are unable to continue the test will be concluded. After driving the simulator, the participant will be questioned in regards to the scenarios they just ran and their preference of head-up display design for fog conditions. Attached is a copy of each questionnaire used.

Since this simulation study is looking at both fog warning systems and managed lane conditions, the scenarios that the subjects will run involve completely different conditions. To keep things more in order and consistent, the groups of scenarios will each be based on one study. For the first group, both a freeway and arterial road will be generated and along them will contain a random fog and sign condition. In order to create a valid experiment, a pool of many different scenarios with varying conditions will be created, but only a few will be used randomly on each participant. The same applies for the managed lane as multiple conditions could be present and needs to be tested.

Ideally seven random scenarios will be chosen for both the fog and managed lane simulations, each taking around 4 to 6 minutes. After all this simulation data is collected, analysis will begin to determine correlation between driving conditions and participant data.

There are four recording devices that are used by this simulator. One device is pointed directly at the participant's feet and will record only their feet. One is directed towards their face and another towards their hands. The last recording device will be located behind the participant, recording the monitors and where they direct the simulated vehicle. It is necessary to note that the researchers will be the only people that will access these videos and they will be deleted immediately after the necessary data is collected. The videos will be stored in a locked, safe place. The data collected from these videos include, but are not limited to, eye movements, gas and brake pedal usage, and head movements. There is very minimal risk when using the MiniSim. The only risk the subjects have in using the simulator is motion sickness. In this case, the subject would be provided water and a cool place to sit. The motion sickness will be monitored by the research assistants who will watch for signs of uneasiness.

Data collected during the experiment range from how the subject uses there pedals to how often they switch lanes to swerving. Data will also be collected using the questionnaires. This data includes age, gender, years of driving experience, years of driving experience in Florida, how often a person uses toll roads or roads susceptible to fog, occupation, range of income, highest level of education, how realistic the person thought the scenarios were, etc.

For the fog related scenarios, the participant will drive through arterial lanes with varying fog and warning system conditions. These scenarios will be based in Paynes Prairie, Gainesville;

a location that has seen severe crashes in the past due to visibility issues. By basing our study on this location, we gain the added benefit of using data collected from the actual site to compare and validate the simulator results. As previously stated, multiple scenarios will be made for different situations including fog density and warning system presence. Normally each scenario will begin under clear or slight fog conditions and as the driver proceeds down the courses, the set conditions will begin to change. From this pool of scenarios, 3 scenarios will be randomly selected for each participant to run.

The managed lane simulation will be based on the managed lane on Interstate Road 95 in Miami, Florida. In order to merge into managed lane, drivers need to change multiple lanes. Thus, it could be extremely dangerous if the length for drivers to change lanes from ramp to managed lane or from managed lane to ramp is not enough. There are two major cases we need to consider: first, a distance from an upstream managed lane exit to the next downstream off-ramp; second, a minimum distance from an upstream on-ramp to the next downstream managed lane entry. Drivers require sufficient time to decide to use (or leave) the managed lane. This decision making process takes more time compared to general lane changing, merging or diverging, as they need to reasonably think if they have a willingness to pay the current toll rate to improve mobility (e.g., reduced travel time).

7g) Data Specimen Management

N/A

7h) Provisions to Monitor

N/A

7i) Withdrawal

If participants show continuous or extreme signs of motion sickness, he or she will be withdrawn from the simulation test. Once withdrawn, the participant will be given a place to rest and water until they feel well enough to leave.

In a situation where a participant was withdrawn from a test, the data collected will most likely be invalidated and will not be used. However, if the participant completes a specific scenario prior to the issues causing the withdrawal to occur, then the data for those scenarios might still be usable. Also since the participant withdrew from the experiment early, whatever form of compensation offered will be changed based on how long the testing process took.

8. RISKS

The main risk that is encountered while driving in the simulation is motion sickness, or any other form of motion related ailments. If a subject begins to feel any uneasiness or needs a break, they will be free to do so. Once out of the simulator, the sickness should subside momentarily. At the end of the test, subject will also be questioned to give them time to relax and will be offered a place to rest if they need some time before they leave. Also, were any serious problem occur, a researcher will be with the subject at all times so participants should never be along for long periods of time.

9. POTENTIAL BENEFITS

Overall there is no real direct benefit towards participants in this study other than compensation or learning something about the transportation engineering field and simulation research. The participant will also be contributing to research for safer and more efficient roadways.

10. PROVISIONS TO PROTECT PRIVACY OF PARTICIPANT

The simulation tests will be conducted behind closed doors with only the research assistants and participant present. The data collected from the subject will be completely anonymous, where no information collected from the participant will be related to a name or identity. If subjects are not comfortable answering a question, such as income or crash history, a value range will be provided to choose from or the participant has the right to not answer. The data collected will be strictly used for academic purposes and will only be accessible to those involved in the research group.

11. PROVISIONS TO MAINTAIN CONFIDENTIALITY

In order to maintain confidentiality of the data, as well as the participants, all data collected will be kept secure where only research staff will be able to access and look at it. Subject names will also not be used, recorded, or related to the data collected from the participants in order to assist in creating anonymous data. The data is also going to be restricted to limited use, not only by who can access it but also where it can be accessed. The data will be stored for at least five years after the research study has been completed, per UCF IRB Policies and Procedures.

12. MEDICAL CARE AND COMPENSATION FOR INJURY

N/A

13. COSTS TO PARTICIPANTS

Participants may incur a cost for parking, if this occurs, they will be reimbursed.

14. CONSENT PROCESS

All consent will be taken care of at the very start of the study, prior to any simulation testing on the participant. Each participant will be given an informed consent form that they are to go over and sign before any testing can begin. While the participant does this, the available staff at the time will go over the form with them, ideally in the first 10 minutes, covering the most important parts of the document and check with the participant to ensure that they understand what is being discussed. This means that before any testing has begun, the participant will have been given a verbal form of consent for both what is expected of the simulation as well as understanding. The potential participants will be asked if they have had a seizure or if they have a history of seizures. They will be excluded from partaking in the study if they answer “yes” to this question. Also, since the participant if free to withdraw from the simulation at any time, a person’s willingness to continue shows adequate ongoing consent.

Since all the participants expected to take part in this experiment are Florida residents, we can assume that practically all of the participants will have English as a primary language or at least have a firm grasp the language. This will be the only language spoken during the study and we will not be able to recruit participants that do not know English.

15. CONSENT DOCUMENTATION

A written consent form will be provided prior to any testing, and will be gone over by the tester to ensure the participant understands everything. Before the simulation is started, each participant will be given a consent form that goes over what is expected of them and any possible health advisories. This consent form must be read and sign by any participant before any testing can begin so each participant knows what to expect. The assistant conducting the research will also be available to answer any questions the participant may have and go over the consent form with them. Once this is done, the participant will be given preliminary questions, including questions on the variables of interest (age, gender, etc.).

16. VULNERABLE POPULATIONS

N/A

17. DRUGS AND DEVICES

N/A

18. MULTI-SITE HUMAN RESEARCH

N/A

19. SHARING RESULTS WITH PARTICIPANTS

N/A

SUMMARY

Through observation of the results of these simulation scenarios, we hope to use the findings to determine more efficient ways to use warning systems for adverse weather conditions, as well as improve efficiencies at managed lane. The work done and data collected also provides a base for other research projects and studies to read the data or do further testing on the results. As far as fog research, these studies can include closer analysis on the type of warning systems used. These managed lane studies will comprise of determining safe length of location of weave access zones nearby on- or off- ramps. Again, one of the biggest issues with simulation studies is validation of the simulation environment to accurately reflect real world data. Luckily, this will not be too big of an issue due to having access to traffic data collected from the sites of interest.

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Evaluating Managed Lane and Fog Systems Conditions Using Driving Simulation

Informed Consent

Principal Investigator:	Mohamed Abdel-Aty, PhD. P.E.
Co-Investigator(s):	Yina Wu, PhD Candidate Qing Cai, PhD Candidate
Sub-Investigator(s):	Jaeyoung Lee, PhD Juneyoung Park, PhD
Sponsor:	Florida Department of Transportation National Center for Transportation Systems Productivity and Management UTC SAFER-SIM UTC
Investigational Site(s):	University of Central Florida, Department of Civil, Environmental, and Construction Engineering

Introduction: Researchers at the University of Central Florida (UCF) study many topics. To do this we need the help of people who agree to take part in a research study. You are being invited to take part in a research study which will include about 54 people from around the Orlando area as well as faculty, staff, and students at UCF. You have been asked to take part in this research study because you are within the age range of 18-65 and have driver's license. You must be 18 years of age or older to be included in the research study.

The people conducting this research are Yina Wu and Qing Cai of UCF Department of Civil, Environmental, and Construction Engineering. Jaeyoung Lee, Juneyoung Park, and will also be helping with this research. The researchers are collaborating with Dr. Michael Knodler and Dr. Donald Fisher from the University of Massachusetts Amherst, as well as graduate students from the University of Puerto Rico in Mayaguez. Because the researchers are graduate students, they are being guided by Mohamed Abdel-Aty, PhD P.E., a UCF faculty advisor in the department of Civil, Environmental, and Construction Engineering.

What you should know about a research study:

- Someone will explain this research study to you.
- A research study is something you volunteer for.
- Whether or not you take part is up to you.
- You should take part in this study only because you want to.
- You can choose not to take part in the research study.
- You can agree to take part now and later change your mind.
- Whatever you decide it will not be held against you.
- Feel free to ask all the questions you want before you decide.

Purpose of the research study: The purpose of this study is to evaluate driver behavior (1) in fog conditions along a roadway with or without fog systems presence and (2) on managed lanes and general purpose lanes under different operating conditions.

What you will be asked to do in the study: The laboratory assistant, with whom you will interact, will give you a questionnaire to fill out before and after the experiment has been completed. This questionnaire will be kept confidential. You do not have to answer every question or complete every task. You will not lose any benefits if you skip questions or tasks. The laboratory assistant will then have you sit in the driver's seat of the simulator, which contains a steering wheel, gas and brake pedals, buttons that will be explained, three monitors that display the simulation world you will drive in, and another small monitor that displays the car's dashboard information. Before starting the actual testing scenarios, the laboratory assistant will execute a practice simulation, which involves a simple roadway and intersection. This practice scenario can be used to better acquaint you with the displays and how the vehicle operates.

Once you feel comfortable enough with the simulator, you will have a short break if needed and then continue on to the experiment. The experiment will consist of seven different and random scenarios that will last about 3-6 minutes each. You will finish four scenarios during your first visit, and finish three scenarios during the second visit. You will also have a 5-minute break in between each scenario if needed. Each visit should last a maximum of 30 minutes.

Location: As noted previously, the study will be done using a driving simulator. The simulator will be located on the main campus of the University of Central Florida. It is in the Engineering 2 building, room 325A.

Time required: We expect that you will be in this research study twice for, at the very most, 30 minutes each time.

Audio or video taping: You will only be videotaped during this study. If you do not want to be videotaped, you will still be able to be in the study. Discuss this with the researcher or a research team member. If you are videotaped, the tape will be kept completely confidential in a locked, safe place. The tape will be erased or destroyed immediately after we process the data. There are four recording devices that are used by this simulator. One device is pointed directly at your feet and will record only your feet. One is directed towards your face and another towards your hands. The last recording device will be located behind you, recording the monitors and where you direct the simulated vehicle. It is necessary to note that the videos will be kept confidential and only the researchers will be the only people that will access these videos. The data collected from these videos include, but are not limited to, eye movements, gas and brake pedal usage, and head movements.

Funding for this study: This research study is being paid for by the Florida Department of Transportation, National Center for Transportation Systems Productivity and Management UTC, and SAFER-SIM UTC.

Risks: Side effects of VE (virtual environment) use may include stomach discomfort, headaches, sleepiness, dizziness and decreased balance. However, these risks are no greater than the sickness risks you may be exposed to if you were to visit an amusement park such as Disney Quest (Disney Quest is a VE based theme park), Disney World or Universal Studios parks and ride attractions such as roller coasters. You will be given 5-minute breaks during the exercise, if necessary, to lessen the chance that you will feel sick. If you experience any of the symptoms mentioned, please tell the researcher and remain seated until the symptoms disappear. Water will also be provided to you if needed. Please let the researcher know if you have had a seizure or have a history of seizures.

Benefits: The benefits of this experiment will include contributing to the safety of future roadway designs and help researchers better understand driving habits in various driving conditions. There is no actual compensation or other payment to you for taking part in this study.

Confidentiality: We will limit your personal data collected in this study to people who have a need to review this information. We cannot promise complete secrecy. Organizations that may inspect and copy your information include the IRB.

Study contact for questions about the study or to report a problem: If you have questions, concerns, or complaints, or think the research has hurt you, talk to Yina Wu, Graduate Student, Transportation Engineering Program, Department of Civil, Environmental, and Construction Engineering, by email at jessicawyn@knights.ucf.edu, Qing Cai, Graduate Student, Transportation Engineering Program, Department of Civil, Environmental, and Construction Engineering, by email at qingcai@knights.ucf.edu or Dr. Mohamed Abdel-Aty, Faculty Supervisor, Department of Civil, Environmental, and Construction Engineering, by email at m.aty@ucf.edu .

IRB contact about your rights in the study or to report a complaint: Research at the University of Central Florida involving human participants is carried out under the oversight of the Institutional Review Board (UCF IRB). This research has been reviewed and approved by the IRB. For information about the rights of people who take part in research, please contact: Institutional Review Board, University of Central Florida, Office of Research & Commercialization, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901. You may also talk to them for any of the following:

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

I acknowledge that I have read and agree to the above Terms and Conditions.

Print Name: ________________ Signature: ________________ Date:________________

SIMULATOR QUESTIONNAIRE

Before the Experiment

16. How old are you?

    ____

17. What is your ZIP code (9-digit, on your driver license)?

					--				

18. What is your highest level of education?
    f. Less than high school diploma
    g. High school diploma
    h. Associate bachelors' degree
    i. Bachelor's degree
    j. Advanced degree or professional degree

19. Are you a professional driver / Does your job involve driving?
    a. Yes
    b. No

20. How long have you been driving a car?

    ____

21. How many years have you been driving in Florida?

    ____

22. Where did you learn how to drive?
    c. In Florida
    d. Outside Florida, but in United States
    e. Outside United States

23. What vehicle do you usually drive?
    f. Passenger Car
    g. Light Truck or Van
    h. Motorcycle

i. Recreational Vehicle (RV)
j. Other. If so, what is the vehicle type: ____________

24. How often do you typically drive?
e. 1-5 trips per week
f. 1-2 trips per day
g. 3-5 trips per day
h. 5+ trips per day

If never, please explain:

25. Have you ever used a high-occupancy vehicle lane (HOV), a high-occupancy toll lane (HOT), or an express lane before?
a. Yes
b. Don't remember
c. No

26. Have you ever driven in any fog conditions in the past year?
c. Yes
d. No

27. Have you ever driven a car with Head-up display (HUD)?
c. Yes
d. No

28. Have you been involved in any vehicular crash in the last 5 years?
c. Yes
d. No

If so, what was the crash type (e.g. sideswipe, rear-end, head-on, etc.)?

How many cars were involved?

Where did the crash occur (e.g. intersection, highway, toll plaza, etc.)?

Did you receive a citation when you were involved in the crash?

SIMULATOR QUESTIONNAIRE

After the Experiment

6. How do you feel during the experiment?

1	2	3	4	5
Very bad	Bad	Neither good nor bad	Good	Very good

7. Do you think the scenarios were logical and realistic to an actual life situation?

1	2	3	4	5
Very bad	Bad	Neither good nor bad	Good	Very good

8. Do you think the weaving length of the managed lane scenarios is enough for you to cross the four general purpose lanes?

1	2	3	4	5
Not at all enough	Not very enough	Somewhat enough	Enough	Very enough

9. Did you feel comfortable when you continuously change 3 lanes in the managed lane scenarios?

1	2	3	4	5
Not at all comfortable	Not very comfortable	Somewhat comfortable	Comfortable	Very comfortable

10. Under the connected vehicle environment, how helpful were the "Fog Ahead" and "Keep Your Distance" warnings in the Head-up Display?

1	2	3	4	5
Not at all helpful	Not very helpful	Somewhat helpful	Helpful	Very helpful

11. Under the connected vehicle environment, how helpful was the "Curve Ahead" warning in the Head-up Display?

1	2	3	4	5
Not at all helpful	Not very helpful	Somewhat helpful	Helpful	Very helpful

12. Under the connected vehicle environment, how helpful was the "Slow Vehicle Ahead" warning in the Head-up Display?

1	2	3	4	5
Not at all helpful	Not very helpful	Somewhat helpful	Helpful	Very helpful

13. Under the connected vehicle environment, how helpful was the warning sounds with the Head-up Display?

1	2	3	4	5
Not at all helpful	Not very helpful	Somewhat helpful	Helpful	Very helpful

14. Do you have any suggestions or feedback on how to improve the simulation or have any complaints in regards to the scenarios you ran?

APPENDIX C: APPROVAL OF HUMAN RESEARCH FOR DRIVING SIMULATOR EXPERIMENT #1

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Mohamed A. Abdel-Aty and Co-PIs: Kali Marie Carroll, Ryan Michael Selby**

Date: **April 14, 2015**

Dear Researcher:

On 4/14/2015 the IRB approved the following human participant research until 04/13/2016 inclusive:

Type of Review:	Submission Response for UCF Initial Review Submission Form Expedited Review
Project Title:	Evaluating Toll Plazas and Visibility Conditions Using Driving Simulation
Investigator:	Mohamed A. Abdel-Aty
IRB Number:	SBE-15-11026
Funding Agency:	Florida Department of Transportation(FLDOT), Georgia Institute of Technology, University of Iowa
Grant Title:	
Research ID:	16508026, 16508025 & 1058231

The scientific merit of the research was considered during the IRB review. The Continuing Review Application must be submitted 30days prior to the expiration date for studies that were previously expedited, and 60 days prior to the expiration date for research that was previously reviewed at a convened meeting. Do not make changes to the study (i.e., protocol, methodology, consent form, personnel, site, etc.) before obtaining IRB approval. A Modification Form **cannot** be used to extend the approval period of a study. All forms may be completed and submitted online at https://iris.research.ucf.edu .

If continuing review approval is not granted before the expiration date of 04/13/2016, approval of this research expires on that date. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

Use of the approved, stamped consent document(s) is required. The new form supersedes all previous versions, which are now invalid for further use. Only approved investigators (or other approved key study personnel) may solicit consent for research participation. Participants or their representatives must receive a copy of the consent form(s).

All data, including signed consent forms if applicable, must be retained and secured per protocol for a minimum of five years (six if HIPAA applies) past the completion of this research. Any links to the identification of participants should be maintained and secured per protocol. Additional requirements may be imposed by your funding agency, your department, or other entities. Access to data is limited to authorized individuals listed as key study personnel.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Patria Davis on 04/14/2015 03:34:32 PM EDT

IRB Coordinator

APPENDIX D: APPROVAL OF HUMAN RESEARCH FOR DRIVING SIMULATOR EXPERIMENT #2

University of Central Florida

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Mohamed A. Abdel-Aty** and Co-PIs: **JaeYoung Lee, Juneyoung Park**

Date: **March 08, 2017**

Dear Researcher:

On 03/08/2017 the IRB approved the following human participant research until 03/07/2018 inclusive:

Type of Review:	IRB Continuing Review Application Form Expedited Review
Project Title:	Evaluating Toll Plazas and Visibility Conditions Using Driving Simulation
Investigator:	Mohamed A. Abdel-Aty
IRB Number:	SBE-15-11026
Funding Agency:	Florida Department of Transportation(FLDOT), Georgia Institute of Technology, University of Iowa
Grant Title:	Evaluating Toll Plazas and Visibility Conditions Using Driving Simulation
Research ID:	1650-8026, 1620-7100

The scientific merit of the research was considered during the IRB review. **NOTE: Because this study was not approved before the IRB expiration date, there was a lapse in IRB approval from 3/7/2017 to the new approval date above.** The Continuing Review Application must be submitted 30days prior to the expiration date for studies that were previously expedited, and 60 days prior to the expiration date for research that was previously reviewed at a convened meeting. Do not make changes to the study (i.e., protocol, methodology, consent form, personnel, site, etc.) before obtaining IRB approval. A Modification Form cannot be used to extend the approval period of a study. All forms may be completed and submitted online at https://iris.research.ucf.edu .

If continuing review approval is not granted before the expiration date of 03/07/2018, approval of this research expires on that date. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

Use of the approved, stamped consent document(s) is required. The new form supersedes all previous versions, which are now invalid for further use. Only approved investigators (or other approved key study personnel) may solicit consent for research participation. Participants or their representatives must receive a copy of the consent form(s).

All data, including signed consent forms if applicable, must be retained and secured per protocol for a minimum of five years (six if HIPAA applies) past the completion of this research. Any links to the identification of participants should be maintained and secured per protocol. Additional requirements may be imposed by your funding agency, your department, or other entities. Access to data is limited to authorized individuals listed as key study personnel.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Gillian Amy Mary Morien on 03/08/2017 12:41:59 PM EST

IRB Coordinator

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