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Improving Traffic Safety And Drivers' Behavior In Reduced Visibility Conditions

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IMPROVING TRAFFIC SAFETY AND DRIVERS' BEHAVIOR IN REDUCED VISIBILITY CONDITIONS

by

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ABSTRACT

This study is concerned with the safety risk of reduced visibility on roadways. Inclement weather events such as fog/smoke (FS), heavy rain (HR), high winds, etc, do affect every road by impacting pavement conditions, vehicle performance, visibility distance, and drivers' behavior. Moreover, they affect travel demand, traffic safety, and traffic flow characteristics. Visibility in particular is critical to the task of driving and reduction in visibility due FS or other weather events such as HR is a major factor that affects safety and proper traffic operation. A real-time measurement of visibility and understanding drivers' responses, when the visibility falls below certain acceptable level, may be helpful in reducing the chances of visibility-related crashes.

In this regard, one way to improve safety under reduced visibility conditions (i.e., reduce the risk of visibility related crashes) is to improve drivers' behavior under such adverse weather conditions. Therefore, one of objectives of this research was to investigate the factors affecting drivers' stated behavior in adverse visibility conditions, and examine whether drivers rely on and follow advisory or warning messages displayed on portable changeable message signs (CMS) and/or variable speed limit (VSL) signs in different visibility, traffic conditions, and on two types of roadways; freeways and two-lane roads. The data used for the analyses were obtained from a self-reported questionnaire survey carried out among 566 drivers in Central Florida, USA.

Several categorical data analysis techniques such as conditional distribution, odds' ratio, and Chi-Square tests were applied. In addition, two modeling approaches; bivariate and multivariate probit models were estimated. The results revealed that gender, age, road type, visibility condition, and familiarity with VSL signs were the significant factors affecting the likelihood of reducing speed following CMS/VSL instructions in reduced visibility conditions.

Other objectives of this survey study were to determine the content of messages that

would achieve the best perceived safety and drivers' compliance and to examine the best way to improve safety during these adverse visibility conditions. The results indicated that "Caution-fog ahead-reduce speed" was the best message and using CMS and VSL signs together was the best way to improve safety during such inclement weather situations.

In addition, this research aimed to thoroughly examine drivers' responses under low visibility conditions and quantify the impacts and values of various factors found to be related to drivers' compliance and drivers' satisfaction with VSL and CMS instructions in different visibility and traffic conditions.

To achieve these goals, Explanatory Factor Analysis (EFA) and Structural Equation Modeling (SEM) approaches were adopted. The results revealed that drivers' satisfaction with VSL/CMS was the most significant factor that positively affected drivers' compliance with advice or warning messages displayed on VSL/CMS signs under different fog conditions followed by driver factors. Moreover, it was found that roadway type affected drivers' compliance to VSL instructions under medium and heavy fog conditions. Furthermore, drivers' familiarity with VSL signs and driver factors were the significant factors affecting drivers' satisfaction with VSL/CMS advice under reduced visibility conditions. Based on the findings of the survey-based study, several recommendations are suggested as guidelines to improve drivers' behavior in such reduced visibility conditions by enhancing drivers' compliance with VSL/CMS instructions.

Underground loop detectors (LDs) are the most common freeway traffic surveillance technologies used for various intelligent transportation system (ITS) applications such as travel time estimation and crash detection. Recently, the emphasis in freeway management has been shifting towards using LDs data to develop real-time crash-risk assessment models. Numerous studies have established statistical links between freeway crash risk and traffic flow characteristics. However, there is a lack of good understanding of the relationship between traffic flow variables (i.e. speed, volume and occupancy) and crashes that occur under reduced visibility (VR crashes).

Thus, another objective of this research was to explore the occurrence of reduced visibility related (VR) crashes on freeways using real-time traffic surveillance data collected from loop detectors (LDs) and radar sensors. In addition, it examines the difference between VR crashes to those occurring at clear visibility conditions (CV crashes). To achieve these objectives, Random Forests (RF) and matched case-control logistic regression model were estimated.

The results indicated that traffic flow variables leading to VR crashes are slightly different from those variables leading to CV crashes. It was found that, higher occupancy observed about half a mile between the nearest upstream and downstream stations increases the risk for both VR and CV crashes. Moreover, an increase of the average speed observed on the same half a mile increases the probability of VR crash. On the other hand, high speed variation coupled with lower average speed observed on the same half a mile increase the likelihood of CV crashes.

Moreover, two issues that have not explicitly been addressed in prior studies are; (1) the possibility of predicting VR crashes using traffic data collected from the Automatic Vehicle Identification (AVI) sensors installed on Expressways and (2) which traffic data is advantageous for predicting VR crashes; LDs or AVIs. Thus, this research attempts to examine the relationships between VR crash risk and real-time traffic data collected from LDs installed on two Freeways in Central Florida (I-4 and I-95) and from AVI sensors installed on two

Expressways (SR 408 and SR 417). Also, it investigates which data is better for predicting VR crashes.

The approach adopted here involves developing Bayesian matched case-control logistic regression using the historical VR crashes, LDs and AVI data. Regarding models estimated based on LDs data, the average speed observed at the nearest downstream station along with the coefficient of variation in speed observed at the nearest upstream station, all at 5-10 minute prior to the crash time, were found to have significant effect on VR crash risk. However, for the model developed based on AVI data, the coefficient of variation in speed observed at the crash segment, at 5-10 minute prior to the crash time, affected the likelihood of VR crash occurrence. Argument concerning which traffic data (LDs or AVI) is better for predicting VR crashes is also provided and discussed.

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LIST OF ABBREVIATIONS

ATIS	Advanced Traveler Information System
AVI	Automatic Vehicle Identification
CMS	Changeable Message Signs
CV	Clear Visibility
DMS	Dynamic Message Sign
ESS	Environmental Sensor Station
FARS	Fatality Analysis Reporting System
FDOT	Florida Department of Transportation
FS	Fog/Smoke
HCM	Highway Capacity Manual
HR	Heavy Rain
ITS	Intelligent Transportation System
LDs	Loop Detectors
RF	Random Forests
RWIS	Road Weather Information System
SWS	Safety Warning System
TMC	Traffic Management Center
UCF	University of Central Florida
VMS	Variable Message Sign
VR	Visibility Related
VSL	Variable Speed Limit

CHAPTER 1. INTRODUCTION

1.1 Overview

Inclement weather events such as Fog/Smoke (FS), Heavy Rain (HR), high winds, etc, do affect roadways by impacting pavement conditions, vehicle performances, visibility distances, and drivers' behavior. Moreover, they affect travel demand, traffic safety, and traffic flow characteristics. Visibility in particular is critical to the task of driving and reduction in visibility due FS or other weather events such as heavy rain is a major traffic operation and safety concern.

Patches of fog and wildfires have become a recurring problem for the safety and operation of Florida highways. In Florida, these conditions could be a result of sudden dense fog, fires (whether wild or controlled), and heavy pockets of rain or hail. Florida is among the top states in the United States regarding traffic safety problems resulting from adverse visibility conditions due to FS and HR.

Considering data queried from the Fatality Analysis Reporting System (FARS), 3729 fatal crashes occurred in the United States between 2000 and 2007 where FS was the main contributing factor. Florida was the third after California and Texas with 299 fatal crashes due to FS. Although, the percentage of visibility related (VR) crashes is small compared to crashes that occurred at clear visibility conditions, these crashes tend to be more severe and involve multiple vehicles. The most recent example for VR crashes in Florida is the 70 vehicle pileup on I-4 in Polk County, Florida in January 2008. This multi vehicle crash caused 5 fatalities, many injuries, and shutting down I-4 for extended time.

Thus, there is a need to detect any reduction in visibility and develop ways to convey warnings to drivers in an effective way. A real time measurement of visibility as well as understanding drivers' responses when the visibility falls below certain acceptable levels may help in reducing the chances of visibility-related crashes.

Moreover, there are many fog warning systems that inform drivers of sudden drop in visibility especially due to fog. However, these systems were designed as fixed stations and hence, it is not possible to reinstall them at other locations. Unlike other states, there are no fixed locations for fog/smoke in Florida. Therefore, there is a need to develop a portable system that continuously detects any reduction in visibility and reports this information to the appropriate Traffic Management Center (TMC). The design and components of the portable visibility system that was developed by researchers at UCF as well as a preliminary testing for the system's performance are discussed and presented in Chapter 3.

Furthermore, Underground loop detectors (LDs) are the most common freeway traffic surveillance technologies used for various intelligent transportation system (ITS) applications such as travel time estimation and crash detection. Recently, the emphasis in freeway management has been shifting towards using LDs data to develop real-time crash-risk assessment models. Numerous studies have established statistical links between freeway crash risk and traffic flow characteristics. However, there is a lack of good understanding of the relationship between traffic flow variables (i.e. speed, volume and occupancy) and crashes that occur under reduced visibility (visibility related crashes).

Moreover, two issues that have not explicitly been addressed in prior studies are; (1) the possibility of predicting VR crashes using traffic data collected from the Automatic Vehicle

Identification (AVI) sensors installed on Expressways and (2) which traffic data is advantageous for predicting VR crashes; LDs or AVIs.

1.2 Research Objectives

The objectives of this research are as follows:

1. To gain a good understanding of the factors affecting drivers' stated behavior in adverse visibility conditions, and to examine whether drivers rely on and follow advisory or warning messages displayed on portable changeable message sign (CMS) and/or variable speed limit Sign (VSL) in different visibility, traffic conditions, and on two types of roadways; freeways and two-lane roads. To achieve these goals, a survey-based study was designed and undertaken in Fall 2009, targeting licensed drivers in Orange and Seminole counties as a representative of Central Florida drivers. A total of 566 respondents participated in this study through three survey approaches; handout, interactive, and online questionnaire.

The research issues investigated in this survey-based study are:

- Whether drivers follow warning messages displayed on CMS and/or VSL signs in adverse visibility conditions and rely on such messages,
- Drivers' stated responses to different visibility conditions,
- What differentiates drivers who claim to be more or less likely to comply with CMS and VSL instructions,
- What is the content of warning messages that would achieve the best perceived safety and driver stated compliance in reduced visibility conditions?

- What are the options that would be preferred during driving through FS: using CMS only, using VSL signs only, using CMS and VSL signs together, or close the road during such adverse visibility conditions?
- What are the differences in drivers' responses to reduction in visibility for freeways versus two-lane roads?

To achieve this goal, several categorical data analysis techniques such as conditional distribution, odds' ratio, and Chi-Square tests were applied. In addition, two modeling approaches; bivariate and multivariate probit models were estimated.

2. To thoroughly examine drivers' responses under low visibility conditions and quantify the impacts and values of various factors found to be related to drivers' compliance and drivers' satisfaction with VSL and CMS instructions in different visibility, traffic conditions over freeways and two-lane roads. To achieve these goals, Explanatory Factor Analysis (EFA) and Structural Equation Modeling (SEM) approaches were adopted.
3. To understand the traffic precursors that affects the risk of VR crashes. In other words, to explore the occurrence of visibility related (VR) crashes on freeways using real-time traffic surveillance data (speed, volume and occupancy) collected from underground loop detectors (LDs) and radar sensors located on Interstate-4 and Interstate-95 in Central Florida potentially associated with VR crash occurrence. Random Forests (RF), a relatively recent data mining technique, was used to indentify significant traffic flow variables affecting VR crash occurrence. In addition, matched case-control logistic regression model was estimated. The purpose of using this statistical approach is to explore the effects of traffic flow variables on VR crashes while controlling for the

effect of other confounding variables such as crash time and the geometric design elements of freeway sections (i.e. horizontal and vertical alignments).

4. To examine the possibility of predicting VR crashes using traffic data collected from the Automatic Vehicle Identification (AVIs) sensors installed on Expressways (SR408 and SR417) and to investigate which traffic data is advantageous for predicting VR crashes; LDs or AVIs. The approach adopted here involves developing Bayesian matched case-control logistic regression using the historical VR crashes, LDs and AVIs data.

1.3 Dissertation Organization

Following this chapter, a detailed literature review of the relevant studies is provided in Chapter 2 of this dissertation. The design and components of the portable visibility system that was developed by researchers at UCF as well as a preliminary testing for the system's performance are discussed and presented in Chapter 3.

The survey design and content, the evaluation of the quality and completeness of data received from the three surveys approaches, and some recommendations for improving future surveys design and response are presented in Chapter 4.

Chapter 5 discusses the description of the survey sample, analysis of the participants' responses, several categorical data analysis techniques (conditional distribution, odds' ratio, and Chi Square tests), bivariate and multivariate probit models and structural equation modeling that were applied to achieve the objectives of that survey-based study.

Chapter 6 examines the prediction of VR crashes on Freeways using real-time LDs traffic data while, chapter 7 explores the occurrences of VR crashes on expressways using real-time AVIs traffic data. Argument concerning which traffic data (LDs or AVIs) is better for predicting VR crashes is also provided and discussed in Chapter 7.

Finally, Chapter 8 summarizes the key findings, conclusions and recommendations that were drawn from this research.

CHAPTER 2. LITERATURE REVIEW

The literature review is divided into five sections. Section 1 discusses previous studies that addressed weather impacts on highway networks. Weather impacts on Highway mobility, traffic flow characteristics, and traffic safety are also presented in that section. Section 2 reports prior studies that investigated drivers' response to adverse weather conditions using questionnaire surveys, driving simulator and field experiments. Section 3 summarizes existing visibility warning systems. Section 4 examines prior studies that established statistical links between crash risk and real-time traffic flow variables. Finally, some conclusions from the literature review are presented in section 5.

2.1 Weather Impacts on Highway Networks

Adverse weather conditions have a major impact on safety, mobility and productivity of our Nation's roads. Weather affects roadway safety by increasing crash risk, as well as exposure to weather-related hazards. Weather impacts roadway mobility by increasing travel time delay, reducing traffic volumes and speeds, increasing speed variance and decreasing roadway capacity. Weather events influence productivity by disrupting access to road networks, and increasing road operating and maintenance costs (U.S. FHWA, 2009).

2.1.1 Weather Impact on Highways' Mobility and Traffic Flow Characteristics

Adverse weather conditions often diminish visibility distances, reduce tire-pavement traction, and cause drivers to slow down, or increase following distances on highways. Consequently, that often leads to delays, capacity reduction, trip rescheduling, rerouting, reduced mobility, and reduced travel reliability. Several prior studies indicated that traffic volumes decrease during winter storms such as McBride et al. (1977), Hanbali (1994), Nixon (1998), and Knapp (2000). Shah et al. (2003) revealed that weather events have a greater impact on increasing congestion in urban areas.

In a study of weather impacts on a Texas freeway, Gordon (1996) indicated that rain reduced capacity by 14 to 19%. In addition, Chin et al. (2002) showed that capacity on U.S. freeways and principle arterials in 1999 was reduced by more than 11% due to fog, snow and ice. Liang et al. (1998) indicated that the speed of vehicles on any roadway depends on five factors: the speed limit, the geometry of the roadway (the horizontal and vertical alignments), the density of the traffic stream, the condition of the roadway surface, and environmental factors that may affect a driver's visibility such as snow or fog.

Han et al. (2003) examined the travel delays on all urban and rural freeways and principal arterials in the nation's highway system in 1999 due to inclement weather in order to have a better appreciation of the magnitude of the problems traffic and transportation professionals face each year. The travel delays were estimated based on Highway Capacity Manual (HCM) 2000. The main result from this study was that approximately 46 million hours of traffic delay on major U.S. highways in 1999 were lost due to adverse weather conditions such as fog, ice, and snow storms. Moreover, the findings showed that the majority of the delay occurred during winter and early spring.

Goodwin (2003) summarized the impacts of various weather events on roadways, traffic flow, and operational decisions (as shown in Table 2-1).

Table 2-1: Weather impacts on roads, traffic and operational decisions (Source: Goodwin; 2003)

Road Weather Variables	Roadway Impacts	Traffic Flow Impacts	Operational Impacts
Air temperature and humidity	N/A	N/A	Road treatment strategy (e.g., snow and ice control)
Wind speed	• Visibility distance (due to blowing snow, dust). • Lane obstruction (due to wind-blown snow, debris).	• Traffic speed. • Travel time delay. • Accident risk.	• Vehicle performance (e.g., stability). • Access control (e.g., restrict vehicle type, close road). • Evacuation decision support.
Precipitation (type, rate, start/end times)	• Visibility distance. • Pavement friction. • Lane obstruction.	• Roadway capacity. • Traffic speed. • Travel time delay. • Accident risk.	• Vehicle performance (e.g., traction). • Driver capabilities/behavior. • Road treatment strategy. • Traffic signal timing. • Speed limit control. • Evacuation decision support. • Institutional coordination.
Fog	• Visibility distance	• Traffic speed. • Speed variance. • Travel time delay. • Accident risk.	• Driver capabilities/behavior. • Road treatment strategy. • Access control. • Speed limit control.
Pavement temperature	• Infrastructure damage	N/A	• Road treatment strategy
Pavement condition	• Pavement friction. • Infrastructure damage.	• Roadway capacity. • Traffic speed. • Travel time delay. • Accident risk.	• Vehicle performance. • Driver capabilities/behavior (e.g., route choice). • Road treatment strategy. • Traffic signal timing. • Speed limit control.
Water level	• Lane submersion.	• Traffic speed. • Travel time delay. • Accident risk.	• Access control. • Evacuation decision support. • Institutional coordination.

In addition, nearly all traffic engineering manuals and specifications used to estimate highway capacity assume clear weather conditions. However, for many northern states, inclement weather conditions occur during a significant portion of the year and hence estimation of highway capacity using these guidelines would be inaccurate.

Therefore, Maze et al. (2005) quantified the impact of rain, snow, and pavement surface conditions on freeway traffic flow for the metro freeway region around the Twin Cities in Iowa. The main objective of this study was to estimate the capacity and speed reductions under adverse weather conditions. The results indicated that lower visibility (i.e., due to fog events) caused capacity reductions of 10–12% and speed reductions of 6–12%. However, speed reductions for visibility (< 0.25 mile) were significantly greater than other visibility categories presented in this study. Also, the authors of this study presented a comparison of percentage reductions in capacity and average operating speeds with the Highway Capacity Manual 2000 (as shown in Table 2-2).

Table 2-2: Comparison of percentage reductions in capacity and average operating speeds with the Highway Capacity Manual 2000 (Source: Maze et al. 2005)

Variable	Range	Assumed Corresponding Categories from the Highway Capacity Manual (2000)	Capacities (percentage reductions)		Average operating speeds (percentage reductions)	
			HCM (2000)	This study	HCM (2000)	This study
Rain	0-0.01 inch/hour	Light	0	1-3	2-14	1-2.5
	0.01-0.25 inch/hour	Light	0	5-10	2-14	2-5
	> 0.25 inch/hour	Heavy	14-15	10-17	5-17	4-7
Snow	<= 0.05 inch/hour	Light	5-10	3-5	8-10	3-5
	0.06-0.1 inch/hour	Light	5-10	5-12	8-10	7-9
	0.11-0.5 inch/hour	Light	5-10	7-13	8-10	8-10
	> 0.5 inch/hour	Heavy	25-30	19-28	30-40	11-15
Temperature	10°-1° Celsius		N/A	1	N/A	1-1.5
	0°- (-20°) Celsius		N/A	1.5	N/A	1-2
	< -20° Celsius		N/A	6-10	N/A	0-3.6
Wind Speed	16-32 km/hr		N/A	1-1.5	N/A	1
	> 32 km/hr		N/A	1-2	N/A	1-1.5
Visibility	1-0.51 mile		N/A	9	N/A	6
	0.50–0.25 mile		N/A	11	N/A	7
	< 0.25 mile		N/A	10.5	N/A	11

N/A – Not Available

Maze et al. (2006) reviewed prior studies that investigated weather's impact on traffic demand, traffic safety, and traffic flow characteristics. The findings pointed out that weather conditions have an important impact on traffic safety, traffic demand, and traffic flow. In addition, it was found that roadway traffic volumes reduced by less than 5% during rainstorms, and from 7 to 80% for snowstorms. The results of this study indicated also that road weather information systems (RWIS) are very beneficial tool for traffic management.

Pisano and Goodwin (2004) reported the impacts of inclement weather on traffic flow and described an emerging concept of operations for a system-wide approach to traffic management in adverse weather to assess weather's impacts and implement operational strategies that improve safety, mobility, and productivity. They stated the required future research that is needed in order to apply the weather-responsive traffic management. They also highlighted the concept of operation by the following questions.

- *What data, processes, and procedures are needed by traffic managers to support weather-responsive traffic management?*
- *How should weather-related data, processes, and procedures be integrated with other transportation management systems and activities?*
- *What additional resources are needed to support weather-responsive traffic management?*

2.1.2 Impacts on Traffic Safety

Most of earlier studies that studied weather impacts on traffic safety such as McBride et al. (1977), Brodsky and Hakkert (1988), Perry and Symons (1991), Savenhed (1994), Shankar et al. (1995), Scharsching (1996), Brow and Baass (1997), Khattak et al. (1998, 2000), Norrman et al. (2000), and Eissenberg (2004), showed that crash rates increase during inclement weather such as fog, rain, snow, storm, high winds and as roadways became wet or snow or ice-covered.

Maze et al. (2006) indicated that during reduced visibility conditions (<0.25 mile) and high wind speeds (> 40 miles per hour), crash rates increased to about 25 times the normal crash rate.

Edwards (1996) examined the spatial dimension of weather-related road crashes using data extracted from police crash report forms. A comparison between frequency of crash occurrence and weather conditions across England and Wales was done. The main finding from this study was that the reporting of crashes in hazardous weather broadly follows the regional weather patterns for those hazards.

Lynn et al. (2002) studied fog-related crashes on the Fancy Gap and Afton Mountain sections of I-64 and I-77 in Virginia because these interstates have a long history of fog-related crashes. The main objective of this study was to evaluate the nature and severity of the problem of fog-related crashes in this area, to identify alternative solutions and technologies to address the problems. The primary recommendations from this study were to install variable message signs (VMS) to warn drivers of fog-related vehicle stops or slowdowns and to use highway advisory radio within the fog zone to communicate with drivers.

Less effort has been devoted to explore how weather-related risks vary over time, and what these variations inform us about interactions between weather and other risk factors. In this regard, Andrey et al. (2003) examined temporal variations in weather-related collision and injury risk using collision and weather data for Ottawa, Canada over the period 1990-1998. In this study, to estimate and compare the risk of collision and injury during precipitation, a matched-pair approach was used to define precipitation events and corresponding controls. The findings revealed that collision crash risk increased significantly-by about 50% for winter precipitation and by more than 100% for rain. In addition, collision risks were high during the early winter season and on weekends compared to weekdays.

2.2 Drivers' Response to Reduced Visibility Conditions

Drivers' responses to both traffic and environmental conditions can be examined through a variety of approaches, including questionnaire surveys, driving simulator experiments, and network monitoring. The relatively low cost of questionnaire surveys, compared to the other approaches, has encouraged researchers to use it as a way to collect data on different driving situations under different traffic and environmental conditions (Chatterjee et al., 2002).

2.2.1 Using Questionnaire Surveys

In general, there are two kinds of questionnaires: a stated preference (SP) survey, examining human response to a hypothetical situation, and a revealed preference (RP) survey, investigating human response derived from a real-life choice situation in the physical world. The primary shortcoming of SP data is that they might not be harmonious with actual behavior.

A number of prior studies examined consistency between RP and SP data. By comparing SP data to actual trip data, Loomis (1993) found that SP relating to intended trips under alternative quality levels are valid and reliable indicators of actual behavior. Cumming et al. (1995) compared real purchasing behavior for private goods with dichotomous choice (DC) contingent valuation questions. They found that the proportion of DC “yes” responses exceeds the proportion of actual purchases. Also, Johannesson et al. (1998) showed that hypothetical "yes" responses overestimate the real purchases.

Yannis et al. (2005) indicated that some participants may have the tendency to exaggerate when they respond to SP questions and hence, more attention should be given to the results explanation and conclusions.

Despite those drawbacks, questionnaire surveys have been commonly used so far to study drivers’ responses to Advanced Traveler Information System (ATIS) and to adverse weather conditions. Clearly, the surveys can provide valid results and indications. However, actual magnitude of these results should be viewed carefully and interpreted conservatively.

The SP surveys have been widely adopted in numerous transportation studies. Abdel-Aty et al. (1994), Khattak et al. (1996), Mahmassani et al. (2003), Iragüen and Ortúzar (2004), Tilahun et al. (2007), Junyi et al. (2008), Carlsson et al. (2010) and Correia and Viegas (2011) used SP method to identify the behaviors of drivers with ATIS deployments.

2.2.1.1 Drivers’ responses to ATIS

Many previous studies focused on studying commuters’ responses and satisfactions with traveler advisory systems such as variable message signs.

Haselkorn et al. (1989) examined the influence of traffic information from commercial radio, television traffic announcements, DMS, highway advisory radio and telephone information services on driver departure time and route choice behavior. A driver mail-back survey was undertaken in Seattle in September 1988. A total of 3893 participants sent complete responses (40% response rate). Using principal components factor analysis, it was found that commuting distance and time characteristics, attitudes towards different sources of traffic information (radio–based, television, DMS, etc) and commuter characteristics were the components related to route choice.

Harris and Konheim (1995) surveyed 1002 peak-hour travelers in the New York metropolitan area to investigate driver's satisfaction with ATIS. The findings revealed that approximately 88% of the drivers believe that ATIS are important in providing information about location and duration of delays and alternative route travel times. In addition 78% of commuters were willing to pay for ATIS.

In addition, using a questionnaire survey, Benson (1996) investigated drivers' behaviors when they encounter Dynamic Message Signs (DMSs). He examined whether drivers noticed and therefore comply with DMSs, The findings revealed that approximately 20% out of 500 respondents ignored DMSs instructions while driving.

Emmerink et al. (1996) surveyed road users in the Amsterdam corridor (on the ring road's access motorways A1, A2 and A4) in July 1994 to examine the impact of both radio traffic information and VMS information on route choice behavior. 2145 questionnaires were distributed among drivers however, only 826 of them were returned (response rate: 38.6%). Discrete choice models were conducted to investigate the factors that influence route choice behavior. The results revealed that women were less likely to be influenced by traffic information and the impacts of both radio traffic information and VMS information on route choice behavior were very similar. In addition, the results indicated that there is a positive correlation between the use of radio traffic information and VMS information.

Chatterjee et al. (2002) conducted SP questionnaires to study driver response to VMS in London. The main objective of this study was to investigate the effect of different messages displayed on VMS on route choice. Three questionnaires were conducted in this study. The first questionnaire focused on studying drivers' attitudes to London VMS information. However, the second questionnaire investigated how drivers would respond to different VMS messages. Logistic regression models were developed to predict the probability of diversion in response to different VMS messages. The third questionnaire was conducted during the activation of an immediate warning message. The results showed that one third of motorists saw the information that was displayed on VMS however, few of them diverted.

Zwahlen and Russ (2002) evaluated a real-time travel time prediction system (TIPS) in a construction work zone that includes CMS. The main aim was to evaluate the travel time and distance to the end of the work zone displayed on CMS to motorists. They surveyed the motoring public regarding their acceptance of this system. A total of 660 completed surveys were returned and analyzed (21% response rate). 97% of surveyed motorists indicated that TIPS that provide real-time travel time information in advance of work zones and in advance of open exit ramps is either outright helpful or maybe helpful.

Al-Deek et al. (2003) investigated predictive information on traveler behavior using Computer Assisted Telephone Interview (CATI) and web-based (online) survey. A total of 400 and 439 responses were collected using the CATI and web-bases surveys, respectively. The results showed that crash location and expected delay were the most needed information by drivers.

Lai and Yen (2004) examined how DMS affected driver behavior such as changing lanes, route changing, and decreasing speed using a questionnaire survey. 312 respondents participated in the survey. The main results showed that gender, age, and education were the most significant factors affecting drivers' preference for DMS. Drivers also were asked about their preference of color, and display formats of DMS. The analysis of survey revealed red and orange colors as well as flashing formats for the messages were preferred by most of participants.

Peeta and Ramos (2006) examined commuters' responses to traffic information provided through DMS using a SP survey using three different administration methods: an on-site survey, a mail-back survey, and an Internet-based survey. The findings showed that a combination of survey administration methods may generate more representative data. In addition, the results showed that a high correlation between DMS message type and driver response was existed.

In addition, a number of earlier studies have used images of CMS to explore driver comprehension and responses to the information displaying on CMS. For instance, using a SP survey, Wardman et al. (1997) evaluated the effect of information provided by CMS on drivers' route choice. Lai and Wong (2000) examined driver comprehension of the traffic information presented on CMS.

Moreover, using laptop computers, Dudek and Ullman (2002) investigated the effect of flashing an entire message, flashing one line and alternating text on one line on drivers' comprehension and recall. Using driving simulation experiments, Wang and Cao (2005) studied the influences of CMS format and number of message lines on drivers' response time. Dudek et al. (2006) examined the effect of displaying CMS with dynamic features on drivers' comprehension and response time. Ullman et al. (2007) investigated the ability of motorists to capture and process information on two CMS used in sequence. Finally, Lai (2010) examined the effects of color scheme and message lines of CMS on driver performance.

2.2.1.2 Drivers' responses to inclement weather

Noticeably, very few prior studies examined drivers' behavior in adverse weather conditions such as rain, snow, fog/smoke using questionnaire surveys.

Kilpelainen and Summala (2007) examined the effects of adverse weather and traffic weather forecasts on driver behavior in Finland using a questionnaire on perceptions of weather, pre-trip acquisition of weather information, and possible changes in travel plan. The questionnaire was conducted in rural service stations in different weather and driving conditions. The questionnaires were distributed and instantaneously collected. A total of 1437 complete questionnaires were collected and analyzed. Drivers were asked to rate the current driving conditions on a three steps scale (normal, bad, very bad), classify the slipperiness on a five-step scale (ranging from very slippery to not slippery), to mention whether they had acquired weather-related information for the trip, to report their decisions before and during the trip, and to estimate their speed, headways and overtaking frequency compared to those on the same road in good weather and driving conditions. The authors also collected data from traffic weather forecasts, weather measurement stations, and automatic traffic counters concerning the same area/road. The findings revealed that drivers, who had acquired information, had also made more changes to travel plans. On the other hand, they estimated prevailing risks higher than those who did not receive weather information. The results suggest that drivers' behavior is basically affected by the prevailing observable conditions rather than traffic weather forecasts.

2.2.2 Using Driving Simulator Experiments

Driving Simulators have been used in many prior studies as it is a very economical and a safer option compared to field studies. Driving simulators have been used on a broad variety of experiments where most of them focused on studying drivers' behavior under conditions that will not be safe to test in the real world.

Ng and Mannering (1998) developed a driving simulator experiment that collected data from four different advisory scenarios: 1) in-vehicle information (they called this type of information IVD); 2) out of vehicle information (VMS); 3) combination of in-vehicle and out of vehicle; and 4) No information present. Furthermore, there were three main messages viewed by the subjects that drove the VMS or IVD scenario: 1) fog ahead – slow down 45 mph; 2) curvy road – drive slowly; and 3) snow plow ahead – 35 mph. Static speed limit signs showed a maximum of 65 mph. In addition, two types of weather conditions (fog and no fog) and two types of incidents (snowplows or no snowplows) were incorporated for each sign.

The authors did find statistical differences in the average speed when fog or snowplows were present. Moreover, they discovered that the subjects that drove the "no sign" condition presented higher speeds than the ones that drove a sign condition.

Ikeda et al. (2002) examined whether factors like vision, visual perception, cognition, reaction time, and driving knowledge were affected by the drivers' age. Twelve subjects participated in the driving experiment where they were asked to follow traffic signals and signs and preceding cars during a 2 km stretch. It was found that depending on age, drivers have reaction times of 0.3 and 0.42 seconds. Also, the required time for judgment and recognition of another vehicle for older drivers is shorter than the one for younger drivers. Due to deterioration of information processing caused by aging, older drivers are not good at processing multiple tasks, but they are faster than young drivers at recognizing individual tasks.

Dudek et al. (2005) conducted driving simulator study to examine the effects on motorists of the following three types of CMS dynamic display features: 1) flashing an entire one-phase message; 2) flashing one line of a one-phase message; and 3) alternating text on one line of a three-line CMS while keeping the other two lines of text constant on the second phase of the message thus displaying redundant information. The results indicated that flashing messages may have an adverse effect on message comprehension for unfamiliar drivers.

Mitchell et al. (2005) investigated the use of a driving simulator to evaluate the effectiveness of traffic safety countermeasures such as reduced speed limit signs, rumble strips, and reduced lane width in freeway work zones. The main finding of this study was that a narrow traffic lane appeared to be effective in reducing average speeds through the work zone when compared to the base scenario (no countermeasures). However, the placement of rumble strips was effective in reducing average speeds only in the transition area.

Dudek et al. (2006) employed a driving simulator experiment to evaluate flashing message features on VMS. The results indicated that no differences in the average reading time between the two types of display and among age groups, education levels, and gender were observed. However, a flashing message might not provide the same effect as the static message when unfamiliar drivers read the message.

Broughton et al. (2007) examined factors that govern car following under conditions of reduced visibility due to fog. Using a driving simulator, the behavior of drivers following a lead vehicle at 13.4 m/s (30 mph) or 22.4 m/s (50 mph) under three visibility conditions (clear or one of two densities of simulated fog) were observed. The results revealed that many drivers strive to maintain visible contact with the lead vehicle when driving through dense fog however; headway time might be too short for adequate safety. In addition, they indicated that even drivers who do not maintain visual contact with the lead vehicle may still constitute a hazard for following drivers who seek to maintain visible contact with them by following too closely. Finally, they suggested that a built-in vehicle's device that provides the driver with a substitute visual image would mitigate the unsafe headway times necessary to maintain visual contact.

Reimer et al. (2007) explored the effects of age, gender, and time of day on drivers' performance using a driving simulation experiment. The results revealed that time of day, age, and gender significantly affected drivers' speed. In the late afternoon period, drivers drove significantly slower than drivers in other time periods. Moreover, it was found that old females (50 years old or more) tended to driver more slowly. In addition, time of day and age affected driver's speed and reaction time however; gender did not show significant effects.

Andersen et al. (2008) examined the effects of reduced visibility of scene information from fog on car following performance using a driving simulator. The main finding from this study was that the presence of fog in a car following task has a greater effect on responding to variations in speed rather than variations in headway distance.

2.2.3 Using Field Experiments

Many prior research efforts investigated drivers' responses to adverse weather conditions such as reduction in visibility due to FS by observing traffic spot speeds such as Hogema and Horst (1997), Edwards (1999), Maze et al. (2006) and MacCarley et al. (2006).

For example, Hogema and Horst (1997) evaluated the Dutch fog warning system in terms of driving behavior for a period of more than 2 years after implementing the system. The results showed that the system has a positive effect on speed choice in fog as it resulted in a decrease of speed of about 8 to 10 kph.

MacCarley et al. (2006) examined drivers' responses to messages displayed by a CMS warning of fog ahead and advising specific speeds at lower visibility levels. The speed, length and time of detection were individually recorded for all vehicles over a two-year period of study at four sites: two prior to exposure to the CMS, and two after exposure to the CMS. The results indicated that the mean speed decreased by an average of 1.1 mph compared with the mean speed of traffic in the absence of a message.

2.3 <u>Existing Visibility warning Systems</u>

Nowadays, there are many fog warning systems to warn drivers of sudden drops in visibility especially due to fog. This section presents a literature review for the existing fog warning and detection systems.

2.3.1 Projects in USA

2.3.1.1 Alabama DOT low visibility warning system

In fall 1999, the Alabama Department of Transportation (DOT) deployed a low visibility warning system on a prone fog area near Mobile, Alabama (Goodwin 2003). This system consisted of 6 visibility sensors with forward-scatter technology that were installed at about one-mile (1.6-kilometer) intervals. About 25 Closed Circuit Television (CCTV) cameras were used for monitoring traffic data. Via a fiber optic cable communication system, field sensor data were transmitted to a central computer in the control room. Also to display advisories or regulations to drivers, 24 VSL and 5 DMS signs were used. Operators displayed messages on DMS and changed speed limits with VSL based on the current visibility conditions (as shown in Table 2-3).

Goodwin (2003) indicated that Alabama’s low visibility system was effective in improving safety, reducing average speed and minimizing crash risk in low visibility condition.

Table 2-3: Alabama DOT low visibility warning system strategies (Source: Goodwin; 2003)

Visibility Distance	Advisories on DMS	Other Strategies
Less than 900 feet (274.3 meters)	"FOG WARNING"	Speed limit at 65 mph (104.5 kph)
Less than 660 feet (201.2 meters)	"FOG" alternating with "SLOW, USE LOW BEAMS"	• "55 MPH" (88.4 kph) on VSL signs • "TRUCKS KEEP RIGHT" on DMS
Less than 450 feet (137.2 meters)	"FOG" alternating with "SLOW, USE LOW BEAMS"	• "45 MPH" (72.4 kph) on VSL signs • "TRUCKS KEEP RIGHT" on DMS
Less than 280 feet (85.3 meters)	"DENSE FOG" alternating with "SLOW, USE LOW BEAMS"	• "35 MPH" (56.3 kph) on VSL signs • "TRUCKS KEEP RIGHT" on DMS • Street lighting extinguished
Less than 175 feet (53.3 meters)	I-10 CLOSED, KEEP RIGHT, EXIT ½ MILE	Road Closure by Highway Patrol

2.3.1.2 California DOT motorist warning system

In 1996, California Department of Transportation (Caltrans), District 10, implemented a low visibility warning system to warn drivers of adverse visibility on I-5, Stockton, CA. To collect traffic and weather data, the system includes 36 traffic speed monitoring sites, 9 complete Environmental Sensor Stations (ESS), and 9 DMS for warning drivers (see Table 2-4).

Figure 2-1 shows one of the California's ESS. Each ESS includes a forward-scatter visibility sensor, a rain gauge, wind speed and direction sensors, a relative humidity sensor, a thermometer, a barometer, and a remote processing unit (Goodwin; 2003).

(Source: Goodwin; 2003)

Figure 2-1: California DOT ESS

Table 2-4: California DOT motorist warning system messages (Source: Goodwin; 2003)

Conditions	Displayed Message
Average speed between 11 and 35 mph (56.3 kph)	“SLOW TRAFFIC AHEAD”
Average speed less than 11 mph (17.7 kph)	“STOPPED TRAFFIC AHEAD”
Visibility distance between 200 and 500 feet (152.4 meters)	“FOGGY CONDITIONS AHEAD”
Visibility distance less than 200 feet (61.0 meters)	“DENSE FOG AHEAD”
Wind speed greater than 35 mph	“HIGH WIND WARNING”

Traffic and environmental data were transmitted from the field to TMC via dedicated, leased telephone lines. The evaluation of this system should that it improved highway safety by reducing the number of visibility related crashes (MacCarley 1998, 1999).

2.3.1.3 Florida Tampa Bay area motorist warning systems for fog-related incidents

The analysis of traffic crashes at Tampa Bay revealed that it has a history of fog related problems, and has an average of 22 "heavy fog" days every year. Fog events in this area have no fixed locations. Also, there are no established trends by location, therefore no automated fog detection systems have been installed (CUTR; 1997).

2.3.1.4 Georgia automated adverse visibility warning and control system

In 2001, at a site known for fog problems on Interstate Highway 75 in South Georgia, Georgia Tech and the Georgia Department of Transportation (GDOT) jointly implemented an automated adverse visibility warning and control system along 14 miles section of I-75 to warn drivers about adverse visibility conditions.

This system consists of 19 visibility sensors, 2 DMSs, and 5 sets of traffic loops monitor speed and headway for northbound and southbound moving traffic lanes. The data collected by sensors are transmitted to an on-site computer using a fiber-optic communications network. The total project cost for system development and installation was $4 million. In addition, the cost needed to duplicate the system would be approximately $1.7 million (Gimmestad et al. 2004).

2.3.1.5 Idaho DOT motorist warning system

Between 1988 and 1993, 18 low visibility related crashes, involving 91 vehicles and resulting in 9 fatalities and 46 injuries, occurred on a 45-mile stretch of Interstate 84 in southeast Idaho. Therefore, in 1993, to improve the safety in this area, Idaho Transportation Department (ITD) installed weather and visibility warning system at that site to measure three kinds of data: traffic, visibility, and weather data. Furthermore, to measure driver behavior during normal clear days and visibility event periods, automatic traffic counters were used to observe and record the lane number, time, speed, and length of each vehicle passing by the sensor site (Goodwin; 2003).

The system consists of three visibility sensors (as shown in Figure 2-2) to measure reduced visibility conditions and a video camera to provide visual verification of the visibility sensors. The data collected by these sensors are transmitted to a master computer which records readings every five minutes. This project was conducted in two phases. The objective of phase I was to determine if the visibility sensors provide accurate visibility measurements, while the objective of Phase II was to assess whether the VMSs would reduce vehicle speed during periods of low visibility (Kyte et al. 2000).

(Source: Goodwin; 2003)

Figure 2-2: Idaho DOT visibility sensor

In this regards, Liang et al. (1998) studied the effects of visibility and other environmental factors on driver speed. The main objective was to determine the efficacy of using Idaho visibility warning System to warn motorists of inclement weather conditions and to quantify the nature of the speed-visibility relationship.

The results indicated that drivers respond to adverse environmental conditions by reducing their speeds by about 5.0 mph during the fog events and approximately 12 mph during the snow events (Table 2-5). Also, it was found that the primary factors affecting driver speed were reduced visibility and winds exceeding 25 mph. Also, Table 2-6 indicates an initial set of recommended speed levels based on the findings of the aforementioned study.

Table 2-5: Vehicle speed characteristics (mph)
(Source: Liang et al. 1998)

	Number of Events Evaluated	Car/trucks Combined		Passenger Cars Only		Trucks only	
		Mean Speed	Standard Deviation	Mean Speed	Standard Deviation	Mean Speed	Standard Deviation
Base Conditions	3	65.8	2.3	68.4	3.6	63.5	2.6
Fog Events	2	60.8	4.6	64.8	7.2	59.2	4.4
Snow Events	11	53.9	6.3	55.3	7.6	52.5	6.4

Table 2-6: An initial set of recommended speeds (mph)
(Source: Liang et al. 1998)

Visibility (miles)	Night Time Speed	Day Time Speed
0-1	60	62
>1	63	64

2.3.1.6 Maryland I-68 fog detection system

In 2005, a Fog detection system was installed on I-68, Big Savage Mt. The system consists of 4 ground mounted signs with solar powered flashers, 2 upgraded RWIS (camera, radio, remote processing unit, fog sensor), 6 Yagi directional antennas, 3 Omni directional antennas, and10 Spread – spectrum radios (shelf item) (Sabra, Wang & Associates 2003).

2.3.1.7 South Carolina DOT low visibility warning system

In 1992, South Carolina Department of Transportation (DOT) deployed a low visibility warning system on 7 miles (11.3 kilometers) on Interstate 526 to warn drivers of dense fog conditions, reduce traffic speeds, and guide vehicles safely through this fog-prone area.

The system consisted of 5 forward-scatter visibility sensors spaced at 500-foot (152.4 meter intervals, pavement lights installed at 110-foot spacing (33.5 meter), adjustable street light controls, 8 closed circuit television cameras, 8 DMSs, a remote processing unit, a central control computer, and a fiber optic cable communication system. Table 2-7 shows the advisory and control strategies of the system. The South Carolina low visibility warning system improved both mobility and safety on I-526. No fog-related crashes have occurred since the system was deployed (Goodwin; 2003, Schreiner; 2000, and Center for Urban Transportation Research; 1997).

Table 2-7: South Carolina DOT low visibility warning system strategies (Goodwin 2003)

Visibility Conditions	Advisory Strategies	Control Strategies
700 to 900 feet (213.4 to 274.3 meters)	"POTENTIAL FOR FOG" and "LIGHT FOG CAUTION" on DMS	"LIGHT FOG TRUCKS 45 MPH" and "TRUCKS KEEP RIGHT" on DMS
450 to 700 feet (137.2 to 213.4 meters)	"FOG CAUTION" and "FOG REDUCE SPEED" on DMS	Pavement lights illuminated
		"FOG REDUCE SPEED 45 MPH" and "TRUCKS KEEP RIGHT" on DMS
300 to 450 feet (91.4 to 137.2 meters)	"FOG CAUTION" on DMS	Pavement lights illuminated and overhead street lighting extinguished
		"FOG REDUCE SPEED 35 MPH" and "TRUCKS KEEP RIGHT" on DMS
Less than 300 feet	N/A	Pavement lights illuminated and overhead street lighting extinguished
		"DENSE FOG REDUCE SPEED 25 MPH" and "TRUCKS KEEP RIGHT" on DMS
		If warranted, "PREPARE TO STOP", "I-526 BRIDGE CLOSED AHEAD USE I 26/US 17", and "ALL TRAFFIC MUST EXIT" on DMS

2.3.1.8 Tennessee low visibility warning system

In 1990, a multi vehicles visibility related crash, involving 99 vehicles, 42 injuries, and 12 fatalities, had occurred in I-75 in southeastern Tennessee due to reduced visibility (less than 10 ft or 3.1 m). Therefore in 1994, Tennessee Department of Transportation (DOT) and the Tennessee Department of Safety implemented a low visibility warning system on I-75, Tennessee. The system covered 19 miles (30.6 kilometers) and consisted of 2 ESS, 8 forward-scatter visibility sensors, 44 vehicle detectors, 10 DMS, 10 VSL signs, and two highway advisory radio transmitters. Figure 2-3 shows one VSL sign of the Tennessee low visibility warning system. Traffic and environmental data were transmitted from the sensors to on-site computer for processing through underground fiber optic cables then the data were submitted to the central computer in the Highway Patrol office in Tiftonia via a microwave communication system.

Table 2-8 shows the control strategies, while Table 2-9 shows the system strategies of Tennessee visibility warning system.

(Source: Goodwin 2003)

Figure 2-3: Tennessee VSL sign

Table 2-8: Control strategies of Tennessee low visibility warning system (Source: Dahlinger et al. 2001)

Visibility Distance	Control strategies
From 480 feet (146.3 kph) to 1,320 feet	The speed limit is reduced from 65 to 50 mph
From 240 to 480 feet.	The speed limit is lowered to 35 mph (56.3 kph)
Less than 240 feet or 73.2 meters	Road close due to Fog

Table 2-9: System strategies of Tennessee low visibility warning system (Source: Dahlinger et al. 2001)

Conditions	Advisories on DMS	Other Strategies
Speed Reduced	"CAUTION" alternating with "SLOW TRAFFIC AHEAD"	N/A
Fog Detected	"CAUTION" alternating with "FOG AHEAD TURN ON LOW BEAMS"	• "FOG" displayed on VSL signs
Speed Limit Reduced	"FOG AHEAD" alternating with "ADVISORY RADIO TUNE TO XXXX AM"	• "FOG" & Reduced Speed Limits displayed on VSL signs • HAR messages broadcasted
	"FOG AHEAD" alternating with "REDUCE SPEED TURN ON LOW BEAMS"	
	"FOG" alternating with "SPEED LIMIT XX MPH"	
Roadway Closed	"DETOUR AHEAD" alternating with "REDUCE SPEED MERGE RIGHT"	• "FOG" displayed on VSL signs • HAR messages broadcasted • Ramp Gates closed
	"I-75 CLOSED" alternating with "DETOUR"	
	"FOG AHEAD" alternating with "ADVISORY RADIO TUNE TO XXXX AM"	

After deployment of the warning system in 1994, safety improved significantly as only one visibility related crash has occurred due to fog (Dahlinger et al. 1995, 2001), (Tennessee ITS State Status Report 2000).

2.3.1.9 Utah DOT low visibility warning system

In 1988 there was a 66 multi-vehicles crash and in 1991 ten crashes, with three fatalities, occurred on one day due to dense fog on Interstate 215 above the Jordan River in Salt Lake City, Utah. Therefore, during 1995 and 2000, the Utah Department of Transportation

(DOT) deployed a low visibility warning system on two mile (three-kilometer) of Interstate 215 to notify drivers of safe travel speeds and to achieve more uniform traffic flow in cases of reduction of visibility.

The warning system consisted of 4 forward-scatter visibility sensors and 6 vehicle detection sites to collect data on prevailing conditions. The speed, length, and lane of each vehicle were measured by underground loop detectors. Traffic and Environmental data were transmitted to a central computer through Ultra-High Frequency radio modems. In addition, two DMS were used to post advisories to drivers. Table 2-10 shows Utah DOT low visibility warning system messages (Perrin et al. 2000, 2002).

Table 2-10: Utah DOT low visibility warning system messages (Source: Perrin et al. 2000)

Visibility Conditions	Displayed Messages
656 to 820 feet (200 to 250 meters)	"FOG AHEAD"
492 to 656 feet (150 to 200 meters)	"DENSE FOG" alternating with "ADVISE 50 MPH"
328 to 492 feet (100 to 150 meters)	"DENSE FOG" alternating with "ADVISE 40 MPH"
197 to 328 feet (60 to 100 meters)	"DENSE FOG" alternating with "ADVISE 30 MPH"
Less than 197 feet (60 meters)	"DENSE FOG" alternating with "ADVISE 25 MPH"

Perrin et al. (2002) evaluated Utah low visibility warning system in reducing the variation between speeds which is the most important factor in reducing fog-related crashes. To achieve this goal, they tested a fog-prone area of I-215 in Salt Lake City, Utah, during three phases. Phase I was the base case, no VMSs were used in this phase. In phase II, the warning system was implemented and VMSs were used. Phase III data was collected following VMS installation during the winter of 1999-2000. The displayed VMSs, based on measured visibility, are listed below in Table 2-11.

The results of this research showed that Utah warning system successfully reduced speed variation by an average 22%. This finding supports a prior idea that informing drivers of a safe speed during adverse visibility conditions is much better than leaving each driver to decide their own safe speed. In summary, Utah fog warning system, failed to reduce mean speed, but it succeeded in reducing the variation between vehicle speeds.

Table 2-11: Highway visibility range criteria for changeable message signs (Source: Rockwell 1997)

Highway Visibility Range	Message
> 250 meters	No message
200 – 250 meters	"Fog Ahead"
150 – 200 meters	"Dense Fog" alternating with " advise 50 mph
100 – 150 meters	"Dense Fog" alternating with " advise 40 mph
60 – 100 meters	"Dense Fog" alternating with " advise 30 mph
< 60 meters	"Dense Fog" alternating with " advise 25 mph

Furthermore, several fog warning systems, in use in the United States, are provided with a 24-hour police presence to help control speeds, verify visibility problems, and assist in cases of emergencies. Some fog warning systems in other states are actually run by state or local police. The cost of fog mitigation systems depends upon many factors such as the type and numbers of fog detection sensors, VMSs, and VSL signs, communication between fog sensors, etc. Lynn et al. (2002) summarized the cost of some low visibility warning systems in the United States (as shown in Table 2-12).

Braham et al. (2000) implemented a vision support system to warn drivers in conditions of reduced visibility. The system consisted of an infrared camera for detecting objects and a virtual image for presenting the images from the camera to the drivers. Using a driving simulator, human factors evaluations were conducted in a series of trials. The findings indicated that the system might have a positive impact on driver behavior and on road safety by encouraging drivers to increase their headways in reduced visibility conditions.

Table 2-12: Cost of low visibility warning systems in the United States (Source: Lynn et al. 2002)

Location	Length	Visibility/Weather Detectors	VMSs	Traffic/Speed Detectors	Cost
I-10 (Mobile, Alabama)	6.2 miles	6 visibility sensors	4 VMSs, CCTV	Loop detectors	$18,000 excluding VMSs and loops
Rt. 99/I-5 (San Joaquin Valley, California)	Unknown	15 Road Weather Information System (RWIS) stations, plus fog detectors, visibility test signs	80 VMSs	None	$3,600,000
I-5/Rt. 205 (Stockton, California)	16 miles	9 RWIS stations	9 VMSs	36 inductive loop sensors	$2,750,000 -- $2,770,000
Planned I-75 (Georgia / Florida border)	2 miles	19 visibility sensors	Light emitting diode (LED) VMSs	5 loop detectors	$1,410,500
I-25 (Colorado)	Unknown	None, visibility reported by CDOT personnel	6 roadside VMSs, overhead VMSs	None	$275,000
I-69 (Fort Wayne, Indiana)	¾ mile	1 visibility sensor	LED VMSs	None	$155,000
I-40 (Haywood County, North Carolina)	5 miles	3 visibility sensors	2 VMSs	None	$1,100,000
Rt. 22 (Crescent Mountain, Pennsylvania)	2 miles	1 RWIS	VMSs, Highway Advisory Radio	None	$411,010 plus $1,200,000 in upgrades
I-75 (Calhoun, Tennessee)	19 miles	8 fog detectors, 2 RWIS stations	20 VMSs	22 speed detectors	$4,460,580
I-215 (Salt Lake City, Utah)	Unknown	4 fog sensors	2 VMSs	6 loop detectors	$461,000

2.3.2 Projects in England

In 1990, an automatic fog warning system (M25 London Automatic Fog-Warning System) was designed by Traffic Control and Communications Division of the Department of Transport, London. This system was installed on the M25 London orbital motorway to warn drivers about formation of fog by displaying “Fog” legend on roadside matrix signals. Transport Research Laboratory of the United Kingdom, evaluated the effectiveness of the system in reducing the variation in vehicles’ speeds during inclement visibility conditions due to fog. Based on data measured from 6 test sites, the results revealed that there was about a 1.8 mph reduction in mean vehicle speeds when the signals were switched on (Cooper and Sawyer; 1993, MacCarley; 1999).

2.3.3 Projects in the Netherlands

The Dutch Ministry of Transport implemented an automatic fog warning system to achieve safer driving behavior during adverse visibility conditions along 12 km (7.4 mile) section of the A16 Motorway in the Netherlands. The system consisted of 20 visibility sensors to continuously measure the visibility distances. The objective of this system was to warn drivers of reduced visibility conditions (i.e., due to fog) by displaying an explicit fog warning on overhead matrix signs together with a maximum safe speed limit that depends on the actual measured visibility distance.

Hogema and Horst (1997) evaluated the Dutch fog warning system in terms of driving behavior for a period of more than 2 years after implementing the system. Using subsurface loop detectors at six locations (four experimental and two control locations), continuous traffic measurements for individual vehicles were observed. Data on the local visibility conditions and on the messages displayed on the matrix signs were available on a 1-min basis. The results showed that the system has a positive effect on speed choice in fog as it resulted in a decrease of speed of about 8 to 10 kph.

2.3.4 Projects in Finland

Rama et al. (2000) investigated the effects of two VMS on driver behavior. The two signs were a warning sign for slippery road conditions and a minimum headway sign. A before-and-after experiment was performed at three test sites in Finland with an after period covering two winter seasons. The slippery road condition sign decreased the mean speed on slippery roads by 1-2 km/h in addition to the decrease caused by the adverse road conditions. Moreover, the minimum headway sign decreased the proportion of headways shorter than 1.5 s for cars in car-following situations, in addition to a speed reduction of 1 km/h.

Luoma et al. (2000) indicated that the signs may have other effects on driver behavior besides those measurable in terms of speed and headway that were found in Rama et al. (2000). Therefore, this study was designed to investigate such potential effects. To achieve this goal, 114 drivers who had encountered the slippery road condition sign and 111 drivers who had encountered the sign showing recommended minimum headway in adverse road surface conditions were interviewed. The results indicated that these VMS have other effects, such as the refocusing of attention to seek cues on potential hazards, testing the slipperiness of the road, and more careful passing behavior.

2.3.5 Projects in Saudi Arabia

Al-Ghamdi (2004) evaluated the effectiveness of a fog detection and warning system on driver behavior in terms of reduction in average speed, speed variability in the traffic stream, and choice of time headway. This system was installed on a 2-km section of a two-lane, rural highway in the Al-Baha region of Saudi Arabia. The system consisted of a visibility sensor, a point detection device that utilizes infrared technology to measure visibility, and a VMS. In addition, NC-97, an advanced traffic counter classifier, was used to measure traffic data (i.e., speed, headway, vehicle classification, and volume). Only one message was used during the project and the VMS was activated once the sensor detects a reduction in visibility less than 200 m.

The main result from this study indicated the system was ineffective in reducing speed variability. However, the system reduced mean speed throughout the experimental sections by about 6.5 kph. On the other hand, this study had three drawbacks: (1) the frequency of the signs within and before the fog-prone area was not tested, (2) no different messages and speeds were tested, and (3) The distance from the sign at which drivers resume their normal speed was not measured.

2.3.6 Summary of Existing Fog Warning Systems

Reviewing the existing visibility warning systems revealed that they have many limitations. First, these systems were designed specifically for one road location (fixed systems) and hence, it is not possible to reinstall them at other locations. Second, they are not cost-effective in terms of system's components, management and maintenance. Finally, most of them depend on AC power supply and fiber-optic cable for internal communication thus; they are not suitable in the absence of AC power. Therefore, there is a need to design a portable detection and warning system that is developed from components that are inexpensive and available commercially.

Chapter 3 presents the design and components of the portable visibility system that was developed by researchers at UCF. A preliminary testing for the system's performance is also discussed and presented in Chapter 3.

2.4 Relationship between Crash Characteristics and Real-Time Traffic Flow variables

Subsurface loop detectors (LDs) are the most common freeway traffic surveillance technologies used for various intelligent transportation system (ITS) applications such as travel time estimation and crash detection. Recently, the emphasis in freeway management has been shifting towards using LD data to develop real-time crash-risk assessment models.

Numerous studies have established statistical links between freeway crash risk and traffic flow characteristics. However, there is a lack of good understanding of the relationship between traffic flow variables (i.e. speed, volume and occupancy) and crashes that occur under reduced visibility (visibility related crashes).

Earlier studies that examined relationships between traffic flow variables and crashes can be categorized into two types; aggregate and disaggregate studies (Golob et al. 2004). Regarding aggregate studies such as Zhou and Sisiopiku (1997), the units of analysis represent crash counts or rates for specific time and location. For similar time and location, traffic flow is represented by parameters of statistical distributions of traffic flow. Concerning disaggregate studies, the units of analysis are individual crashes and traffic flow is represented by the corresponding traffic flow variables at the same time and location of each crash (Golob et al. 2004).

In this regard, the relationship between historical crash occurrence and loop detectors data gathered from stations surrounding the crash location have been explored by numerous studies to develop crash prediction models. These models were developed by several of the earlier studies such as Madanat and Liu (1995), Oh et al. (2001), Lee et al. (2002, 2003), Golob and Recker (2003), Abdel-Aty et al. (2004, 2008), Abdel-Aty and Pande (2005), and Pande and Abdel-Aty (2006).

Madanat and Liu (1995) used traffic stream and environmental conditions measured by surveillance sensors for developing binary logit models. The objective was to estimate the crash likelihood for two types of crashes, namely, crashes and overheating vehicles. The results indicated that merging section, visibility, and rain were the significant variables affecting the crash likelihood prediction.

Oh et al. (2001) used the Bayesian classifier to categorize the two possible traffic flow conditions; crash versus normal traffic flow. The results showed that five minutes standard deviation of 30-second speed measurements was the significant factor leading to crash occurrence.

Lee et al. (2002) developed a log-linear model for predicting crashes using LD data. They refined this model in a later study (Lee et al. 2003). The results revealed that the coefficient of variation in speed (CVS) was the significant factor affecting the probability of crash occurrence.

In order to determine how crash characteristics are related to traffic flow conditions at the time of occurrence, Golob and Recker (2003) developed a method involves nonlinear canonical correlation applied together with cluster analyses. The results revealed that interactions between traffic flow conditions and accident propensities vary with environmental factors. Twenty one traffic flow regimes for three different ambient conditions were identified: eight regimes for dry roads during daylight, six regimes for dry roads at night, and seven regimes for wet conditions (based on condition of the roadway surface: wet or dry).

Abdel-Aty et al. (2004) adopted matched case-control logistic regression for developing a crash likelihood prediction model using real-time traffic variables measured through serious of LDs. The findings showed that the average occupancy observed at the upstream station along with the CVS at the downstream station, both during 5-10 minutes prior to the crash, were the significant factors affecting crash likelihood.

Abdel-Aty and Pande (2005) used Bayesian classifier based methodology, probabilistic neural network to identify patterns in the freeway LDs data that potentially lead to traffic crashes. The logarithm of CVS observed from the nearest station to the crash location and two stations immediately preceding it upstream during 10-15 minutes prior to the crash time were the inputs to the final classification model.

Pande and Abdel-Aty (2006) predicted the occurrence of lane–change related crashes on freeways using the classification tree procedure. The results showed that average speeds upstream and downstream of the crash location, difference in occupancy on adjacent lanes and standard deviation of volumes and speed downstream of the crash location were the significant variables affecting crash occurrence.

Abdel-Aty et al (2008) used Random Forests and multilayer perception neural network for assessing safety on Dutch freeways using LDs data. The results indicated that the average and standard deviation of speed and volume were significantly related to real-time crash likelihood.

Obviously, very few studies investigated the relationship between real-time traffic parameters and crash occurrences while controlling for visibility and/or weather conditions. For example, Golob and Recker (2001) examined how the types of freeway accidents are related to both the flow of traffic, and weather and ambient lighting conditions. The results indicated that median traffic speed and temporal variation in speed in the left and interior lanes are strongly related to the type of collision. Also, when controlling for weather and lighting conditions, the findings suggested that crash severity is influenced more by volume than by speed.

In addition, Dion and Rakha (2006) indicated that in recent years, there has been a growing emphasis on employing Automatic Vehicle Identification (AVI) data for the provision of real-time travel time information to motorists within Advanced Traveler Information Systems (ATIS).

2.5 Conclusions from the Literature Review

Considering the aforementioned studies, in spite of the fact that many studies have extensively analyzed drivers' behavior in response to DMS, VSL signs, unexpected congestion, and the impact of both radio traffic information and variable message sign information, very few studies have examined drivers' behavior at different visibility conditions using a questionnaire survey. Therefore, one objective of this study is to gain a better understanding of drivers' behavior under different visibility and traffic conditions and identifying the factors that might affect their reaction and preferences under such adverse conditions using multiple survey approaches; handout, interactive and online survey. The survey design and content is presented in Chapter 4. In addition, the analysis of the survey is illustrated and discussed in Chapter 5.

In addition, reviewing the existing visibility warning systems revealed that they have many limitations. First, these systems were designed specifically for one road location (fixed systems) thus it is not possible to reinstall them at other locations. Second, they are not cost-effective in terms of system's components, management and maintenance. Finally, most of them depend on AC power supply and fiber-optic cable for internal communication thus; they are not suitable in the absence of AC power. Therefore, the researchers at UCF developed a portable visibility detection and warning system. The system was developed from components that are inexpensive and available commercially. Another advantage is that the system can be powered using car batteries instead of AC power. The system components and a preliminary testing for the system's performance are discussed and presented in Chapter 3.

Moreover, numerous studies have established statistical links between freeway crash occurrence and traffic flow variables at normal visibility conditions (clear weather conditions).

However, there is a lack of studies that strive to gain a good understanding of the relationship between traffic flow characteristics and crashes occurring under reduced visibility (visibility related crashes). Therefore, one objective of this study is to develop a visibility related crash prediction model for freeways using real-time traffic flow variables observed from loop detectors and radar sensors. Chapter 6 discusses data collection and preparation, and presents prediction of VR crashes on Freeways.

Finally, two issues that have not explicitly been addressed in prior studies are; (1) the possibility of predicting VR crashes using traffic data collected from the Automatic Vehicle Identification (AVI) sensors installed on Expressways and (2) which traffic data is advantageous for predicting VR crashes; LDs or AVIs. Thus, Chapter 7 examines the relationships between VR crash risk and real-time traffic data collected from LDs installed on two Freeways in Central Florida (I-4 and I-95) and from AVIs sensors installed on two Expressways (SR 408 and SR 417). Also, it investigates which data is better for predicting VR crashes (LDs or AVIs).

CHAPTER 3. PORTABLE VISIBILLITY WARNING SYSTEM

This chapter presents the components and a preliminary evaluation of a portable visibility warning system that was developed by the researchers at the University of Central Florida (UCF), Orlando, USA. The development of this system was completed in June 2010.

3.1 System Components and Operation

Low visibility scenarios can occur due to a variety of conditions such as fog, smoke, smog or heavy rain. They can occur anywhere, and are especially dangerous on freeways and in rural areas. To cope with a variety of operational scenarios, a visibility detection system needs careful consideration for mobility, power, and communication technologies.

UCF portable visibility detection and warning system consists of several components that are illustrated in more detail in this section. Initially for the prototype, the hardware is composed of four stations, each is connected to a visibility sensor; and each of these four stations is monitored and controlled by a micro controller installed in a unit attached to it. The proposed structure of the system is shown in Figure 3-1. One of the stations performs as a base station which carries out all the communication processes between the different stations and the traffic management center (TMC) and Changeable Message Signs (CMS). The components of the base and the station are shown in Figure 3-2 and Figure 3-3, respectively.

Each station contains the following components:

- Radio antenna
- GPS
- Visibility sensor

- XBee Radio (Receiver and Transmitter)
- Mini Computer
- USB hub
- Power regulator
- Power distributor
- Battery

Each station continuously detects highway visibility distances and save them on a flash memory attached to the mini computer. Then every station transmits this information as messages to the base station. These messages contain the visibility distance (measured by the visibility sensor), coordinates of a station (estimated by GPS), and time and date of each message. In addition to the components mentioned above, base station contains XTend radio for communication between base and CMS. It also contains a cellular modem for communication between the base and TMC.

Therefore, the visibility system is designed to be autonomous in its operation and decision-making. It continuously monitors visibility distances. Whenever hazardous conditions are detected, it automatically generates warning messages that can be displayed to motorists on CMS and VSL signs.

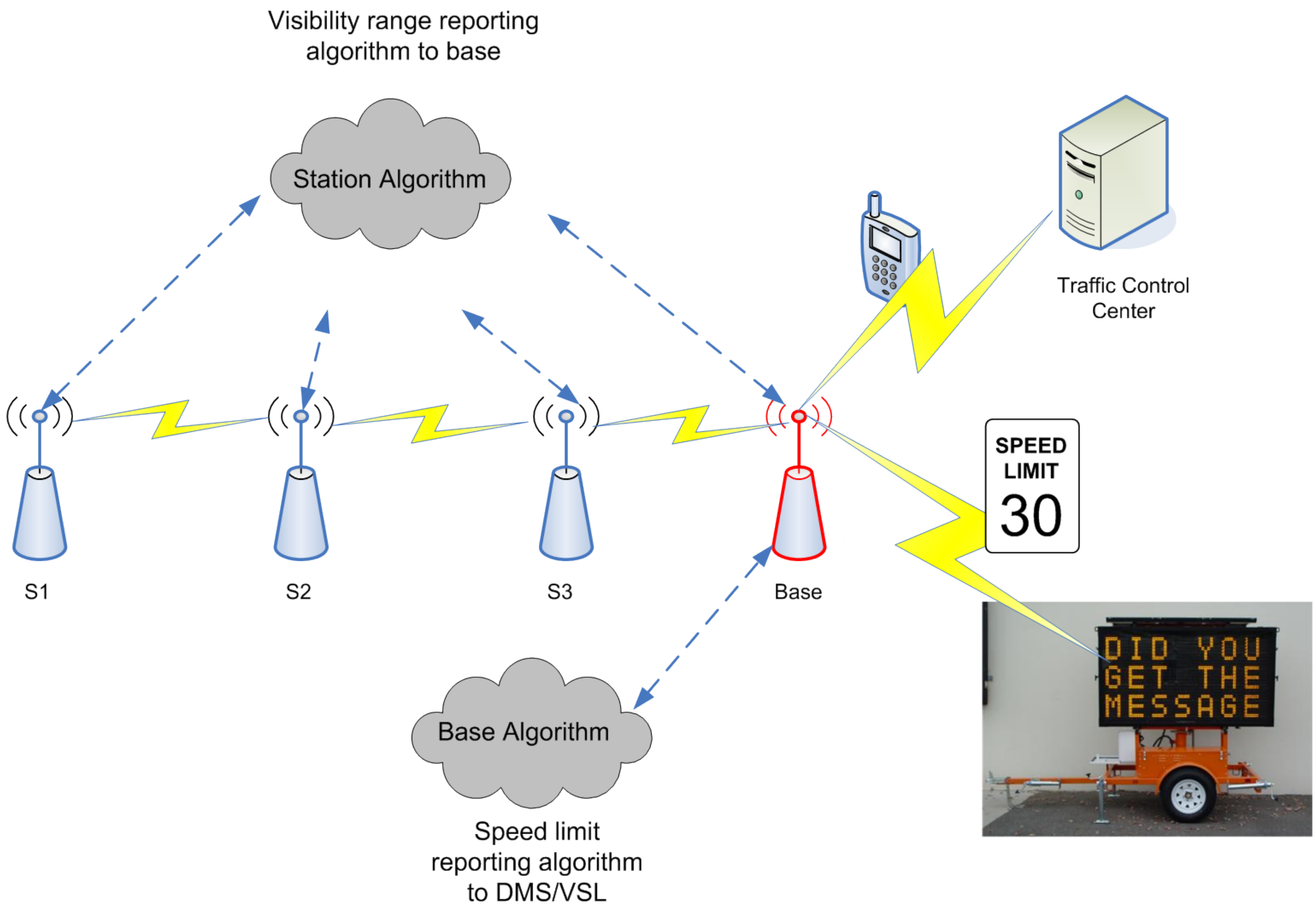
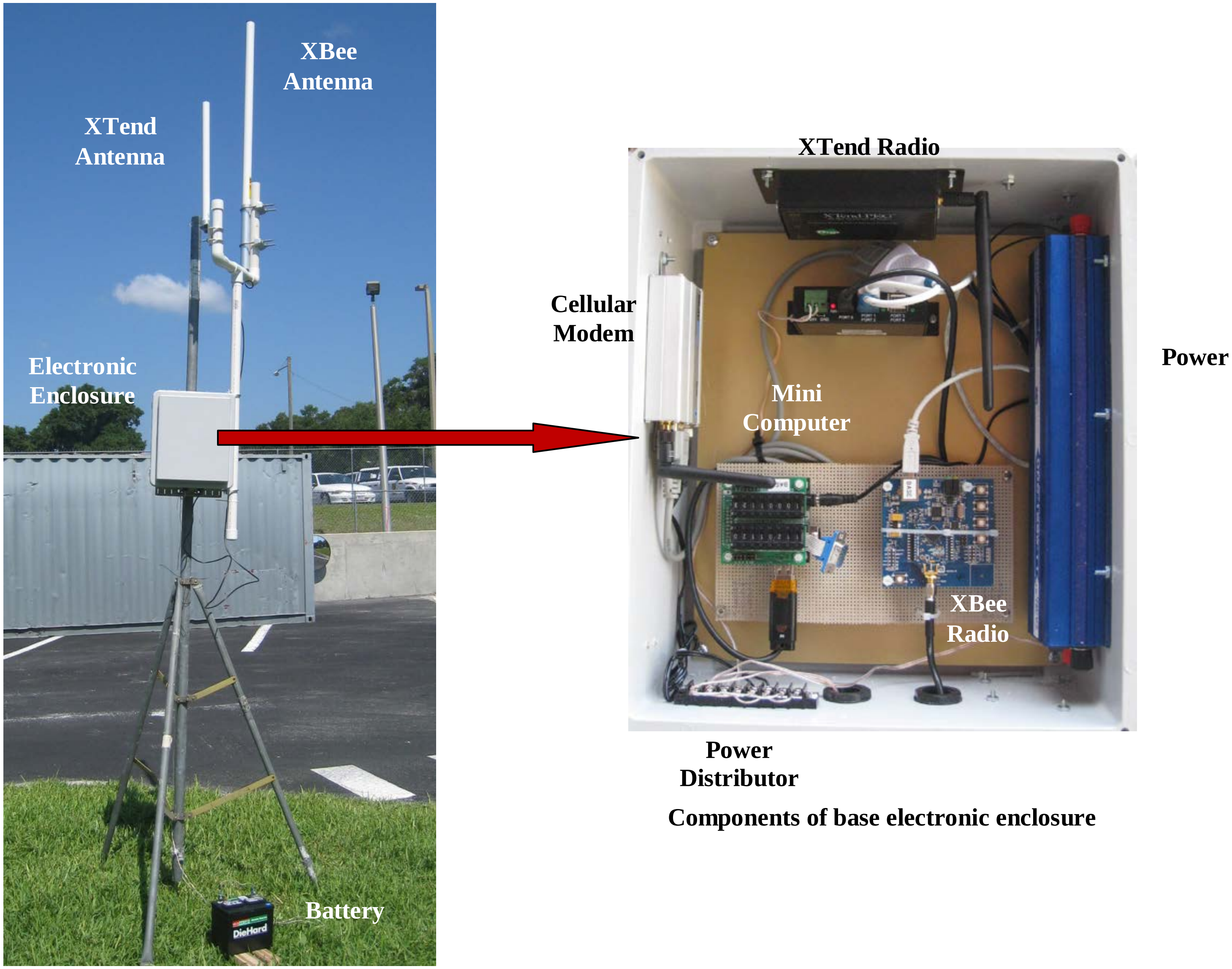
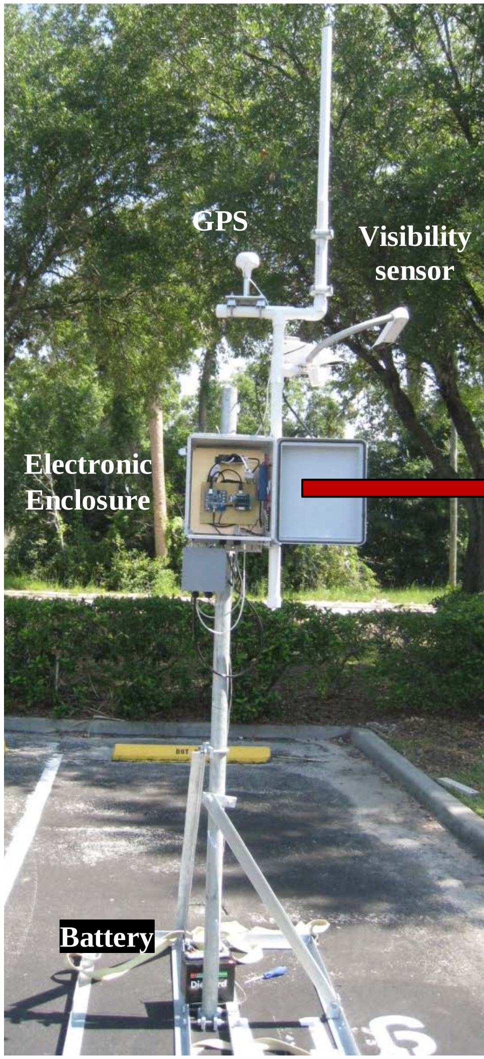


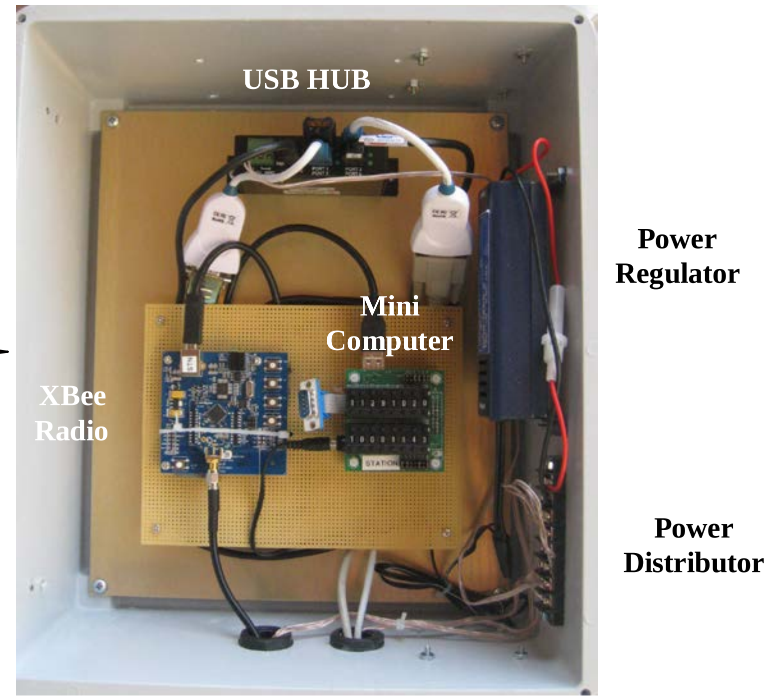
Figure 3-1: Visibility system components



Components of base electronic enclosure

Figure 3-2: Base components





Components of station electronic enclosure

Figure 3-3: Station components

3.2 Communications

Communication is the important part of the system; the system includes two types of communication links. First, the internal communication link (data from sensors and base station) is a 900 MHz radio. The second type is cellular communication which is used to exchange information from the base station to the TMC. Any system is useless if it cannot report real-time visibility conditions for warning drivers and TMC about reduced visibility conditions. For this reason, the selection of a reliable communication system is of utmost importance. Thus, to avoid typical line of sight limitations inherent in communication technologies such as WiFi, the spread spectrum, etc., researches at UCF proposed the use of cell-based communication. This communication mode guarantees national coverage and reduces hardware costs. Also, since this system is designed to report on exceptional bases, data costs should be minimal.

3.3 System Operation

The visibility system is designed to be autonomous in its operation and decision-making. It continuously monitors visibility. Whenever hazardous conditions are detected, it automatically generates warning messages that can be displayed to motorists. Two types of messages are generated; speed advisories and warning messages of poor visibility. The automatic messages are selected by a computer algorithms based on the measured visibility distance and the maximum safe speed.

3.4 Software Design and Algorithms

The system's software control runs on a micro controller attached to the base station and executes a real-time operating structure. The system controls the entire baseline functions necessary to operate the overall system, including data acquisition, data storage, system control, and self monitoring. Specifically, the system reads from 4 fog sensors, while controlling up to four CMSs. This overall functionality is obtained through individual software modules, which are illustrated in the diagram shown in Figure 3-4. The design of the system is extendible to include additional fog sensors, VSL signs, flashing lights and DMSs to expand the capability of the system to cover longer segments of roads in fog prone areas.

There are two main algorithms that have been designed to control the communications process and data reporting frequencies. One of these algorithms controls the communications between the stations and the base, while the other controls the communication between the base and both CMSs and TMC.

As mentioned earlier, each station detects the visibility distance and reports it to the base station. At normal conditions (highway visibility distance > 250 m), the base station receives messages from each station showing the current visibility distance every 15 minutes. Although it is not needed to take any action at normal visibility conditions, it was decided to receive messages from each station to make sure that all stations are working properly. However, once the visibility distance drops below hazardous visibility levels (<250 m), the reporting frequency reduces to 1 minute.

	Inputs	*Algorithms*	*Output*
STATION	▪ Visibility reading ▪ Coordinates ▪ Picture	Station Algorithm	▪ VR reporting frequency ▪ Message to the base with all info.
BASE	▪ Time of last received message ▪ No. of failure reports of each sensor	Report sensor failure algorithm (A1)	▪ Report sensor (i) failure for five times then set its reporting frequency (F) to infinity
	▪ Latest received VR ▪ The worst VR we currently use ▪ Time of last selection of worst VR	Select worst (VR) algorithm (A2)	▪ Select a new worst VR ▪ Identify sensor having worst VR (i) ▪ Send message to TMC including all info. corresponding to this sensor
	▪ The worst VR ▪ Posted speed limit (PS)	Speed limit (SL) selection algorithm (A3)	▪ Warning message ▪ Recommended speed limit ▪ Flash lights status
	▪ Recommended speed limit ▪ Recommended message to display	Speed limit displaying sequence algorithm (A4)	▪ Determine weather to send messages to DMSs and VSLs or not
DMS	▪ Receive messages from Base ▪ Base failure	DMS Algorithm	▪ Warning message to the motorists. ▪ Advisory speed limit. ▪ Display bank
TMC	▪ Receive messages from Base	TMC Algorithm (Failure Warning)	▪ Warns operator of station/base failure ▪ Data Storage

Figure 3-4: Structure of the system algorithms

3.5 Testing the Radios' Range

The objectives of testing the radios' range of the developed visibility detection and warning system were to determine the maximum range between two successive radios (one at the base and the other at the station) and to examine the possibility of using an intermediate radio (hopping) to increase the range between the base and the stations' radios. The testing of radios' range was divided into two stages. The first stage was conducted in the lab to make sure that the system components are working properly however; the second stage was conducted in the field to examine the system performance in real life.

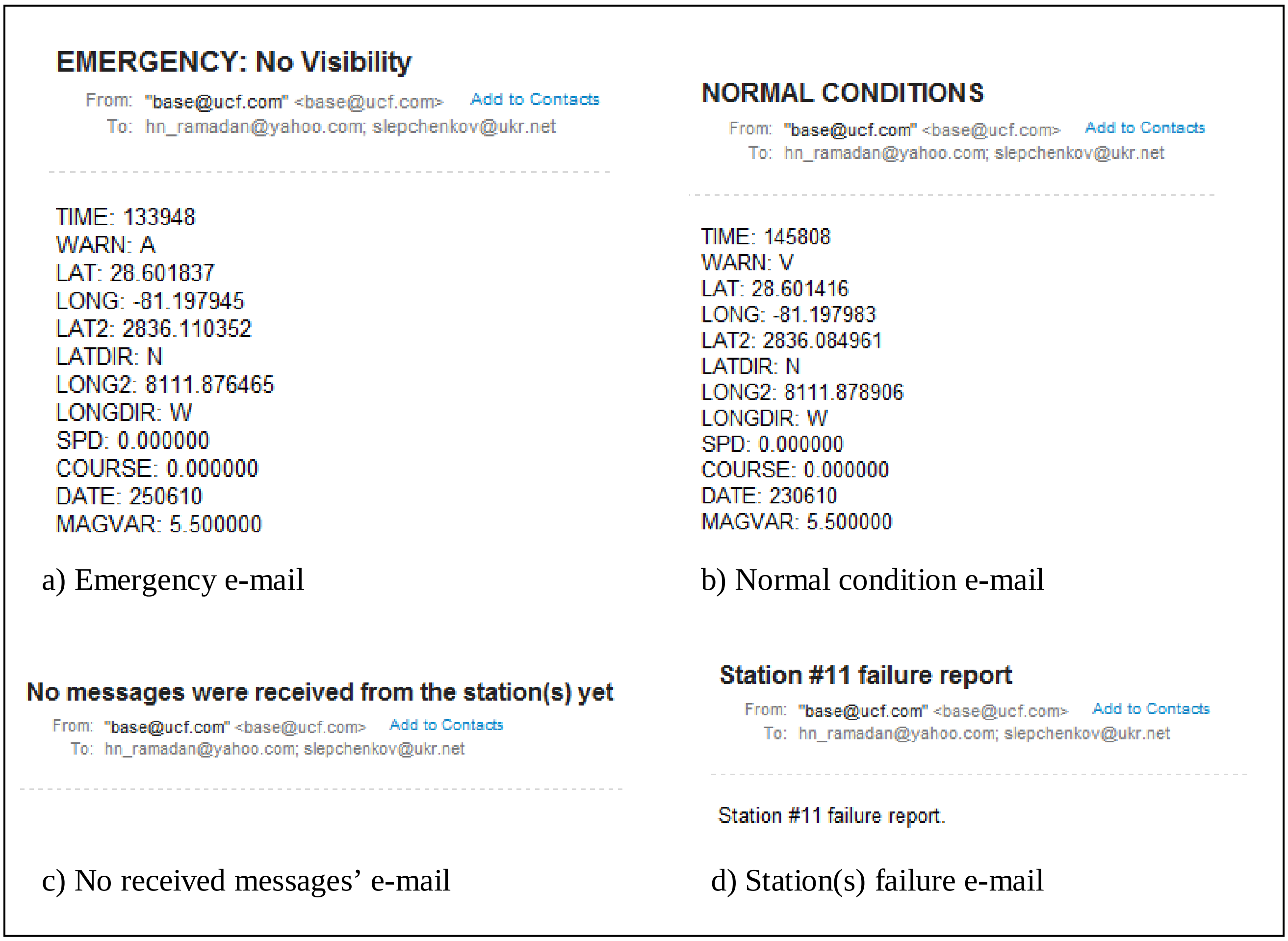
To test the system in the field, the station and the base were installed at the UCF campus. To simplify the test, the base station was installed on a truck and powered using a generator. A laptop was attached to the base to check the receiving messages from the station. During movement with the base away from the station, the base was receiving messages until the distance increased more than 0.6 mile. At that point the communication between the base and the station was lost. After using an intermediate radio (hopping) between the base and the station, the radios' range increased to about 1.2 mile.

3.6 Testing the System's Performance

This section presents the preliminary performance's testing of this visibility system. The base and station were installed as shown in Figure 3-2 and Figure 3-3**,** respectively. To check the performance of the base algorithm, the base was powered first using a car battery. Since the station was not powered yet, the base sent an e-mail to TMC showing that no messages were received from station(s) yet. This initial e-mail implies that the base is working properly, and either the station(s) was non-powered yet or has a technical problem. Once the station was powered, a message with the current visibility distance was sent (e.g., normal visibility condition) to the base station which submitted an e-mail to TMC titled “normal conditions” and contains station’s number, position (latitude and longitude), time and date of message. To test the performance of the system in poor visibility conditions, a cloth bag was put on the visibility sensor (because no fog existed when conducting the test). Thus the visibility measurement dropped to zero and the station sent this message to the base which reported TMC with an emergency e-mail titled “emergency: no visibility”. These warning e-mails can enable the TMC and/or FDOT to take the appropriate decisions at such adverse visibility conditions. Table 3-1 summarizes the titles of all e-mails that could be sent to TMC/FDOT at all visibility levels. Once the cloth bag was removed away from the visibility sensor, the station reported normal visibility condition to the base. However, according to the design of the base algorithm, 5 minutes later the base informed the TMC about improving the visibility range. The same email messages or modification could also be sent to the CMS. Moreover, to test the base algorithm when loosing communication between base and station(s), the base station was moved away from the station. When the communication was lost, the base is programmed to send an e-mail to TMC entitled “Station # 11 failure report”. This e-mail is important as it helps TMC to identify which station has a problem so a technician can be dispatched to fix this problem immediately. Later, after installing an intermediate radio, the base started again to receive messages from the station. Figure 3-5 show examples of warning’s e-mail messages sent to TMC.

Table 3-1: E-mail message titles and frequency of reporting messages to TMC

	E-mail Title	Highway Visibility Range
1	EMERGENCY: No Visibility	< 20ft
2	URGENT: Extremely low Visibility	< 200ft
3	WARNING: Moderate visibility	If visibility is between 200-500 ft
4	WARNING: Fog or Smoke Conditions affecting visibility	If visibility is between 500-800 ft
5	NORMAL CONDITIONS	Visibility greater than 800 ft
Frequency of reporting to TMC		
Every hour		Normal conditions.
Every 1 Minute		in Emergency
Every 5 minutes		otherwise


EMERGENCY: No Visibility
From: "base@ucf.com" <base@ucf.com> Add to Contacts
To: hn_ramadan@yahoo.com; slepchenkov@ukr.net

TIME: 133948
WARN: A
LAT: 28.601837
LONG: -81.197945
LAT2: 2836.110352
LATDIR: N
LONG2: 8111.876465
LONGDIR: W
SPD: 0.000000
COURSE: 0.000000
DATE: 250610
MAGVAR: 5.500000

a) Emergency e-mail

NORMAL CONDITIONS
From: "base@ucf.com" <base@ucf.com> Add to Contacts
To: hn_ramadan@yahoo.com; slepchenkov@ukr.net

TIME: 145808
WARN: V
LAT: 28.601416
LONG: -81.197983
LAT2: 2836.084961
LATDIR: N
LONG2: 8111.878906
LONGDIR: W
SPD: 0.000000
COURSE: 0.000000
DATE: 230610
MAGVAR: 5.500000

b) Normal condition e-mail

No messages were received from the station(s) yet
From: "base@ucf.com" <base@ucf.com> Add to Contacts
To: hn_ramadan@yahoo.com; slepchenkov@ukr.net

c) No received messages' e-mail

Station #11 failure report
From: "base@ucf.com" <base@ucf.com> Add to Contacts
To: hn_ramadan@yahoo.com; slepchenkov@ukr.net

Station #11 failure report.

d) Station(s) failure e-mail

Figure 3-5: Examples of warning's E-mail messages sent to TMC

3.7 Conclusions

This chapter presents the design of a visibility detection and warning system that was developed by researchers at UCF. A discussion of the system components and performance was introduced. The preliminary testing of this visibility system indicates that it can detect any reduction in visibility in a timely manner and respond accordingly in real-time to convey specific warning messages either by reporting these messages to TMC/FDOT through e-mails or by displaying a warning message and an advisory safe speed at each visibility level using CMS and VSL signs, respectively. However, before reaching a final conclusion about the performance of this visibility detection system, conducting another field study at real fog condition is still needed.

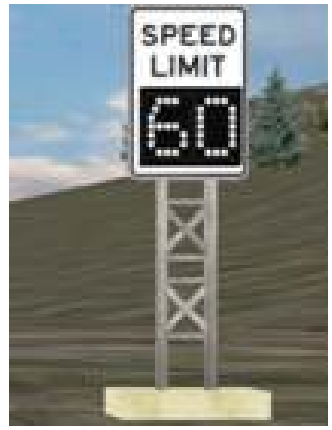
CHAPTER 4. SURVEY DESIGN AND CONTENT

This chapter presents the design and administration of a survey-based study focusing on understanding commuters' response to different visibility conditions due to fog/smoke in Central Florida. A total of 566 respondents participated in this study through three survey approaches; handout, interactive, and online questionnaire. The evaluation of the quality and completeness of data received from the three surveys approaches as well as recommendations for the improvement of future survey design and response are presented in this chapter.

4.1 Survey Design

To achieve the objectives of this survey, different scenarios consisting of several visibility levels, traffic conditions, warning messages and advice displayed on CMS and VSL signs were designed using driving simulation software, L-3 Scenario Editor. There is no doubt that it would have been better to use real pictures in this study. However, the scenario editor software was used to develop those scenarios since it was not possible to find real pictures for all the scenarios that were developed. Snapshots at different fog levels, traffic conditions, and based on the two roadway types were prepared before designing the two survey forms. It is worth mentioning that due to limited budget and the various scenarios that were investigated in the present study, neither field studies nor driving simulator experiments were feasible. Examples of information displayed on both CMS and VSL signs are shown in Figure 4-1.

CMS



VSL

Figure 4-1: Examples of information displayed on CMS and VSL signs

Prior studies such as Huang et al. (2010) revealed that most of the fog/smoke related crashes (48.3%) occurred on four lane roadways followed by two-lane roads with 33.8%. Therefore, two surveys were conducted in the present study: freeways' survey and two-lane roads' survey to examine drivers' behavior in response to reduction in visibility on those types of roadways. The two survey forms are similar in all questions; both of them contained 31 questions. However, the only difference was in the snapshots that were developed. Each respondent got only one of the two surveys randomly. For clarity, Figure 4-2 and Figure 4-3 show samples questions from the freeway's survey and two-lane road's survey, respectively.

In summary, the two survey forms were designed to obtain the following information from each respondent:

- Gender (male or female).
- Age (18-25, 26-35, 36-50, 51-65, over 65 years).
- Education (Graduate school or higher, college degree, some college, high school, did not graduate from high school).
- Number of years the drivers had a valid driver's license.

- Number of traffic citations (i.e. traffic rule violations) in the previous 3 years.
- Involvement in any fog/smoke or heavy rain related crashes.
- Frequency of freeways/ two-lane roads use?
- Drivers' familiarity with CMS and VSL signs.
- Drivers' behavior when they encounter CMS at two traffic conditions (no car leading ahead, and car leading ahead).
- Drivers' behavior when they encounter a VSL sign at four fog conditions (very light fog, light fog, medium fog, and heavy fog) and two traffic conditions (no car leading ahead, and car leading ahead).
- Drivers' satisfaction with the importance of CMS and VSL signs in providing information that may help to manage the traffic flow along Highways and consequently reducing the chances of a crash.
- Drivers' satisfaction with using two successive CMS prior to Fog/ smoke zones.
- Which one of the following would improve safety during driving through fog/smoke highways segments: using CMS only or using VSL signs only or using CMS and VSL signs together or closing the road during such adverse weather conditions?
- What is the best CMS message that can be used to warn drivers about any reduction of visibility due to fog/smoke and drivers will most likely comply with it.
- Drivers' behavior when they encounter a sudden reduction in visibility due to fog, smoke, or heavy rain while they are driving on a freeway/ two lane roads.
- Drivers' ranking for the actions/responses that they can do when they encounter a sudden reduction in visibility due to fog, smoke, or heavy rain while they are driving on a freeway/ two lane roads.

If you were driving on a freeway with a speed limit of 65 mile/hour (mph), and you encounter a Variable Speed Limit (VSL) sign of 40 mile/hour (mph) in order to reduce the chances of accident that may occur because of a sudden reduction in visibility due to fog/smoke. What will you do in each of the following cases?
Note: in case you will reduce your speed (answers c or d), please specify your reduced speed

Heavy Fog (some vehicles ahead)

a) Do nothing
b) Follow other vehicles' speed.
c) Reduce speed to ………..mph
(Please specify your reduced speed)
d) Put blinkers on and reduce speed to……mph
(Please specify your reduced speed)

Figure 4-2: Sample question from the freeway's survey

If you were driving on a two lane road with a speed limit of 45 mile/hour (mph), and you encounter a Variable Speed Limit (VSL) sign of 25 mile/hour (mph) in order to reduce the chances of accident that may occur because of a sudden reduction in visibility due to fog/smoke. What will you do in each of the following cases?
Note: in case you will reduce your speed (answers c or d), please specify your reduced speed

Heavy Fog (some vehicles ahead)

a) Do nothing
b) Follow other vehicles' speed.
c) Reduce speed to ………..mph
(Please specify your reduced speed)
d) Put blinkers on and reduce speed to……mph
(Please specify your reduced speed)

Figure 4-3: Sample question from the two lane road's survey

4.2 <u>Survey Pilot Test</u>

A pilot test of the surveys was conducted in the Central Florida region. Ten survey forms were distributed among undergraduate students, graduate students, and professors at University of Central Florida. In addition, one survey form was sent to a Transportation Engineer at the Florida Department of Transportation (FDOT) as shown in Table 4-1.

Table 4-1: Number of persons who participated in the pilot test of the surveys

Participants in the pilot test	No. of participants
Undergraduate students	1
Graduate Students	5
Professors and post doctors	3
Transportation Engineers at FDOT	1

The survey forms were revised after feedback was received. Questions that were considered ambiguous to individuals who read the survey were rewritten and more pictures were added to make the questions be easier and more understandable in the final surveys. Revisions included wording ambiguity, verb tenses, and the inclusion of relevant questions and options that were not considered in the preliminary survey forms.

4.3 <u>Determining the Required Sample Size of Survey</u>

The minimum sample size can be estimated using the full factorial design. The factors affecting the survey design and their associated levels are summarized in Table 4-2.

Table 4-2: Factors affecting survey design and their levels

Factors	Levels
Type of survey	3 levels: mail, interactive, and online survey
Road type	2 levels: freeway and 2 lane roads
Gender	2 levels: male and female
Age groups	5 levels: 18-25, 26-35, 36-50, 51-65, and over 65
Education	5 levels: Graduate school or higher, college degree, some college, high school, and did not graduate from high school

Therefore, the minimum survey size = 3*2*2*5*5 = 300

To be more conservative, we recruited more than 500 participants in the survey as indicated in the following sections.

4.4 Sampling Procedure and Survey Methods

The survey targeted a random sample of licensed drivers living in Orange and Seminole counties. Respondents were limited to adults over 18 years of age who have a valid driver's license. Based on the review of previous studies, it was found that mail-in questionnaires yield low response rates, and do not provide interaction between the interviewer and the respondent. Hence, mail-in questionnaire was not undertaken. Also, phone interviews were not used because of the need to incorporate images in the survey questions.

According to TCRP (2006), the use of Internet-based survey only usually does not provide a representative sample of the population due to some population segments not having access to the Internet or not having good knowledge about using the Internet. Thus, it was decided to implement a 3-way approach to conduct the survey for both freeways and 2-lane roads. The three survey types incorporated were handout, interactive, and online questionnaires.

4.4.1 Handout Questionnaire

The first survey approach was handout questionnaires. In this approach, 300 survey forms were printed for each roadway type. These survey forms were distributed randomly in November 2009 among colleagues, friends, family, neighbors, faculty and staff who live in Central Florida. Each one of them has received from 5 to 20 survey forms and he/she was asked to distribute them among his/her colleagues, friends, neighbors and family members. They were asked to return them once they are completed.

Out of the 600 distributed survey forms, a total of 376 forms were received back (62.7% response rate). However, only 279 handout surveys' forms were considered complete, 74% complete responses (questions completed). The remaining forms had more than 30% missing responses (questions) and hence, they were disregarded. Based on the respondents' feedback, the questionnaire took on average 10 minutes to be completed. It is worth mentioning that handout surveys are better than the regular mail-back surveys due to the presence of personal interaction between the surveyor and respondents.

4.4.2 Interactive Questionnaire

The second survey method was an interactive questionnaire. In this survey method, the surveyor meets with a group of people at the same time and location and explains the purpose of the survey and the steps they should follow to complete the questionnaire. In the current study, the interactive survey was presented to two undergraduate classes and one graduate class at the University of Central Florida in November 2009. Two presentations were designed for the two survey forms in power point format. Each session gets either the freeway or 2-lane version. After distributing the questionnaires to the respondents, each question or picture was presented in a full screen using a projector. Participants were responding while the surveyor was explaining what is meant by each question and interacting with them. Also, participants were allowed to ask questions. The presentation and interaction was carefully considered so that the questions are clarified but not to bias the responses. Each interactive questionnaire session lasted on average 20 minutes. The interactive survey sample contained 102 participants. However, only 91 forms were used in the analysis, 89% complete responses (questions completed). Again the remaining forms had more than 30% missing responses and thus they were disregarded.

4.4.3 Online Questionnaire

Online surveys have become more widespread in recent years. The advantages of adopting online questionnaires include the possibility of sending a participation request to randomly selected subjects using e-mail addresses. Second, respondents' responses are automatically saved in a database existing in the survey's server, and can be retrieved at a later time for data analysis. This simplifies the data processing for the analyst, eliminates coding errors and reduces labor costs. Therefore, online questionnaires are less time consuming and less labor-intensive than the other survey methods. Third, the use of graphical user interface (GUI) and images provide the ability to better understand the questionnaire aspects (Abdel-Aty and Abdelwahab, 2001; Peeta and Ramos, 2006). On the other hand, the limitations of online surveys include the need accessibility of Internet and some knowledge of using the Internet by the participants.

In this study, links for either survey type (freeway or 2-lane road) were sent randomly to about 200 commuters in the Central Florida region in November 2009. Participants were asked to estimate how many minutes they took to complete the survey and report it to the surveyor. Also, 500 cards containing links to either survey forms were distributed randomly to drivers in Central Florida.

At the beginning of each survey form, an introduction was provided explaining the purpose of the survey and some guidelines for completing the survey. The advantages of the present online survey include a warning pop-up appearing above any unanswered question asking the respondents that this is required (as shown in Figure 4-4). This option might help to increase the percent of complete responses in the online survey. The second advantage is that respondents cannot enter the same answer for two or more options in question 31 (as shown in Figure 4-5). Out of 231 received responses (33% response rate), 196 complete responses were used in the analysis, 85% complete responses (questions completed), as the remaining forms had more than 30% missing responses. Based on respondents' feedback, the online questionnaire took on average 8 minutes to be completed.

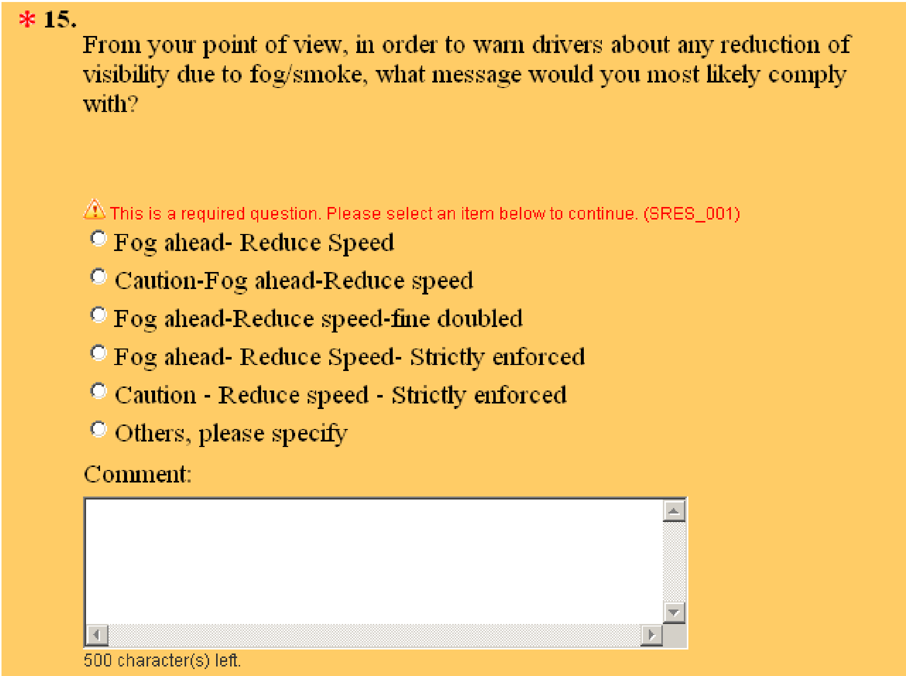


Figure 4-4: A warning hint about unanswered question in the online survey

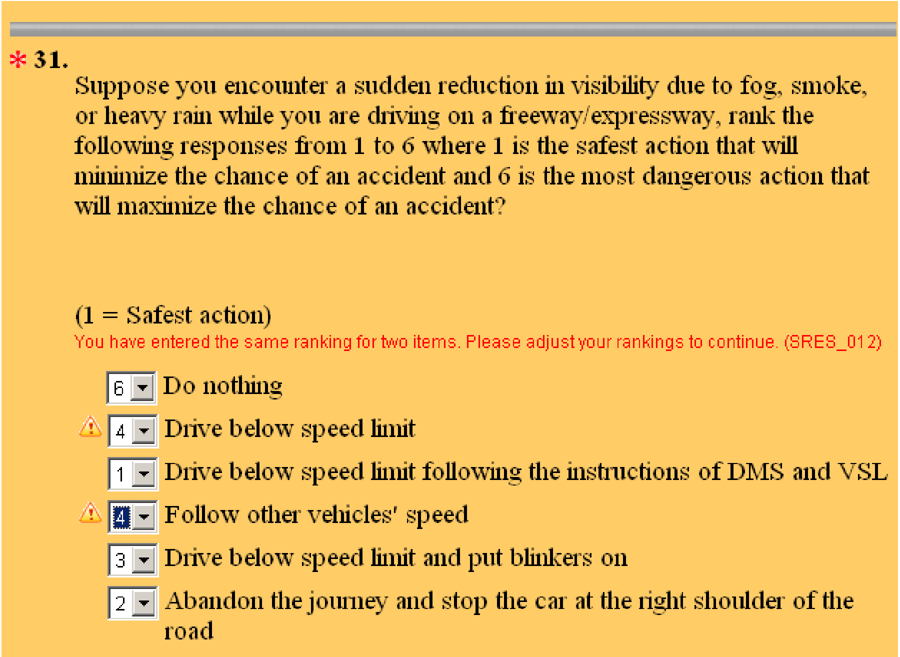


Figure 4-5: A warning hint about entering the same ranking for two options in question 31 in the online survey

4.4.4 Validating Survey Sample

To test whether the sample well represents the licensed drivers in Orange and Seminole counties, the percentages of gender and age groups of the survey sample were compared to the corresponding percents of the licensed drivers in Orange and Seminole counties (January 2009) that were obtained from the Florida Department of Highway Safety and Motor Vehicles (DHSMV). Distributions of gender and age groups for the survey sample and licensed drivers in Orange and Seminole counties in January 2009 are given in Table 4-3 and Table 4-4, respectively.

Table 4-3: Distribution of gender for the survey sample and licensed drivers in Orange and Seminole counties

Gender	Survey		Licensed Drivers in Orange and Seminole counties (January, 2009)	
	Sample	%	Pop.	%
Male	310	54.8	615735	50.4
Female	256	45.2	606070	49.6
Total	566	100	1221805	100

Table 4-4: Distribution of age groups for the survey sample and licensed drivers in Orange and Seminole counties

Age Groups	Survey		Licensed Drivers in Orange and Seminole counties (January, 2009)	
	Sample	%	Pop.	%
18-25	173	30.6	191925	16.1
26-35	120	21.2	255735	21.5
36-50	136	24.0	369507	31.0
51-65	98	17.3	243635	20.5
Over 65	39	6.9	130335	10.9
Total	566	100	1191135	100

To achieve this objective, Chi-Square test for specified proportions and a large-sample test of hypothesis about a population proportion (Z-test) were developed as follows:

4.4.4.1 Chi-Square test for specified proportion

Hypothesis testing 1

H_0: P_1 = 0.504, P_2 = 0.496 (the observed proportions of males and females in the survey sample are not significantly different from the corresponding proportions of licensed drivers in Orange and Seminole counties).

H_a: at least one of the multinomial probabilities does not equal its hypothesis.

Test Statistic

Chi-Square = 4.3244, DF=1, P-value=0.0876 > 0.05

Therefore, it can be concluded that the observed proportions of males and females in the survey sample are not significantly different from the proportions of licensed male and female drivers in Orange and Seminole counties

Hypothesis testing 2

H_0: $P_1 = 0.161$, $P_2 = 0.215$, $P_3 = 0.310$, $P_4 = 0.205$, $P_5 = 0.109$ (the observed proportions of age groups in the survey sample are not significantly different from the corresponding proportions of licensed drivers in Orange and Seminole counties).

H_a: at least one of the multinomial probabilities does not equal its hypothesis

Test Statistic

Chi-Square = 93.6088, DF=4, P-value=0.0001 < 0.05 then null hypothesis can be rejected. Therefore, it can be concluded that at least one of the observed proportions of age groups in the survey sample is significantly different from the corresponding proportions of licensed drivers in Orange and Seminole counties. To investigate which age group has this difference, Z test was developed.

4.4.4.2 Z- Test

Hypothesis testing

H_0: $P = P_0$ (the proportion of every age group in the survey sample is not significantly different from the corresponding proportion of licensed drivers in Orange and Seminole counties).

H_a: $P \neq P_0$ (the proportion of every age group in the survey sample is significantly different from the corresponding proportion of licensed drivers in Orange and Seminole counties).

Test Statistic

Test statistic: $Z = \frac{P-P_0}{\sqrt{P_0 * q_0/n}} = \frac{0.306-0.161}{\sqrt{0.161*0.839/173}} = 5.19 \rightarrow$ **null hypotheses can be rejected**

Test statistic: $Z = \frac{P-P_0}{\sqrt{P_0 * q_0/n}} = \frac{0.212-0.215}{\sqrt{0.215*0.785/120}} = -0.08 \rightarrow$ null hypotheses can't be rejected

Test statistic: $Z = \frac{P-P_0}{\sqrt{P_0 * q_0/n}} = \frac{0.24-0.31}{\sqrt{0.31*0.69/136}} = -1.76 \rightarrow$ null hypotheses can't be rejected

Test statistic: $Z = \frac{P-P_0}{\sqrt{P_0 * q_0/n}} = \frac{0.173-0.205}{\sqrt{0.205*0.795/98}} = -0.78 \rightarrow$ null hypotheses can't be rejected

Test statistic: $Z = \frac{P-P_0}{\sqrt{P_0 * q_0/n}} = \frac{0.069-0.109}{\sqrt{0.109*0.891/39}} = -0.801 \rightarrow$ null hypotheses can't be rejected

It can be realized that the percent of age group 18-25 (30.6%) is over-represented in the survey sample because a large percent of the sample were students at UCF. However, in general we can say that there are no significant differences between the age groups percents in the survey sample and in the licensed drivers in Orange and Seminole counties.

In summary, considering the above mentioned results, it was concluded that there is no significant difference between the percentages of males, females, age groups in the survey sample and licensed drivers in Orange and Seminole counties. Hence, it was concluded that the survey sample well represented the licensed drivers in Orange and Seminole counties.

4.5 Response Analysis

A total of 566 responses were used in this study. About 49.3% of these responses were from handout survey, 16% through the interactive survey, and 34.7% via the Internet. As mentioned earlier, the online survey has the shortest average time needed to be completed, followed by handout, then interactive survey; 8, 10, and 20 minutes, respectively. Also, the interactive survey has the highest percent of complete responses (questions completed) with 89%, followed by online survey with 85%, and followed by handout questionnaire with 74%, respectively. Designing the online survey in a graphical user interface manner could be the reason why it had the shortest average time and the second highest percent of complete responses after the interactive survey. Also, in the interactive survey; surveyors had a direct interaction with the participants to explain any ambiguousness they may find and this could explain why it took the longest time.

The advantages and limitations of the three survey methods used in this study are summarized in Table 4-5. According to Table 4-5, it can be concluded that the interactive survey approach is recommended in future studies since it has high response rate, high control of interview situation, high percent collection of detailed information, and the highest percent of complete responses. This result is consistent with Nachimas (1996). On the other hand, the disadvantages include that it has the longest time needed to complete the survey and it is difficult to identify respondents. Therefore, the second recommended survey type is the online survey.

Table 4-5: Comparison between survey methods used in the current study

Criterion	**Current study**		
	Handout	**Interactive (controlled group)**	**Online (web-based)**
Cost	Low	Moderate	Low
Response rate	Low	High	Moderate
Control of interview situation	Low	High	Moderate
Collection of detailed information	Moderate	High	High
Speed of collecting survey forms	Low	Moderate	High
Average time to complete the survey forms (in minutes)	10	20	8
Percent of complete responses (questions completed)	74%	89%	85%

To investigate the differences between handout, interactive and online questionnaires, conditional distribution, odds ratio, Chi-squared test, and Ridit analyses were developed. The results of conditional distributions and odds ratios are listed in Table 4-6.

The odds ratios were estimated for each group with respect to the last category of that group. Concerning the gender, the odds ratio of males equals 1.52, which implies that the odds (or likelihood) of responding through the online survey are 1.5 times higher for males than for females. Also regarding age, for example, the odds ratio of the age group 18-25 equals 2.7, which means that the odds of responding via the Internet is 2.7 times higher for the age group of 16-25 than for the over 65 years old age group. This result supports the hypothesis that young respondents are more likely to respond to the online survey than old participants.

With respect to the education levels, it was found that the odds ratio of education level "graduate school or higher" equals 4.04, which indicates that the odds of responding through the online survey are 4 times greater for this specific level than for respondents who did not graduate from high schools. This finding supports the idea that Internet users might have a higher level of education and awareness and therefore, are keen to respond in questionnaires related to studies that are of interest. In this regards, the results shown in Table 4-6 indicate that the majority of Internet respondents (87.75%) have some college degree or higher. In addition, Table 4-6 revealed that the majority of the Internet respondents (85.2%) are younger than 51 years old.

Table 4-6: Distribution of gender, age, and education by response method

(The percent between parentheses is cell size relative to the group total)

Factor		Response method			Total	Odds ratio*
		Handout	Interactive	online		
Gender	Male	126 (45.16%)	75 (82.41%)	109 (55.61%)	310 (54.77%)	1.52
	Female	153 (54.84%)	16 (17.58%)	87 (44.39%)	256 (45.23%)	1
	Total	279 (100%)	91 (100%)	196 (100%)	566 (100%)	
Age	18-25	64 (22.94%)	69 (75.82%)	55 (28.06%)	188 (33.22%)	2.70
	26-35	62 (22.22%)	15 (16.48%)	53 (27.04%)	130 (22.97%)	2.68
	36-50	86 (30.82%)	6 (6.59%)	59 (30.10%)	151 (26.67%)	2.16
	51-65	45 (16.13%)	1 (1.11%)	22 (11.22%)	68 (12.01%)	1.54
	Over 65	22 (7.89%)	0 (0.00%)	7 (3.58%)	29 (5.13%)	1
	Total	279 (100%)	91 (100%)	196 (100%)	566 (100%)	
Education	Graduate school or higher	52 (18.64%)	7 (7.69%)	63 (32.14%)	122 (21.55%)	4.04
	College degree	103 (36.92%)	19 (20.88%)	59 (30.10%)	181 (31.98%)	1.91
	Some College	79 (28.32%)	60 (65.93%)	50 (25.51%)	189 (33.39%)	2.11
	High School	35 (12.54%)	5 (5.50%)	21 (10.71%)	61 (10.78%)	1.99
	Did not graduate from high school	10 (3.58%)	0 (0.00%)	3 (1.54%)	13 (2.30%)	1
	Total	279 (100%)	91 (100%)	196 (100%)	566 (100%)	

* Odds ratio between handout and online survey

Moreover, Chi-square test was developed to test the association between response method and respondents' characteristics; gender, age, and education. It was found that significant associations exist between the response method and the respondents' characteristics. Table 4-7 summarizes the results of Chi-Square Test. However, Chi-square test is not an appropriate test in case of age and education with response method as we would lose crucial information on the natural ordering of age and education categories (Abdel-Aty and Abdelwahab; 2001).

Table 4-7: Summary of the results of Chi-squared test

Association	χ^2	df	P-value
Gender * response method	38.5338	2	<.0001
Age * response method	122.3664	8	<.0001
Education * response method	67.6873	8	<.0001

Therefore, Ridit analysis, a technique that takes advantage of natural ordering, was developed. The first step in Ridit analysis is to select one group to serve as a reference then the average Ridit for the other group (comparison group) can be determined. For more information about Ridit analysis, the reader is referred to Bross (1958) and Fleiss (1981). The Ridits were calculated for age groups as shown in Table 4-8. The handout response group was selected as the reference group and the online response group was selected as the comparison group. The mean Ridit for the online group was 0.214, smaller than 0.5, which implies that the chances are about 2:1 that such an online respondent will be younger than a handout respondent. Again, this means young participants have higher odds of responding via the Internet.

Similarly, Ridits of education levels were estimated. The mean Ridit for the online group was 0.213, smaller than 0.5, then the chances are about 2:1 that such an online respondent will have higher education degree than a handout respondent. This implies that participants with high education have higher odds of responding via the Internet.

In summary, all the preliminary test results (odds ratios, Chi-squared test, and Ridits) revealed that the participants' response method vary by gender, age, and education.

Table 4-8: Ridit estimations for handout and online age groups

Age	Handout survey					Online survey
	Frequency (1)	(2)	(3)	(4)	Ridit (5)	Frequency
16-25	64	32	0	32	0.056	55
26-35	62	31	64	95	0.168	53
36-50	86	43	126	169	0.298	59
51-65	45	22.5	212	234.5	0.414	22
Over 65	22	11	257	268	0.473	7
Average Ridit for the online group					0.214	

The entries in column 2 are half the corresponding values in column 1 (handout frequency)
The entries in column 3 are the accumulated entries in column 1 shifted one category downwards.
The entries in column 4 are the sums of the corresponding entries in columns 2 and 3.
The entries in column 5 are the corresponding entries in column 4 divided by the total sample size "566"
Average Ridit for the online group = ∑ Online frequency x Ridit / Internet sample size = 0.214

4.6 Conclusions Regarding Survey Methods

This chapter presents the design and administration of a survey-based study to explore commuters' responses to different visibility conditions due to fog/smoke. The survey consisted of 566 responses through three different survey approaches; handout, interactive, and online questionnaires. Discussion of the quality and completeness of responses received by these three approaches were presented. Also, the advantages and limitations of the three survey methods used in this study were presented and discussed.

The results indicated that the online survey has the shortest average time needed to be completed, followed by handout, then interactive survey; 8, 10, and 20 minutes, respectively. Also, the interactive survey has the highest percent of complete responses (questions completed) with 89%, followed by online survey with 85%, and followed by handout questionnaire with 74%, respectively. Designing the online survey in a graphical user interface manner could be the reason why it had the shortest average time and the second highest percent of complete responses after the interactive survey. Also, in the interactive survey; surveyors have a direct interaction with the participants to explain any ambiguousness they may find and this could explain why it took the longest time. Moreover, concerning the quality and completeness of responses, it was found that the handout survey is even better than regular mail-back survey as personal interaction exists between the surveyors and respondents in the handout questionnaire case.

In addition, several categorical data analysis techniques were applied to understand the difference between handout, interactive, and online responses. These methods include odds ratio, Chi-squared test, and Ridits analysis.

The results depict that the odds of online responses are much higher for young respondents (18-25 years old). This implies that young respondents are more likely to respond to the online survey than older participants possibly because young respondents are more used to using the Internet than older participants. These results are consistent with the result obtained by Abdel-Aty and Abdelwahab (2001). Also, compared to participants who just have a high school degree or less, the findings revealed that online respondents might have a higher level of education and awareness and therefore, are keen to respond to questionnaires related to studies that could affect and benefit them. In this regards, it was found that the majority of Internet respondents (87.75%) have some college degree or higher.

It can be concluded that the interactive survey approach is recommended in future studies since it has high response rate, high control of interview situation, high percent collection of detailed information, and the highest percent of complete responses. On the other hand, the disadvantages include that it has the longest time needed to complete the survey and it is difficult to identify respondents. Therefore, when conducting an interactive survey is not possible, the second recommended survey type is the online survey as it has the shortest time to be completed and the second highest percentage of complete responses (questions completed) after the interactive survey. Also, conducting the survey with a combination of survey methods such as handout or phone is highly recommended to obtain a well representative survey sample.

CHAPTER 5. SURVEY ANALYSIS

5.1 Description of the Survey Sample

As indicated earlier, a total of 566 responses were used in the analysis presented in this survey study. The frequencies and percentages of the survey sample are summarized in Table 5-1. As shown in Table 5-1, about 54.8% and 45.2% of participants were males and females, respectively. Also, about 49.3% of responses were from the handout survey, 16% through the interactive survey, and 34.7% via the Internet. Moreover, the number of respondents for the freeway and the two-lane road surveys were 262 (46.3%) and 304 (53.7%), respectively.

Respondents were asked if they were involved in previous crashes due to FS or HR. According to Table 5-1, about 3.9% and 10.8% of the respondents reported that were involved in FS and HR-related crashes, respectively.

5.2 Response Analysis

Respondents were asked if they have encountered CMS and VSL signs on freeways/two lane roads. The results indicated that the majority of respondents (83.6% and 68.2%) are familiar with CMS and VSL signs, respectively.

As mentioned earlier, one of the objectives of this study is to determine the content of the message that is perceived to achieve the best safety and achieve drivers' compliance. Considering drivers' opinions, 216 respondents (38%) stated that the best message is "Caution-fog ahead-reduce speed". By testing the homogeneity of proportions of the given messages, the hypothesis that all proportions are equal was rejected at the 5% level of significance (χ^2=274.7, DF=5, p-value<0.0001) which implies that there is significant difference in selection of messages and that the aforementioned message was selected as the best message by the larger proportion of participants. The percentages of drivers' choices for other alternative messages are listed in Table 5-1.

In addition, the responses revealed that the majority of respondents (83.2%) agree with the usefulness of using two successive CMS prior to FS zones for warning drivers about any sudden reduction in visibility. This could provide drivers with another chance to read the content of the warning message of the second CMS if they missed the first one.

Furthermore, drivers were asked about their satisfaction with the usefulness of using CMS and VSL signs on a five-point scale ranging from "strongly disagree" to "strongly agree". About 93.5% of respondents (who agree or strongly agree) reported that they are satisfied with the usefulness of CMS while, 76% of participants (who agree or strongly agree) stated that VSL signs could be useful in reducing the number of FS crashes (as shown in Table 5-1). This difference could be attributed to the fact that drivers in Florida are not familiar with VSL signs compared to CMS.

Another objective of this study was to investigate the best way to improve safety during driving through FS zones based on drivers' expectations and preferences: using CMS only, using VSL signs only, using CMS and VSL signs simultaneously or closing the road during such adverse weather. Most of the respondents (63.8%) stated that using CMS and VSL signs together is the best way to improve safety during reduced visibility conditions (as shown in Table 5-1).

Table 5-1: Survey sample distributions

Variables	Categories	Number of Respondents	Percentages of Respondents
Gender	Male	310	54.8
	Female	256	45.2
Age Groups	18-25	173	30.6
	26-35	120	21.2
	36-50	136	24.0
	+51	137	24.2
Education Levels	Graduate school or higher	122	21.6
	College degree	182	32.1
	Some College	188	33.2
	High School or less	74	13.1
Survey type	Handout	279	49.3
	interactive	91	16.0
	online	196	34.7
Road type	Freeways	262	46.3
	two lane roads	304	53.7
Involved in FS crashes	yes	22	3.9
	no	544	96.1
Involved in HR crashes	yes	61	10.8
	no	505	89.2
Drivers' familiarity with CMS	yes	473	83.6
	no	93	16.4
Drivers' familiarity with VSL signs	yes	386	68.2
	no	180	31.8
Drivers' opinion of the messages that will achieve the best safety and driver compliance	Fog ahead-Reduce speed	71	12.5
	Caution-Fog ahead-reduce speed	216	38.2
	Fog ahead-Reduce speed-fine doubled	91	16.1
	Fog ahead- Reduce speed –Strictly enforced	132	23.3
	Caution- Reduce speed –Strictly enforced	41	7.2
	Other	15	2.7
Drivers' opinion about the best way to improve safety during poor visibility conditions	using CMS only	176	31.1
	using VSL only	16	2.8
	using CMS and VSL together	361	63.8
	close the road	13	2.3
Drivers' satisfaction with the usefulness of CMS in warning them about reduced visibility conditions	Strongly agree	268	47.4
	Agree	261	46.1
	Neither agree nor disagree	24	4.2
	Disagree	13	2.3
	Strongly disagree	0	0
Drivers' satisfaction with the usefulness of VSL in reducing the number of fog related crashes by informing them about safe speed limit under reduced visibility conditions	Strongly agree	187	33.0
	Agree	243	42.9
	Neither agree nor disagree	78	13.8
	Disagree	47	8.4
	Strongly disagree	11	1.9

This result is logical because warning drivers that there is fog ahead using CMS only does not instruct them on what to do. Therefore, using VSL signs is also important to advise drivers about the safe speed at every visibility conditions. This result is consistent with prior studies such as Perrin et al. (2002). The hypothesis that the proportions of all possible ways to improve safety are equal was rejected at the 5% level of significance (χ^2=576.9, DF=3, p-value<0.0001) which means that using CMS and VSL signs together during adverse visibility conditions was preferred by the larger proportion of participants.

To obtain an in-depth understanding of drivers' behavior in response to CMS and VSL instructions at different visibility conditions, 10 scenarios were designed for both; freeways and two-lane roads (as shown in Table 5-2). Two scenarios include two pictures for a freeway/a two-lane road and a CMS displaying the following message: "Fog ahead – speed reduced" (As shown in Figure 5-1). Respondents were asked about their possible actions when driving on a freeway at a speed of 65 mph (or on a two-lane road at a speed of 45 mph), and they encountered a portable CMS advising them to reduce speed due to reduction in visibility at two conditions: low traffic volumes (no car leading ahead) and medium-high traffic volumes (some vehicles are ahead).

Table 5-2: Description of scenarios

Scenario	Sign	Visibility conditions	Traffic conditions
1	CMS	Light fog	No car leading ahead
2			Some vehicles are ahead
3	VSL	Very light fog	No car leading ahead
4		Light fog	
5		Medium fog	
6		Heavy fog	
7		Very light fog	Some vehicles are ahead
8		Light fog	
9		Medium fog	
10		Heavy fog	

If you were driving on a two lane road at a speed of 45 mile/hour (mph) and you encounter a CMS advising you to reduce your speed because of reduction in visibility due to Fog/smoke in order to reduce the chances of an accident. What would you do in each of the following cases?

No car leading ahead

20) a) Do nothing
b) Reduce speed immediately
c) Reduce speed after some time
d) Reduce speed and put blinkers on

car leading ahead

21) a) Do nothing
b) Reduce speed immediately
c) Reduce speed after some time
d) Follow other vehicles' speed regardless of CMS warning
e) Reduce speed and put blinkers on

Figure 5-1: Sample of CMS questions from the two-lane road survey

The other 8 scenarios consisted of 8 pictures for a freeway/two-lane road; each picture contained a VSL sign advising drivers to reduce their speed to 40 mph in the freeway survey and to 25 mph in the two-lane road survey. Four out of these 8 scenarios were designed at low traffic volume and at 4 fog conditions (very light, light, medium, and heavy fog) while, the other 4 scenarios were developed at medium-high traffic volume and at the same 4 fog conditions (as shown in Table 5-2). An example of these questions is shown in Figure 5-2. It is worth mentioning that although using blinkers during driving is not legal in many states, many people do not know and do it anyhow (adding this option was recommended during the pilot survey as it is a common driving behavior . Also, it was decided to study drivers' responses to CMS at only one fog condition (light fog) to reduce the numbers of survey's questions.

If you were driving on a freeway with a speed limit of 65 mile/hour (mph), and you encounter a Variable Speed Limit Sign of 40 mile/hour (mph) to reduce the chances of an accident that may occur because of a sudden reduction in visibility due to fog/smoke. What will you do in each of the following cases?

Note: in case you will reduce your speed (answers c or d), please specify your reduced speed

a) Do nothing
b) Follow other vehicles' speed.
c) Reduce speed to ………..mph (Please specify your reduced speed)
d) Put blinkers on and reduce speed to…...mph (Please specify your reduced speed)

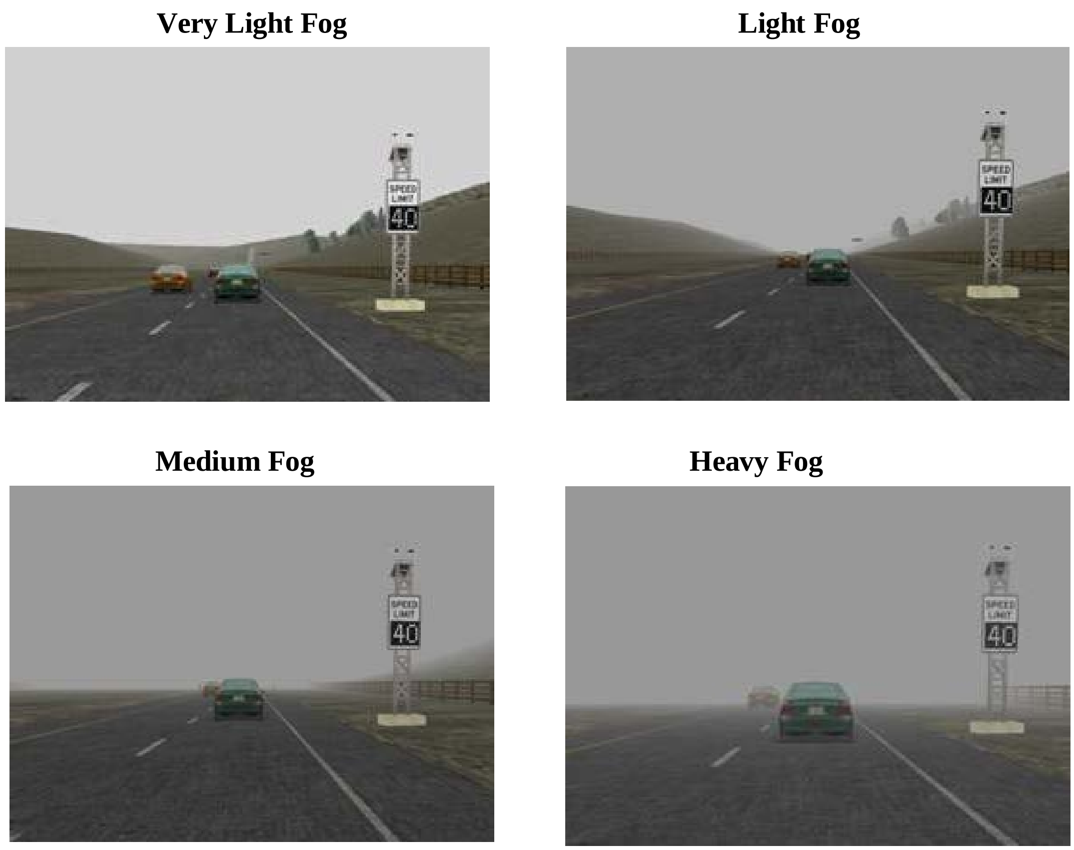


Figure 5-2: Sample of VSL questions from the freeway survey

Drivers' responses to CMS and VSL signs at different fog and traffic conditions for both: freeway and two-lane road cases are summarized in Table 5-3 and Table 5-4, respectively. Table 5-3 indicates that only 37% of the respondents reported that they would reduce speed immediately or reduce speed and put blinkers on when encountered CMS, which advises them to reduce speed due to reduced visibility condition, at low traffic volume while driving on a freeway. At medium-high traffic volume, this percentage increased to 51.6%. This seems reasonable because of the effect of traffic volume as it is one of the most important factors affecting drivers' behavior.

For two-lane road case, the percentages of drivers who were willing to reduce speed immediately or reduce speed and put blinkers on following CMS instructions at low and medium-high traffic volumes are 38.5% and 56.9%, respectively. Again, this result implies that drivers are more cautious when driving at medium-high traffic volume. Although Table 5-3 indicates that drivers are more cautious when driving on two-lane roads at adverse visibility conditions compared with driving on freeways. However, using Z-test, the differences of proportions between drivers' response when driving on freeways and on two-lane roads were not statistically significant.

Table 5-3: Summary of drivers' responses to CMS instructions

Traffic conditions	Fog conditions	Do nothing	Reduce speed after some time	Follow other vehicles' speed	Reduce speed immediately or reduce speed and put blinkers on
Drivers' behavior for Freeway Survey (Sample size = 262)					
Low traffic volume	Light fog	56 (21.4%)	109 (41.6%)	NA*	97 (37%)
Medium – high traffic volume		20 (7.6%)	63 (24%)	44 (16.8%)	135 (51.6%)
Drivers' behavior for Two-Lane Road Survey (Sample size = 304)					
Low traffic volume	Light fog	44 (14.5%)	143 (47%)	NA*	117 (38.5%)
Medium – high traffic volume		11 (3.6%)	71 (23.4%)	49 (16.1%)	173 (56.9%)

* Not Applicable

As shown in Table 5-4, clearly both fog and traffic conditions greatly affect drivers' responses to safe speed limits displayed on VSL signs at each of the aforementioned 8 scenarios. As the visibility distance is reduced and traffic volume increases, drivers tend to follow VSL instructions. With respect to the survey made in freeway, the percentage of respondents who would reduce their speed or reduce speed and put blinkers on increased from 63.4 to 77.1 to 96.6 to 98.5% for low traffic volumes and increased from 44.7 to 51.1 to 76 to 89.7% for medium-high traffic volumes. Higher values were obtained for the two-lane road's survey. Again this implies that traffic volume, type of road, and visibility condition affected the likelihood of reducing the speed following VSL/CMS instructions.

Table 5-4: Summary of drivers' responses to VSL sign instructions

Drivers' behavior for Freeway Survey (Sample size = 262)					
Traffic conditions	**Fog conditions**	**Do nothing**	**Follow other vehicles' speed**	**Reduce speed or reduce speed and put blinkers on**	**Reduce speed to 40 MPH or less**
Low traffic volume	Very light fog	96 (36.6%)	NA*	166 (63.4%)	92 (35.1%)
	Light fog	60 (22.9%)	NA*	202 (77.1%)	104 (39.7%)
	Medium fog	9 (3.4%)	NA*	253 (96.6%)	155 (59.2)
	Heavy fog	4 (1.5%)	NA*	258 (98.5%)	201 (76.7%)
Medium–high traffic volume	Very light fog	43 (16.4%)	102 (38.9%)	117 (44.7%)	93 (35.5%)
	Light fog	22 (8.4%)	106 (40.5%)	134 (51.1%)	107 (40.8%)
	Medium fog	4 (1.5%)	59 (22.5%)	199 (76.0)	159 (60.7%)
	Heavy fog	2 (0.8%)	25 (9.5%)	235 (89.7%)	215 (82.1%)
Drivers' behavior for Two-Lane Road Survey (Sample size = 304)					
Traffic conditions	**Fog conditions**	**Do nothing**	**Follow other vehicles' speed**	**Reduce speed or reduce speed and put blinkers on**	**Reduce speed to 25 MPH or less**
Low traffic volume	Very light fog	110 (36.2%)	NA*	194 (63.8%)	108 (35.5%)
	Light fog	65 (21.4%)	NA*	239 (78.6%)	127 (41.8%)
	Medium fog	8 (2.6%)	NA*	296 (97.4%)	183 (60.2%)
	Heavy fog	2 (0.7%)	NA*	302 (99.3%)	242 (79.6%)
Medium–high traffic volume	Very light fog	44 (14.5%)	113 (37.2%)	147 (48.3%)	117 (38.5%)
	Light fog	24 (7.9%)	121 (39.8%)	159 (52.3%)	141 (46.4%)
	Medium fog	0 (0%)	64 (21.1%)	240 (78.9%)	196 (64.5%)
	Heavy fog	0 (0%)	25 (8.2%)	279 (91.8%)	262 (86.2%)

* Not Applicable

Furthermore, as shown in the last column of Table 5-4, only 35.1% of respondents stated that they would follow VSL signs' instructions (reduce their speed to 40 mph or less) while driving on a freeway at very light fog and low traffic volume. The results also reveal that the percentages of drivers who are willing to follow VSL instructions increase as the visibility distance deteriorates and traffic volume increases. For example, the percentage increased to 82.1% at heavy fog and medium-high traffic volume. The same conclusion applies to two-lane roads but with higher percentages of compliance with VSL instruction. However, using Z and Chi Square tests, no significant differences were found between drivers' responses to VSL signs while driving on freeways versus two-lane roads or while driving at low versus medium-high traffic volumes.

Finally drivers were asked to rank the following six options from the safest action (rank 1) that they thought would minimize the chance of a FS crash to the least action (rank 6): 1) do nothing, 2) drive below speed limit, 3) drive below speed limit following the instructions of CMS and VSL signs, if they are available, 4) follow other vehicles' speed regardless of CMS and VSL warnings, 5) drive below speed limit and put blinkers on, 6) Abandon the journey and stop the car immediately at the right shoulder of the road.

The results revealed that 36.2% of the respondents claimed that following the instructions of CMS and VSL signs is the safest action. Driving below speed limit and putting blinkers on came in the second place with 26.3%. On the other hand, the majority of sample (86%) stated that doing nothing is the most dangerous action. "Abandon the journey and stop the car immediately at the right shoulder of the road" came next with about 10%. Some participants pointed out that the last option is dangerous as it might increase rear-end crashes especially at heavy fog condition.

5.3 Association between Categorical Variables

Prior to the modeling process, conditional distributions, odds' ratios, and Chi square tests were used for preliminary investigation of the differences between drivers' responses to CMS and VSL signs at different traffic and visibility conditions. Table 5-5 summarizes the results of conditional distributions and odds ratios. The odds' ratios were estimated for each group with respect to the first category of that group.

As shown in Table 5-5, concerning the gender, the odds' ratio of females equals 3.7, which implies that when driving at heavy fog and medium-high traffic volume, the odds of following VSL instructions are 3.7 times higher for females than males. Also regarding age, the result supports the hypothesis that older respondents are more likely to respond to VSL instructions than young participants. For example, the results revealed that the likelihood of following VSL instructions is 5.1 times higher for old drivers than for young drivers (18-25 years old).

Regarding drivers' familiarity with VSL signs, it was found that the odds of following VSL instructions are 2.6 times greater for drivers who are familiar with VSL than for those who are not. In addition, the likelihood of following VSL instructions is 2.1 times higher for experienced drivers than drivers who are not familiar with driving at poor visibility conditions. Similar results were obtained for drivers' response to CMS (see Table 5-5). Concerning road type, it was found that the probability of following CMS while driving on two-lane roads is 1.2 times higher than while driving on freeways.

Table 5-5: Conditional distributions and odds ratio

(The percent between parentheses is cell size relative to the group total)

Factor		Driver's response to VSL instructions at heavy fog and medium-high traffic volume		Total	Odds ratio
		Do nothing or follow other vehicles' speed	**Reduce speed or reduce speed and put blinkers on**		
Gender	Male	48 (80%)	262 (51.8%)	310 (54.8%)	1
	Female	12 (20%)	244 (48.2%)	256 (45.2%)	3.7
	Total	60 (100%)	506 (100%)	566 (100%)	
Age	18-25	33 (55%)	140 (27.7%)	173 (30.6%)	1
	26-35	14 (23.3%)	106 (20.9%)	120 (21.2%)	1.8
	36-50	7 (11.7%)	130 (25.7%)	137 (24.2%)	4.4
	+51	6 (10%)	130 (25.7%)	136 (24%)	5.1
	Total	60 (100%)	506 (100%)	566 (100%)	
Drivers' familiarity with VSL signs	No	31 (51.7%)	149 (29.4%)	180 (31.8%)	1
	Yes	29 (48.3%)	357 (70.6%)	386 (68.2%)	2.6
	Total	60 (100%)	506 (100%)	566 (100%)	
Past experience with driving at adverse visibility conditions	No	19 (31.7%)	91 (18%)	110 (19.4%)	1
	Yes	41 (68.3%)	415 (82%)	456 (80.6%)	2.1
	Total	60 (100%)	506 (100%)	566 (100%)	
Involved in FS crashes	No	20 (90.9%)	486 (89.3%)	506 (89.4%)	1
	Yes	2 (9.1%)	58 (10.7%)	60 (10.6%)	1.2
	Total	22 (100%)	544 (100%)	566 (100%)	
Involved in HR crashes	No	55 (91.7%)	450 (88.9%)	505 (89.2%)	1
	Yes	5 (8.3%)	56 (11.1%)	61 (10.8%)	1.4
	Total	60 (100%)	506 (100%)	566 (100%)	
Factor		Driver's response to CMS instructions at medium-high traffic volume		Total	Odds ratio
		Do nothing or reduce speed after some time or follow other vehicles' speed	Reduce speed immediately or reduce speed and put blinkers on		
Gender	Male	162 (62.8%)	148 (48.1%)	310 (54.8%)	1
	Female	96 (37.2%)	160 (51.9%)	256 (54.8%)	1.8
	Total	258 (100%)	308 (100%)	566 (100%)	
Age	18-25	119 (46.1%)	54 (17.5%)	173 (30.6%)	1
	26-35	49 (19.0%)	71 (23.1%)	120 (21.2%)	3.2
	36-50	58 (22.5%)	78 (25.3%)	136 (24.0%)	3.0
	+51	32 (12.4%)	105 (34.1%)	137 (24.2%)	7.2
	Total	258 (100%)	308 (100%)	566 (100%)	
Road Type	freeway	127 (49.2%)	135 (43.8%)	262 (46.3%)	1
	2-lane road	131 (50.8%)	173 (56.2%)	304 (53.7%)	1.2
	Total	258 (100%)	308 (100%)	566 (100%)	
Drivers' familiarity with CMS	No	221 (85.7%)	252 (81.8%)	473 (83.6%)	1
	Yes	37 (14.3%)	56 (18.2%)	93 (16.4%)	1.3
	Total	258 (100%)	308 (100%)	566 (100%)	
Past experience with driving at adverse visibility conditions	No	211 (81.8%)	245 (79.5%)	456 (80.6%)	1
	Yes	47 (18.2%)	63 (20.5%)	110 (19.4%)	1.2
	Total	258 (100%)	308 (100%)	566 (100%)	

Additionally, one more interesting research question was to examine whether drivers' responses to reduced visibility conditions differed for those who were involved in FS or HR crashes. As expected, it was found that when driving at heavy fog and medium-high traffic volume, the odds of following VSL instructions is 1.2 times higher for participants who were involved in FS crashes than those who were not involved in such crashes (as shown in Table 5-5). Similarly, the odds of following VSL signs at heavy fog condition and medium-high traffic volume is 1.4 times higher for participants who were previously experienced HR crashes than those who were not involved in such crashes.

Moreover, Pearson Chi-Square test (χ^2) and Mantel-Haenszel Chi-Square test (CMH) were developed to explore the association between drivers' responses to CMS/VSL signs and other factors such as age, gender, education, drivers' familiarity with CMS/VSL signs, and experience with driving at adverse visibility conditions. Chi-Square test was used to test the independence of every two nominal variables while, CMH test was used to examine the association between every two ordinal variables or between ordinal and nominal variables.

The results showed significant association between drivers' response to VSL/CMS signs and those variables shown in Table 5-6.

Table 5-6: Summary of Pearson Chi-Squared and Mantel-Haenszel tests' results

Factors	Value	DF	P-value
Factors associated with drivers' responses to VSL instructions at heavy fog and medium to high traffic volume (1)			
Gender	χ^2 =20.770	4	0.000
Age	CMH =58.943	12	0.000
Education	CMH =22.978	12	0.028
Drivers' familiarity with VSLS	χ^2 =15.045	3	0.002
Past experience with driving at poor visibility condition	χ^2 =8.391	3	0.039
Factors associated with drivers' responses to VSL instructions at very light fog and low traffic volume (2)			
Gender	χ^2 =7.889	2	0.019
Age	CMH =67.117	8	0.000
Factors associated with drivers' responses to CMS instructions at low traffic volume (3)			
Gender	χ^2 =12.127	3	0.007
Age	CMH =94.622	12	0.000
Education	CMH =43.128	12	0.000
Drivers' familiarity with driving on freeway/2 lane road	χ^2 =9.693	3	0.021
Drivers' familiarity with PCMS	χ^2 =8.668	3	0`.034
Factors associated with drivers' responses to CMS instructions at medium to high traffic volume (4)			
Gender	χ^2 =14.601	4	0.006
Age	CMH =110.418	16	0.000
Education	CMH =35.570	16	0.003
(1) * (2)	χ^2 =62.068	6	0.000
(1) * (3)	χ^2 =105.904	9	0.000
(1) * (4)	χ^2 =129.065	12	0.000
(2) * (3)	χ^2 =141.239	6	0.000
(2) * (4)	χ^2 =109.491	8	0.000
(3) * (4)	χ^2 =652.313	12	0.000

* Only significant associations are shown in the table

In summary, all the preliminary tests' results revealed that the participants' response to CMS and VSL signs instructions vary by gender, age, familiarity with CMS and VSL signs, and experience with driving at adverse visibility condition. Thus, to improve our understanding of the preferences of respondents in following VSL and CMS instructions at such adverse visibility conditions, multivariate analyses; the bivariate and multivariate probit models were employed for further analyses.

5.4 Bivariate and Multivariate Probit Approach

This section emphasizes two methodological approaches for analyzing and modeling drivers' responses to CMS and VSL signs at different visibility and traffic conditions; Bivariate Probit Models (BPM) and Multivariate Probit Model (MPM). Correlated responses often arise in behavioral, medical and psychological researches. BPM and MPM are popular methods for analyzing this kind of data (Lu and Song, 2006).

MPM has been widely used in agricultural, statistical, and economic studies for analyzing potentially correlated multivariate outcomes. These studies include Gibbons and Wilcox (1998), Lansink et al. (2003), and Young et al. (2009). However, MPM has been developed in few transportation related studies such as Choo and Mokhtarian (2008), and Rentziou et al. (2010).

In the present study, BPM and MPM were adopted due to the likely correlation of unobserved effects (between drivers' response to CMS and to VSL signs at different visibility and traffic conditions) which if not accounted for, would lead to biased model coefficient estimates. MPM is a generalization of the BPM used to estimate several correlated binary outcomes jointly (Ashford and Sowden, 1970).

In this study, the BPM was used to identify the dependent variables that better explain drivers' responses to CMS and VSL signs at adverse visibility conditions, and then these dependent variables were used to estimate the MPM. The advantage of using MPM is that all dependent and explanatory factors affecting drivers' responses to CMS and VSL signs at different traffic and visibility conditions can be shown and discussed in one model framework instead of explaining several BPM separately. In addition, correlations between several equations can also be accounted for.

In BPM, the simultaneous estimation of the two models would improve the coefficient estimates by accounting for the correlation between the unmeasured factors (Das et al., 2008). Additionally, one advantage of the BPM is that the estimated values of the first binary dependent variable can be determined and instrumented simultaneously as an explanatory variable in the second model and vice versa (if a relationship between the two variables are thought to exist).

According to Meng and Schmidt (1985), Abdel-Aty et al. (1994), Mohanty (2002) and Greene (2003), the BPM is a natural extension of the probit model that allows two equations with correlated disturbances. The model specification for the simultaneously estimated BPM can be explained as follows:

$$Y_1^* = \beta X_1 + \acute{\varepsilon}_1 \qquad Y_1 = 1 \text{ if } Y_1^* \geq 0; 0 \text{ otherwise} \tag{5-1}$$

$$Y_2^* = \alpha X_2 + \acute{\varepsilon}_2 \qquad Y_2 = 1 \text{ if } Y_2^* \geq 0; 0 \text{ otherwise} \tag{5-2}$$

Where:

Y_1^* and Y_2^* = Estimated dependent variables;

Y_1 and Y_2 = Observed choices for dependent variables;

X_1, X_2 = Vector of explanatory variables influencing choice behavior;

B, α = Coefficient vectors; and

$\acute{\varepsilon}_1$, $\acute{\varepsilon}_2$ = random error term.

The error terms $\acute{\varepsilon}_1$ and $\acute{\varepsilon}_2$ are estimated according to:

$$E\,[\acute{\varepsilon}_1 / x_1, x_2] = E\,[\acute{\varepsilon}_2 / x_1, x_2] = 0 \tag{5-3}$$

$$\mathrm{Var}\,[\acute{\varepsilon}_1 / x_1, x_2] = \mathrm{Var}\,[\acute{\varepsilon}_2 / x_1, x_2] = 1 \tag{5-4}$$

$$\mathrm{Cov}\,[\acute{\varepsilon}_1, \acute{\varepsilon}_2 / x_1, x_2] = \rho \tag{5-5}$$

Where: ρ is the correlation coefficient between the two error terms. If ρ equals zero, the bivariate probit model converges to two separate binomial probit models. In addition, the model parameters of the two probit equations are estimated simultaneously using full information maximum likelihood estimation. Parameters vectors B, α, and ρ are estimated to maximize the likelihood function. Also, significant ρ will imply the presence of unobserved individual factors (heterogeneity) that affect both dependent variables used in the BPM.

Three bivariate probit models were developed after investigating several alternative model formations and dependent variables (as shown in Table 5-7). Drivers' response to VSL signs at heavy fog and medium-high traffic volume (0 if do nothing or follow other vehicles' speed, 1 if reduce speed or reduce speed and put blinkers on) was the first dependent variable in the three models. The second dependent variables in the three fitted BPM were drivers' response to VSL signs at very light fog and low traffic volume (0 if do nothing, 1 if reduce speed or reduce speed and put blinkers on), drivers' response to CMS at low traffic volume (0 if do nothing or reduce speed after some time, 1 if reduce speed immediately or reduce speed and put blinkers on), and drivers' response to CMS at medium-high traffic volume (0 if do nothing or reduce speed after some time or follow other vehicles' speed, 1 if reduce speed immediately or reduce speed and put blinkers on), respectively. Level 0 was considered the base case for each dependent variable (Table 5-7).

The results of the three BPM revealed that gender, age, drivers' familiarity with VSL signs, and road type were the most significant factors affecting the likelihood of reducing speed following the instructions of VSL or CMS in response to adverse visibility conditions.

Table 5-7: Summary of Bivariate probit models
([a] Base case [b] Akaike Information Criterion)

	First BPM Model			Second BPM Model			Third BPM Model		
Variable Description	**Estimate**	**Standard Error**	**P-value**	**Estimate**	**Standard Error**	**P-value**	**Estimate**	**Standard Error**	**P-value**
First equation	***drivers' responses to VSL signs at heavy fog and medium-high traffic condition (Baseline: do nothing or follow other vehicles' speed)***								
Intercept	0.6629	0.1290	0.0000	0.6896	0.1325	0.0000	0.6826	0.1299	0.0000
Gender - male	----- [a]			----- [a]			----- [a]		
Gender - female	0.5889	0.1702	0.0005	0.5569	0.1748	0.0014	0.5747	0.1711	0.0008
Age (18-25)	----- [a]			----- [a]			----- [a]		
Age (36-50)	0.6515	0.2311	0.0048	0.6219	0.2289	0.0066	0.6283	0.2232	0.0049
Age (+51)	0.6556	0.2280	0.0040	0.6036	0.2180	0.0056	0.6239	0.2186	0.0043
Drivers' familiarity with VSL SIGNS (no)	----- [a]			----- [a]			----- [a]		
Drivers' familiarity with VSL SIGNS (yes)	0.5233	0.2045	0.0105	0.4807	0.2168	0.0266	0.5193	0.2075	0.0123
Road type (2-lane road)	----- [a]			----- [a]			----- [a]		
Road type (freeway)	-0.3805	0.2077	0.0670	-0.3319	0.2141	0.1212	-0.3923	0.2175	0.0713
Second equation	***Drivers' responses to VSL signs at very light fog and low traffic volumes (Baseline: do nothing)***			***Drivers' responses to CMS at low traffic volume (Baseline: do nothing or reduce speed after some time)***			***Drivers' responses to CMS at medium-high traffic volume (Baseline: do nothing or reduce speed after some time or follow other vehicles' speed)***		
Intercept	-0.2175	0.1032	0.0350	-1.0576	0.1241	0.0000	-0.4799	0.1149	0.0000
Gender-male	----- [a]			----- [a]			----- [a]		
Gender-female	0.2265	0.1166	0.0520	0.2758	0.1128	0.0145	0.3346	0.1141	0.0034
Age (18-25)	----- [a]			----- [a]			----- [a]		
Age (26-35)	0.4105	0.1468	0.0052	0.6540	0.1630	0.0001	0.6486	0.1534	0.0000
Age (36-50)	0.5372	0.1483	0.0003	0.6067	0.1588	0.0001	0.6419	0.1506	0.0000
Age (+51)	1.2097	0.1673	0.0000	1.2299	0.1589	0.0000	1.2226	0.1567	0.0000
Road type (2-lane road)							----- [a]		
Road type (freeway)							-0.2973	0.1139	0.0091
Error terms correlation coefficient (ρ)	0.3534	0.0899	0.0001	0.3819	0.1149	0.0009	0.3785	0.0969	0.0001
Number of observations	566			566			566		
Log-likelihood at convergence	-499.475			-500.666			-510.442		
AIC [b]	1020.95			1023.332			1044.884		

In addition, to improve our understanding of the factors affecting drivers' behavior at different visibility and traffic conditions, an MPM was developed. Based on the three BPM mentioned above, it was found that the dependent variables that better explain drivers' response to adverse visibility conditions were; drivers' response to VSL at heavy fog and medium-high traffic volume, drivers' response to VSL at very light fog and low traffic volume, and drivers' response to CMS at medium-high traffic volume. Therefore, these three dependent variables were used in MPM.

The MPM estimates, goodness-of-fit statistics, and the correlation coefficient "ρ" between every two error terms in the three equations are presented in Table 5-8. As shown in Table 5-8, the coefficients of correlation "ρ" is statistically different from zero, hence illustrating the validity of using the Multivariate probit framework.

According to the first model, while encountering a heavy fog condition and some vehicles are ahead (medium-high traffic volume), the likelihood of female drivers who are reducing their speed or reducing their speed and putting the blinkers on are more than the corresponding male drivers. This implies that female drivers are more cautious than male drivers.

Concerning age, as age increases, the likelihood of following VSL instruction at heavy fog and medium-high traffic volume increases. The results suggest that compared to young respondents (18-25 years old), old respondents (51 years old or more) are more likely to reduce their speed following VSL instruction. This indicates that maturity and experience are essential factors that affect the driver's response to VSL instructions.

An expected finding is that drivers, who are familiar with VSL signs, are more likely to reduce their speed at heavy fog conditions. This could be attributed to the fact that drivers, who are familiar with VSL signs and aware of its importance in avoiding a potential accident in case of reduced visibility due to FS, are less likely to ignore its instructions.

Regarding the type of road, at 90% confidence, the probability of reducing speed, following VSL at heavy fog and medium-high traffic volume while driving on a freeway, is less than the corresponding probability while driving on a two-lane road. Thus drivers could be more cautious on two-lane roads.

Similar findings were obtained from the second and third equations. The second model suggests that both females and old drivers (51 years old or more) are more likely to reduce their speed following VSL instructions at very light fog and low traffic volume compared to males and young drivers (18-25 years old), respectively.

According to the third probit model, while encountering CMS at medium-high traffic volume which advise drivers to reduce their speed due to reduction of visibility, the likelihood of females and old drivers who are reducing their speed or reducing their speed and putting blinkers on are more than the corresponding males and young drivers. Again, this implies that females and old drivers are more cautious than male and young drivers.

Finally, drivers who drive on a freeway at poor visibility conditions are less likely to respond to CMS instructions compared to those who drive on a two-lane road possibly due to more cautious driving on two-lane roads. It is possible that the presence of medians on freeways could give drivers a better sense of protection from the opposing traffic.

Table 5-8: Multivariate Probit model estimates
([a] Base case [b] Akaike Information Criterion)

Variable Description	Estimate	Standard Error	P-value
First equation : drivers' responses to VSL signs at heavy fog and medium-high traffic volume (Baseline: do nothing or follow other vehicles' speed)			
Intercept	0.5690	0.1463	0.0001
Gender-male	----- [a]		
Gender-female	0.5553	0.1714	0.0012
Age (18-25)	----- [a]		
Age (26-35)	0.2778	0.1712	0.1041
Age (36-50)	0.7678	0.2408	0.0014
Age (+51)	0.7637	0.2356	0.0012
Drivers' familiarity with VSL SIGNS (no)	----- [a]		
Drivers' familiarity with VSL SIGNS (yes)	0.5001	0.2106	0.0176
Road type (2-lane road)	----- [a]		
Road type (freeway)	-0.3508	0.2193	0.1097
Second equation : drivers' responses to VSL signs at very light fog and low traffic volume (Baseline: do nothing)			
Intercept	-0.2299	0.1038	0.0267
Gender-male	----- [a]		
Gender-female	0.2242	0.1174	0.0562
Age (18-25)	----- [a]		
Age (26-35)	0.4501	0.1527	0.0032
Age (36-50)	0.5589	0.1496	0.0002
Age (+51)	1.2241	0.1679	0.0000
Third equation : drivers' responses to CMS at medium-high traffic volume (Baseline: do nothing or reduce speed after some time or follow other vehicles' speed)			
Intercept	-0.5007	0.1155	0.0000
Gender-male	----- [a]		
Gender-female	0.3321	0.1146	0.0038
Age (18-25)	----- [a]		
Age (26-35)	0.6880	0.1569	0.0000
Age (36-50)	0.6574	0.1510	0.0000
Age (+51)	1.2322	0.1571	0.0000
Road type (2-lane road)	----- [a]		
Road type (freeway)	-0.2694	0.1138	0.0179
Error terms correlation coefficient between equations 1 & 2 (ρ_{12})	0.3525	0.0901	0.0001
Error terms correlation coefficient between equations 1 & 3 (ρ_{13})	0.3716	0.0976	0.0001
Error terms correlation coefficient between equations 2 & 3 (ρ_{23})	0.2524	0.0698	0.0003
Number of observations	566		
Log-likelihood at convergence	-835.7581		
AIC [b]	1707.5162		

5.5 Structural Equation Modeling (SEM) Approach

This section examine drivers' responses under low visibility conditions and quantify the impacts and values of various factors found to be related to drivers' compliance and drivers' satisfaction with VSL and CMS instructions in different visibility, traffic conditions, and at two types of roadways; freeways and two-lane roads. To achieve these goals, Explanatory Factor Analysis (EFA) and Structural Equation Modeling (SEM) approaches were adopted.

5.5.1 Explanatory Factor Analysis

Explanatory Factor Analysis (EFA) is a statistical method used to identify the number and nature of the underlying factors (latent variables) that are responsible for the variability in the data. Table 5-9 shows description and input codes of the observed variables used in the present study.

These variables include (1) demographic variables (i.e., gender, age, number of years the driver had a valid driver's license, number of traffic citations in the previous 3 years, involvement in fog/smoke or heavy rain related crashes, and frequency usage of freeways/ two-lane roads), (2) roadway type (the type of survey that each participate responded to: freeways or 2 lane roads), (3) familiarity with CMS and VSL signs, (4) drivers' satisfaction with the importance of using CMS and VSL signs in reduced visibility conditions, (5) drivers' responses to CMS instructions under two traffic conditions (no car leading ahead and some vehicles are ahead), (6) drivers' responses to VSL instructions under four levels of fog (very light, light, medium and heavy) and the same two traffic conditions mentioned above.

It is worth mentioning that nominal variables (such as CMS_follow 1 and CMS_follow 2) were transferred to binary variables. In SEM, this way is preferable as it allow us to indentify the nonlinear influence of nominal variables on endogenous variables (Lee et. al, 2008). Using SAS procedure FACTOR, EFA was performed on the observed variables shown in Table 5-9. The Scree test, a plot of the eigenvalues associated with factor analysis, suggests that the number of meaningful factors to retain is four.

In addition, Table 5-10 shows the Varimax (orthogonal) rotated factor loadings which are the correlations between each observed variable (rows) and each factor (columns). In interpreting the rotated factor pattern, usually a variable is said to load on a given factor if the factor loading is 0.4 or greater for that factor (Hatcher 1994 and Lee et. al, 2008). Using these criteria, four factors were identified. Three observed variables (VSL_follow 1, VSL_follow 5 and VSL_follow 6) were found to load on the first factor, which was subsequently labeled "drivers' compliance with VSL signs under very light/light fog". Also, three variables (VSL_follow 3, VSL_follow 4, and VSL_follow 8) loaded on the second factor, which was called "drivers' compliance with VSL signs under medium/heavy fog". In addition, four variables (Intention, CMS_satisfaction, VSL_satisfaction, and CMS_satisfaction2) loaded on the third factor which was labeled "satisfaction with VSL and CMS signs". Finally, two variables (age and driving_exp) loaded on the fourth factor which was called "driver factors". These four factors account for about 97% of the variance in the data. It is worth noting that two variables (VSL_follow 2 and VSL_follow 7) load on both factors 1 and 2 and hence, they were not used in interpreting the factors.

Table 5-9: Definitions of variable, their codes and statistics

Observed variables		Description and coding of input value	Simple Statistics	
Name	**Description**		**Mean**	**S.D**
Gender	Gender	1 → male 0 → female	0.55	0.50
Age	Age	Continuous variable	37.03	15.31
Driving_exp	Driving experience (number of years the driver had a valid driver's license)	Continuous variable	19.30	14.58
Citation_no	Number of traffic citations in the previous 3 years	Continuous variable	0.66	1.28
FS_crashes	Involvement in fog/smoke related crashes	1 → Yes 0 → No	0.04	0.19
HV_crashes	Involvement in heavy rain related crashes	1 → Yes 0 → No	0.11	0.31
Exposure	Frequency usage of freeways/ two-lane roads	1 → rarely or never 2 → once a month 3 → once in two weeks 4 → once a week 5 → 2-4 times a week 6 → > 4 times a week	4.93	1.44
Road_type	The type of survey that a participant responded to	1 → two-way lane roads 0 → freeways	0.54	0.50
CMS_ familiarity	Drivers' familiarity with changeable message signs	1 → Yes 0 → No	0.84	0.37
VSL_ familiarity	Drivers' familiarity with variable speed limit signs	1 → Yes 0 → No	0.68	0.47
Intention	Willingness to follow VSL and CMS instructions	1 → Strongly disagree 2 → disagree 3 → neither agree nor disagree 4 → agree 5 → strongly agree	4.42	0.683
CMS_ satisfaction	Drivers' satisfaction with the usefulness of CMS in warning them about reduced visibility conditions		4.39	0.68
VSL_ satisfaction	Drivers' satisfaction with the usefulness of VSL in informing them about safe speed limit under reduced visibility conditions		3.97	0.99
CMS_ Satisfaction 2	Drivers' satisfaction with the usefulness of using two successive CMS prior to fog/smoke zones		4.14	0.88
CMS_follow 1	Drivers' responses to CMS at light fog condition and no car leading ahead	1→ reduce speed immediately or reduce speed and put blinkers on 0 → other	0.38	0.49
CMS_follow 2	Drivers' responses to CMS at light fog condition and some vehicles are ahead		0.54	0.50
VSL_follow 1	Drivers' responses to VSL at very light fog and no car leading ahead	Continuous variables (% of reduction of speed following VSL instructions)	19.97	18.10
VSL_follow 2	Drivers' responses to VSL at light fog and no car leading ahead		24.60	17.24
VSL_follow 3	Drivers' responses to VSL at medium fog and no car leading ahead		35.29	12.83
VSL_follow 4	Drivers' responses to VSL at heavy fog and no car leading ahead		42.14	10.58
VSL_follow 5	Drivers' responses to VSL at very light fog and some vehicles are ahead		16.16	19.82
VSL_follow 6	Drivers' responses to VSL at light fog and some vehicles are ahead		18.58	20.25
VSL_follow 7	Drivers' responses to VSL at medium fog and some vehicles are ahead		31.41	19.04
VSL_follow 8	Drivers' responses to VSL at heavy fog and some vehicles are ahead		40.76	16.85

Table 5-10: Varimax rotated factor analysis results

	Factor 1		Factor 2		Factor 3		Factor 4	
Age	31		10		15		93	*
Driving_exp	28		5		12		90	*
Citation_no	-10		-8		-3		-24	
Gender	-10		-6		-18		-7	
FS_crashes	0		-1		1		9	
HV_crashes	-1		-9		-3		7	
Exposure	-2		1		-2		15	
Road type	1		30		-7		-11	
CMS_familiarity	0		-11		2		8	
VSL_familiarity	7		-7		16		16	
Intention	15		12		58	*	3	
CMS_satisfaction	9		10		76	*	3	
VSL_satisfaction	15		8		62	*	-2	
CMS_Satisfaction 2	7		9		57	*	0	
CMS_Follow1	33		32		37		15	
CMS_Follow2	34		27		39		18	
VSL_Follow1	67	*	35		26		13	
VSL_Follow2	59	*	49	*	25		17	
VSL_Follow3	39		79	*	19		16	
VSL_Follow4	25		82	*	13		15	
VSL_Follow5	92	*	14		23		8	
VSL_Follow6	91	*	19		21		12	
VSL_Follow7	52	*	51	*	24		11	
VSL_Follow8	30		58	*	23		18	
Printed values are multiplied by 100 and rounded to the nearest integer. Values greater than 0.4 are flagged by an '*'.								

5.5.2 Reliability Analysis

Cronbach's α (alpha) is a coefficient of consistency that measures how well a set of variables or items measures a single, unidirectional latent construct (Ma et al. 2010). Cronbach's alpha generally increases when the correlations between the items increase. For this reason, it is called the internal consistency or the internal consistency reliability of the test. Moreover, composite reliability is analogous to the coefficient alpha, and reflects the internal consistency of the indicators measuring a given factor (Hatcher 1994).

In this survey study, Cronbach's alpha was applied to evaluate the internal consistency of the four latent factors obtained by EFA. The values of Cronbach's alpha of the observed variables as well as composite reliability of the latent variables are given in Table 5-11**.** A Cronbach's alpha of 0.7 or more indicates acceptable reliability (Nunnally 1978, Hatcher 1994 and Ma et al. 2010). As shown in Table 5-11**,** the reliability of the scales is generally acceptable. This implies that the used scales (latent variables) are valid.

Table 5-11: Cronbach's α-value of latent and observed variables

Latent variable	Observed variable	Reliability	
		Cronbach's α	Composite reliability
Drivers' compliance with VSL at very light / light fog (F1)	VSL_follow 1	0.957	0.919
	VSL_follow 5	0.838	
	VSL_follow 6	0.841	
Drivers' compliance with VSL at medium / heavy fog (F2)	VSL_follow 3	0.750	0.839
	VSL_follow 4	0.726	
	VSL_follow 8	0.881	
Satisfaction with VSL/CMS (F3)	Intention	0.708	0.720
	CMS_Satisfaction	0.716	
	VSL_Satisfaction	0.773	
	CMS_Satisfaction 2	0.704	
Driver factors (F4)	Age	0.842	0.740
	Driving exp.	0.814	
	Citation_no.	0.747	
	Exposure	0.723	

5.5.3 Structural Equation Modeling

Structural Equation Modeling (SEM) represents a combination of two types of statistical techniques: factor analysis and simultaneous equation models. In SEM, variables can be either exogenous or endogenous which allow SEM to handle indirect, multiple, and reverse relationships (Martinez et. al 2010).

SEM is a technique that consists of a set of equations that are specified by direct links between variables and hence it can be called “the simultaneous equations”. However, in SEM, latent variables (unobserved or unmeasured variables) can be introduced (Lee et al. 2008).

The advantages of using SEM include: (1) it can handle complex relationships among variables, where some variables can be hypothetical or unobserved (latent variables); (2) It estimates all coefficients in the model simultaneously and thus, one is able to assess the significance and strength of a particular relationship in the context of the complete model, (3) multi-colinearity can be accounted for, (4) when using latent variables in SEM, measurement error is eliminated and thus more valid coefficients are obtained (Dion, 2008 and Martinez et. al, 2010). Therefore, SEM is an adequate tool to model the complex relationships such as those that are being modeled in this survey study. SEM is applied in this research using SAS software (version 9.2) procedure CALIS.

To develop SEM, the present analysis followed a two-step approach recommended by Anderson and Gerbing (1988). With this approach, the first step involves using confirmatory factor analysis (CFA) to develop an acceptable measurement model. This measurement model describes the nature of the relationship between a number of latent variables and the observed variables that measure those latent variables. However, this measurement model does not specify any causal relationships between the latent variables of interest.

In the second step, the measurement model is modified so that it can describe the relationships among the latent variables. This model usually is referred to as the structural model or the causal model (Hatcher, 1994). Equations 5-6 and 5-7 represent the model specification for the measurement and structural models, respectively (Kim et al. 2011).

$$v_i = \lambda_i F_i + e_i \tag{5-6}$$

Where: v_i is a vector of observed variables; F_i is a vector of latent constructs; λ_i is a vector of parameters and e_i is a vector of measurement errors, and:

$$F_i ** = \beta_i F_i * + \Gamma_i F_i + d_i \tag{5-7}$$

Where: the endogenous variables Fi** is a function of the endogenous effects of mediating variables F_i* and the effects of the exogenous variables F_i plus residual terms d_i. β_i and Γ_i are parameter vectors.

In the present study, to systematically explain drivers' responses under reduced visibility conditions and quantify the impacts and values of various factors found to be related to drivers' compliance and drivers' satisfaction with VSL/CMS instructions in adverse visibility conditions, three research hypotheses and their interactions were investigated and discussed. These research hypotheses are: (1) drivers' compliance with VSL Instructions; (2) drivers' compliance with CMS Instructions and (3) drivers' satisfaction with VSL/CMS Instructions.

Thus, three SEM models were estimated after investigating several SEM structures. These three models investigate drivers' compliance with VSL instructions, drivers' compliance with CMS instructions and drivers' satisfaction with VSL/CMS instructions, respectively, all under adverse visibility conditions.

As shown in Figure 5-3, the measurement model of the first SEM model investigated here consists of 4 latent variables; drivers' compliance with VSL under very light/light fog (F1), drivers' compliance with VSL under medium/heavy fog (F2), satisfaction with VSL/CMS (F3) and driver factors (F4). These four latent variables (represented by F_i in Equation 5-6) are measure by 14 observed variables (represented by v_i in Equation 5-6).

Although the results of EFA showed that only two variables (age and driving experience) are loaded on the fourth latent variable (F4), several demographic observed variables were investigated in the measurement model because prior studies indicated that it is highly desirable to have at least three variables loading on each latent variable (Spector 1992 and Hatcher 1994).

As shown in Figure 5-3, the results revealed that each of F1 and F2 is measured by three observed variables. However, each of F3 and F4 is measured by four observed variables. As indicated earlier, the descriptions of these variables are provided in Table 5-9. As shown in Figure 5-3, rectangles represent observed variables; ellipses represent unobserved latent variables and arrows pointing from the observed variables to latent factors representing regression paths. Additionally, circles with an arrow pointing toward each observed variable represents the measurement error terms (represented by e_i in Equation 5-6). Moreover, each latent factor is connected to every other factor by a curved two-headed arrow meaning that every factor is allowed to covary with every other factor.

Standardized loading factors along with its standard error and t-value are shown in Figure 5-3. In the Figure, the numbers on the arrows are parameter estimates and numbers in parentheses indicate standard errors and t-values. The t values presented in Figure 5-3 represent large-sample t tests of the null hypothesis that the factor loading is equal to zero in the population. The obtained t values showed that all factor loadings were significant at 95% confidence (t-values are greater than 1.96).

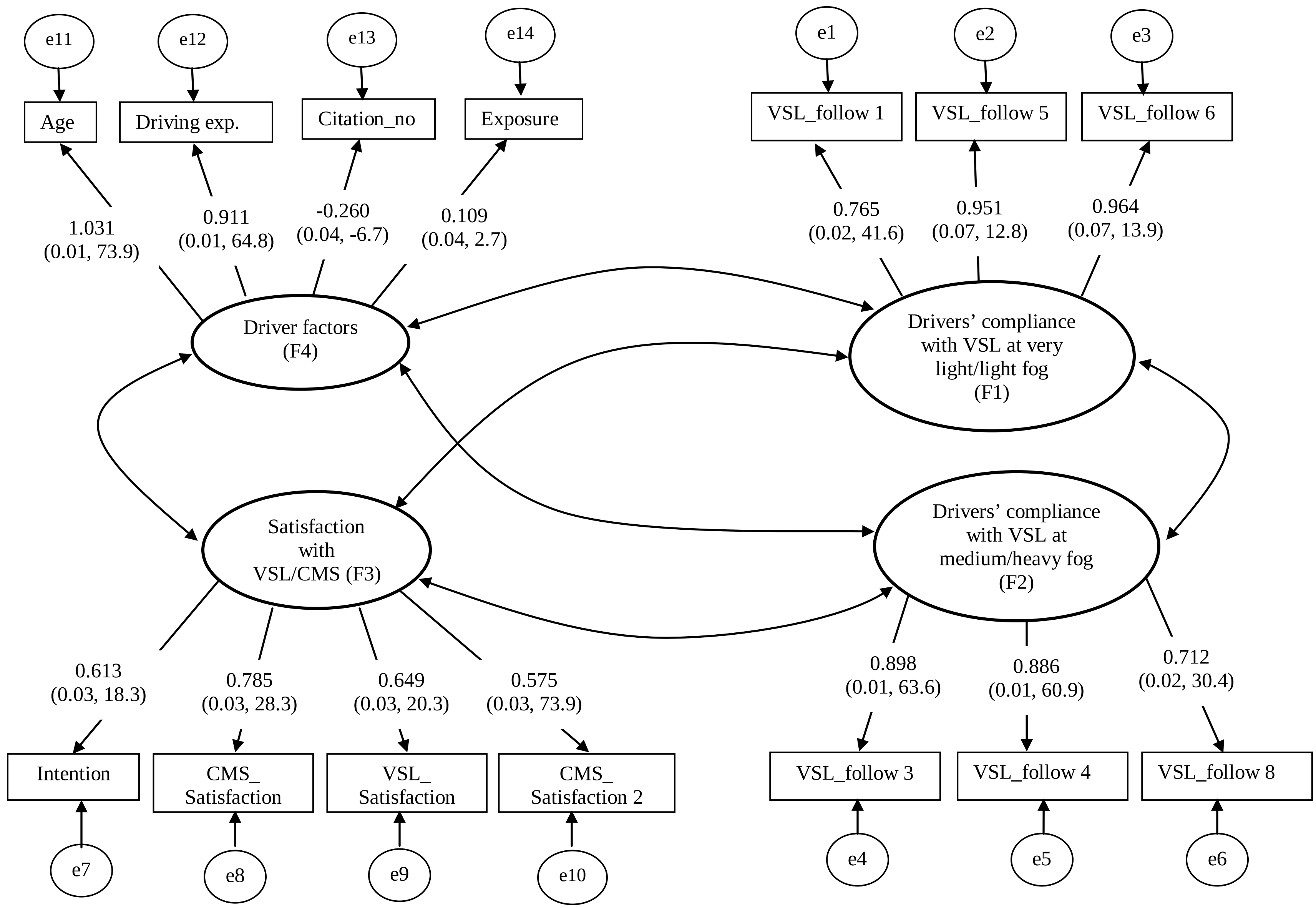


Figure 5-3: The measurement model along with loading factors, standard error and t-values (Model 1)

Regarding the structural model, Figure 5-4 presents the first SEM model that examines drivers' compliance with VSL instructions under different fog conditions. This model was first conceptualized so that it could be refined through SEM. This model was composed based on the relation on the correlations between observed variables and latent variables, as well as correlations among latent variables. As shown in Figure 5-4, the first SEM model consists of the same four latent variables in addition to one observed variable; roadway type (2-lane roads vs. freeway). It was decided to examine the effect of roadway type on drivers' behaviors because our preliminary analysis indicated that there is a significant correlation between the type of road and drivers' behavior under reduced visibility conditions (Hassan et al. 2011).

It is worth mentioning that each latent variable is an unobserved variable that has no established unit of measurement. Therefore, to define the unit of measurement of each latent variable, a non-zero coefficient (usually one) is given to one of its observed variables as an indicator (i.e., reference variable). For that reason, the factor loading of the indicator variable that best represent the corresponding latent variable was fixed at 1 (Hatcher, 1994 and Lee et al. 2008). The final structure of the first SEM model as well as standardized loading factors, standard errors and t-values are given in Figure 5-4. According to the results of first SEM model shown in Figure 5-4, it was found that drivers' satisfaction with VSL/CMS was the most significant factor that positively affected drivers' compliance with VSL under very light or light fog (factor loading=0.372, t-value=9.182). In addition, driver factors (i.e., higher age, longer driving experience, less number of traffic citations and higher usage of freeways/2-lane roads) was found out to positively affect drivers' responses to VSL instructions under very light or light fog (factor loading = 0.351, t-value = 9.637).

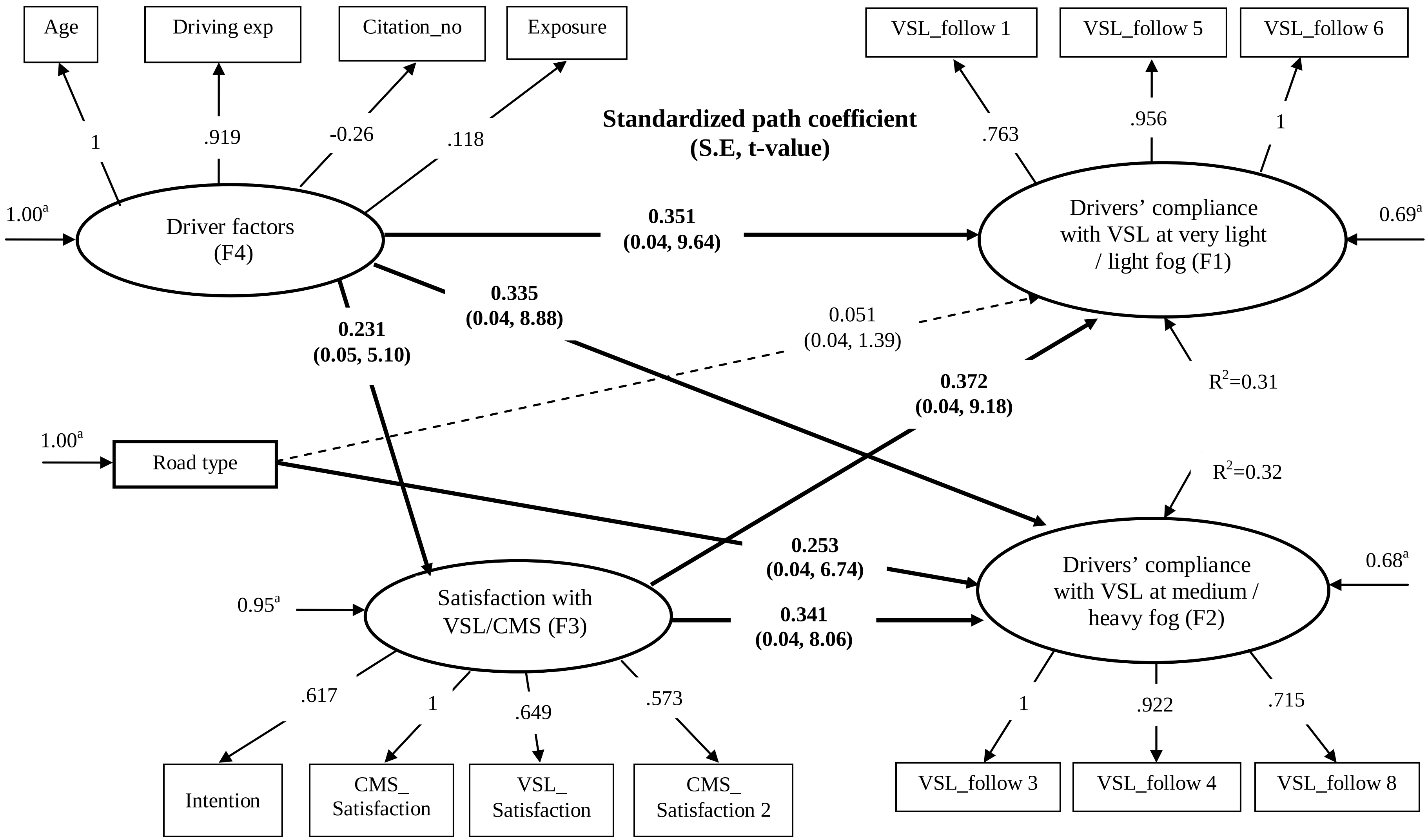


Figure 5-4: Structural equation model of drivers' compliance with VSL instructions (Model 1)

[a]: (Estimates for variance of exogenous variables (i.e., latent, observed, error or disturbance)

However, roadway type (i.e., driving on 2-lane roads vs. freeways) had no direct effect (the hypothesis was rejected as shown in Table 5-12) on drivers' compliance with VSL instructions under very light or light fog (factor loading = 0.051, t-value = 1.389).

Similarly, the results indicated that drivers' satisfaction with VSL/CMS positively affected drivers' behavior (following VSL instructions) under medium or heavy fog (factor loading=0.341, t-value=8.056). Also, driver factors was found out to positively affect drivers' responses to VSL instructions under medium or heavy fog (factor loading = 0.335, t-value = 8.875). Moreover, it was found that roadway type positively affected drivers' compliance with VSL instructions under medium or heavy fog (factor loading = 0.253, t-value = 6.737). This imply that drivers tend to follow VSL instructions under medium or heavy fog while driving on 2-lane roads compared to driving on freeways possibly due to the absence of medians.

In addition, the results revealed that driver factors has indirect effect on drivers' responses to VSL instructions under reduced visibility conditions as it positively affected drivers' satisfaction with VSL/CMS which subsequently positively affected drivers' compliance with VSL instructions under adverse visibility conditions (factor loading = 0.231, t-value = 5.102).

Finally, the first SEM model explained 31% and 32% of total variance in drivers' compliance with VSL under very light/light fog conditions and drivers' compliance with VSL under medium/heavy fog conditions, respectively.

As mentioned earlier, the second SEM model (shown in Figure 5-5) was adopted to examine causal relationships between drives' compliance with warning messages displayed on CMS under reduced visibility conditions and its associated factors. The standardized path coefficients, standard errors and its t-values are presented in Figure 5-5. The results of the second SEM model suggest that drivers' satisfaction with VSL/CMS was the most significant variable that positively affected drivers' compliance with CMS instructions under reduced visibility in both traffic conditions; (1) no car leading ahead and (2) some vehicles are ahead. In addition, it was found that driver factors positively affected drivers' compliance with CMS instructions in both traffic conditions. This result implies that drivers with higher driving experience, less number of traffic citations and higher usage of freeways/2-lane roads are more likely to obey warning messages displayed on CMS under reduced visibility conditions.

Additionally, driver factors positively affected drivers' satisfaction with VSL/CMS. Moreover, the findings revealed that roadway type was found out to positively affect drivers' compliance with CMS only when some vehicles are ahead. This result indicates that when driving on 2-lane roads and some vehicles are ahead, drivers tend to follow CMS instructions compared to driving on freeways. However, when no leading vehicles are ahead, roadway type has insignificant effect on drivers' compliance with CMS instructions.

The second SEM model explained 29% and 28% of the total variance in drivers' compliance with CMS instructions when no car is leading ahead and drivers' compliance with CMS instruction when some vehicles are ahead, respectively.

It is worth mentioning that it was decided to study drivers' responses to CMS under two traffic conditions and under only one reduced visibility condition (light fog) to reduce the number of survey questions.

One interesting research hypothesis was to examine whether drivers' behavior in response to VSL/CMS instructions was affected by the survey method. The hypothesis that the survey method significantly affected drivers' response to VSL/CMS instructions was rejected at the 5% level of significance.

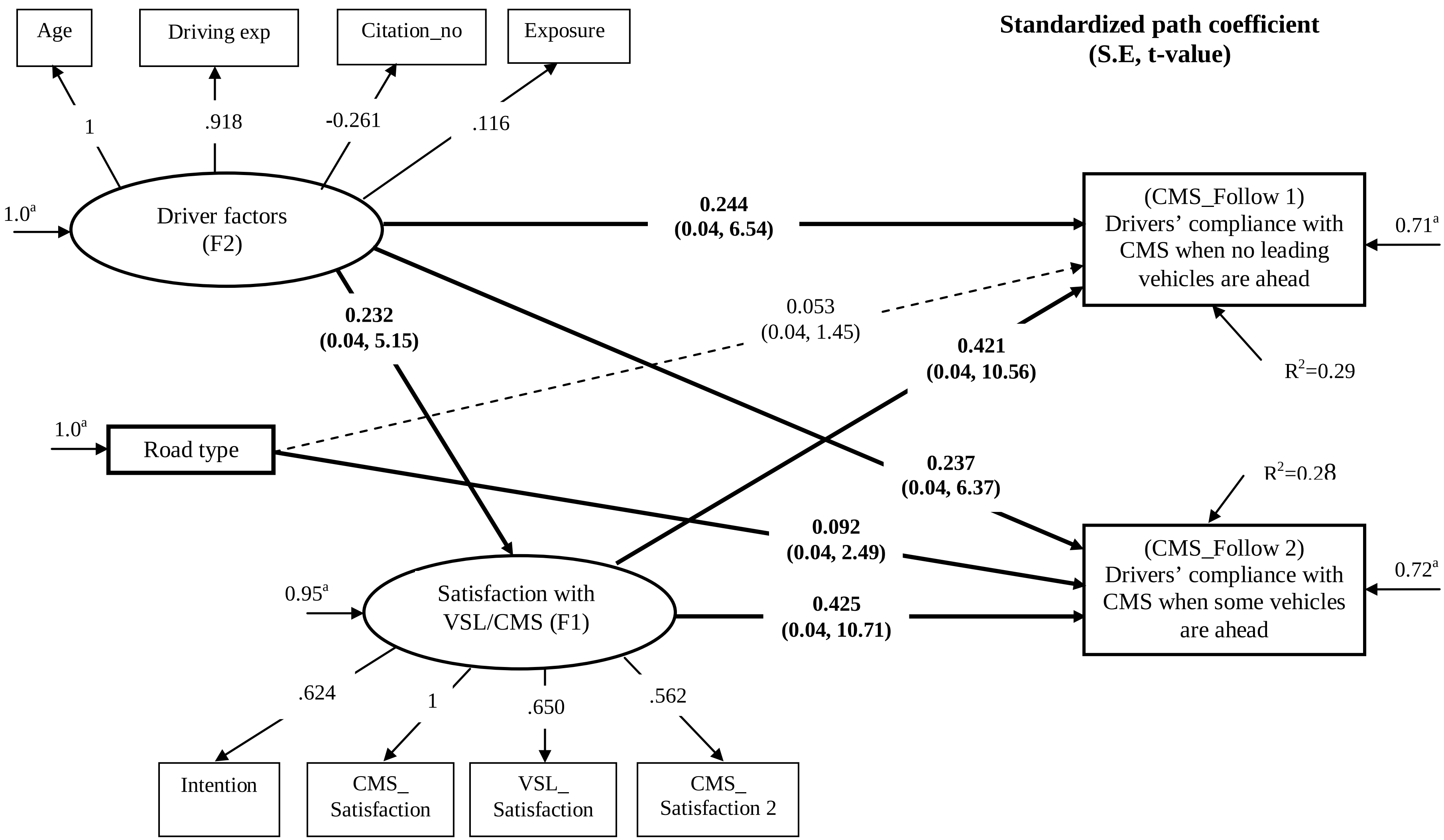


Figure 5-5: Structural equation model of drivers' compliance with CMS instructions (Model 2)

[a]: (Estimates for variance of exogenous variables (i.e., latent, observed, error or disturbance)

The third SEM model developed in this research aimed to examine factors associated with drivers' satisfaction with VSL/CMS instructions. The results (shown in Figure 5-6) indicated that driver factors positively affected drivers' satisfaction with VSL/CMS (factor loading=0.201, t-value=4.4). These results imply that older motorists (experienced drivers) are more satisfied with the usefulness of warning messages/advice displayed on VSL/CMS signs compared to young drivers. In addition, drivers who got traffic citation within the last three years are less satisfied with VSL/CMS. As expected, the results showed that drivers with higher usage of freeways/2 lane roads are more satisfied with VSL/CMS possibly due to the fact that those drivers encounter these signs on daily bases and thus, they are more familiar and satisfied with the role of VSL/CMS in improving safety.

The results also revealed that familiarity with VSL signs positively affected drivers' satisfaction with VSL/CMS (factor loading=0.115, t-value=2.46). However, familiarity with CMS was found to have insignificant effect on drivers' satisfaction with VSL/CMS. One possible explanation is that drivers in Central Florida are more familiar with CMS compared to VSL and hence, drivers, who are familiar with VSL signs, usually are aware of its importance for safety. Again, the results indicated that driver factors has a significant positive effect on familiarity with VSL signs (factor loading=0.186, t-value=4.64). This is logical as older drivers (or experienced drivers) are more familiar with VSL signs compared to young (novel) drivers. Finally, the third SEM model explained 36% of total variance in drivers' satisfaction with VSL/CMS. Table 5-12 summarizes the verification of the research hypotheses of the three SEM models investigated in the present study. The verification of these hypotheses was developed based on the t-values that were estimated for each of the paths between the observed and latent variables.

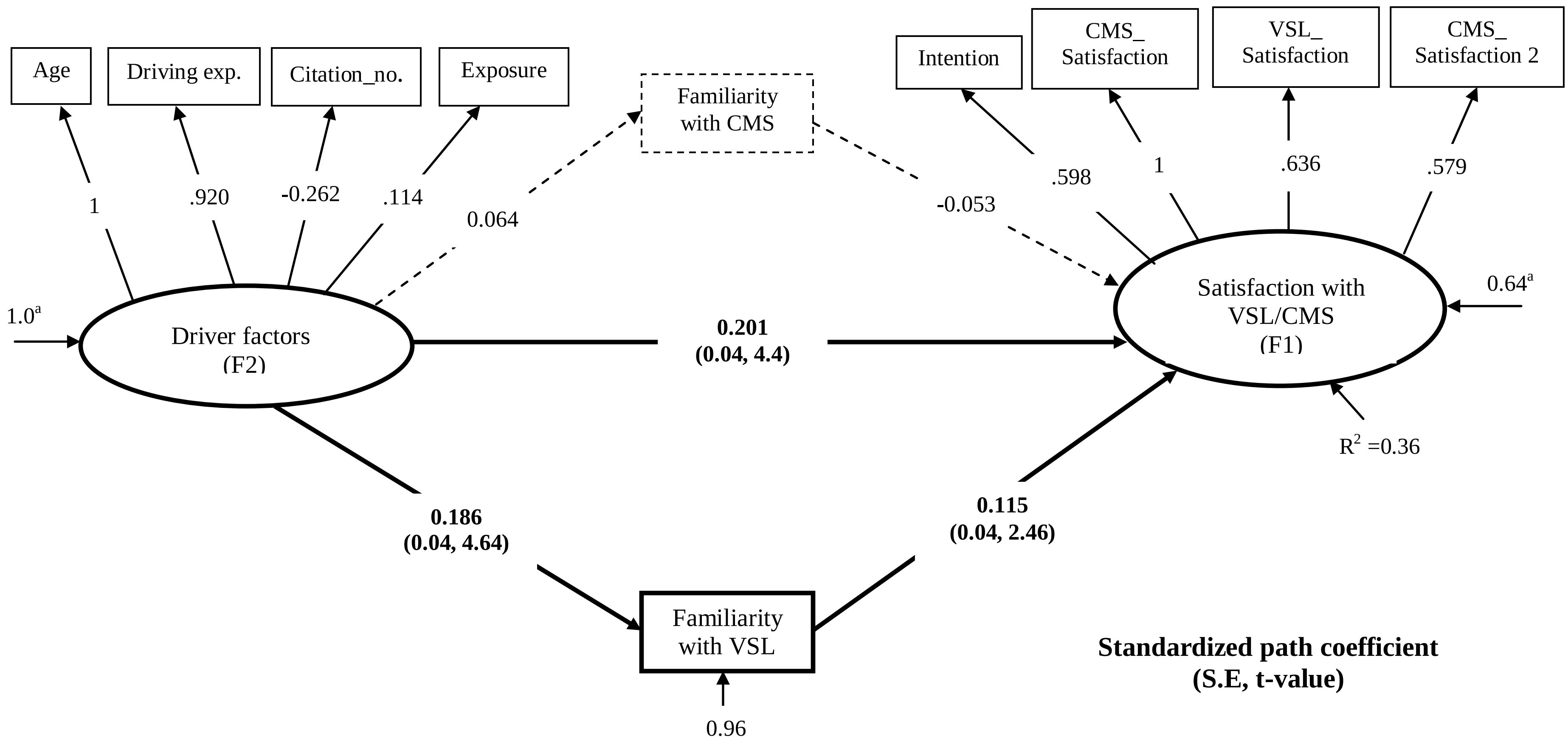


Figure 5-6: Structural equation model of drivers' satisfaction with VSL/CMS instructions (Model 3)

[a]: (Estimates for variance of exogenous variables (i.e., latent, observed, error or disturbance)

Table 5-12: Verification of the three SEM models hypotheses

		Hypothesis	Estimate	Standard error	t-value [a]	remarks
Model 1	H_1	Driver factors will have a positive effect on drivers' compliance with VSL instructions under very light or light fog	0.351	0.036	9.637	Accept
	H_2	Drivers' satisfaction with VSL/CMS will have a positive effect on drivers' compliance with VSL instructions under very light or light fog	0.372	0.041	9.182	Accept
	H_3	***Roadway type will have a positive effect on drivers' compliance with VSL instructions under very light or light fog***	***0.051***	***0.037***	***1.389***	***Reject***
	H_4	Driver factors will have a positive effect on drivers' compliance with VSL instructions under medium or heavy fog	0.335	0.038	8.875	Accept
	H_5	Drivers' satisfaction with VSL/CMS will have a positive effect on drivers' compliance with VSL instructions under medium or heavy fog	0.341	0.042	8.056	Accept
	H_6	Roadway type will have a positive effect on drivers' compliance with VSL instructions under medium or heavy fog	0.253	0.038	6.737	Accept
	H_7	Driver factors will have a positive effect on drivers' satisfaction with VSL/CMS	0.231	0.045	5.102	Accept
Model 2	H_8	Driver factors will have a positive effect on drivers' compliance with CMS instructions when no leading vehicles are ahead	0.244	0.037	6.544	Accept
	H_9	Drivers' satisfaction with VSL/CMS will have a positive effect on drivers' compliance with CMS instructions when no leading vehicles are ahead	0.421	0.039	10.564	Accept
	H_{10}	***Roadway type will have a positive effect on drivers' compliance with CMS instructions when no leading vehicles are ahead***	**0.053**	**0.037**	**1.450**	***Reject***
	H_{11}	Driver factors will have a positive effect on drivers' compliance with CMS instructions when some vehicles are ahead	0.237	0.037	6.369	Accept
	H_{12}	Drivers' satisfaction with VSL/CMS will have a positive effect on drivers' compliance with CMS instructions when some vehicles are ahead	0.425	0.040	10.711	Accept
	H_{13}	Roadway type will have a positive effect on drivers' compliance with CMS instructions when some vehicles are ahead	0.092	0.036	2.491	Accept
	H_{14}	Driver factors will have a positive effect on drivers' satisfaction with VSL/CMS	0.232	0.045	5.151	Accept
Model 3	H_8	Driver factors will have a positive effect on drivers' satisfaction with VSL/CMS instructions	0.201	0.046	4.404	Accept
	H_{16}	***Drivers' familiarity with CMS has a positive effect on drivers' satisfaction with VSL/CMS instructions***	***-0.05***	***0.046***	***-1.146***	***Reject***
	H_{17}	Drivers' familiarity with VSL has a positive effect on drivers' satisfaction with VSL/CMS instructions	0.115	0.047	2.456	Accept
	H_{18}	***Driver factors will have a positive effect on drivers' familiarity with CMS***	***0.064***	***0.042***	***1.516***	***Reject***
	H_{19}	Driver factors will have a positive effect on drivers' familiarity with VSL	0.186	0.040	4.643	Accept

5.5.4 SEM Models Fit Indices

A widely reported goodness of fit index used in SEM analysis is the Chi-square test which provides a test of the null hypothesis that the theoretical model fit the data. If the model fits the data well, Chi-square value should be small and p-value associated with the Chi-square should be relatively large. However, with large samples, the Chi-square statistic will very frequently be increased even if the SEM model provides a good fit (James et al. 1982, Hatcher 1994, Acker and Witlox 2010).

For this reason, prior studies recommended to supplement the Chi-square with some alternative model fit indices. Some commonly fit indices are; Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Comparative Fit Index (CFI), Normed Fit Index (NFI), Non-Normed Fit Index (NNFI), Root Mean Square Error of Approximation (RMSEA).

Table 5-13 shows the goodness of fit statistics of the three SEM models that are presented in this section. As shown in Table 5-13, the models displayed values greater than 0.9 on GFI, AGFI, CFI, NFI, NNFI and a value smaller than 0.05 on RMSEA, indicative of a good fit (Bentler & Bonett 1980, Hatcher 1994, Lee et al. 2008, 2009 and Ma et al. 2010).

Table 5-13: Fit statistics for structural equation models

Fit Index	SEM models			
	Model 1	Model 2	Model 3	Criteria of acceptable fit
Chi-square df p-value	414.944 82 0.0001	213.252 39 0.0001	34.48 25 0.052	Smaller values
Goodness of Fit Index **(GFI)**	0.9224	0.9370	0.9853	> 0.9
Adjusted Goodness of Fit Index **(AGFI)**	0.9064	0.9034	0.9736	> 0.9
Comparative Fit Index **(CFI)**	0.9317	0.9222	0.9931	> 0.9
Normed Fit Index **(NFI)**	0.9167	0.9071	0.9797	> 0.9
Non-Normed Fit Index **(NNFI)**	0.9126	0.9030	0.9901	> 0.9
Root Mean Square Error of Approximation **(RMSEA)**	0.0448	0.0489	0.029	< 0.05

5.6 Summary of Results and Conclusions of the Survey-Based Study

This chapter presented the results of a survey-based study aimed at examining drivers' response to several scenarios of visibility and traffic conditions on two types of roadways; freeways and two-lane roads. Conducting this survey using three approaches (handout, interactive, and online questionnaire) achieved a well representative sample (i.e., the sample was apparently broad and fairly uniform across age, gender, and education).

To understand commuters' behavior, attitudes and preferences at reduced visibility conditions, several categorical data analysis techniques were applied to. These techniques include conditional distributions, odds' ratio, and Chi-Square tests. The results revealed that participants' response to CMS and VSL signs' instructions vary by gender, age, familiarity with CMS and VSL signs, past experience with driving at adverse visibility condition and involvement in FS/HR crashes.

Multivariate and Bivariate Probit Models were estimated to improve our understanding of the preferences of respondents in following VSL and CMS instructions at such adverse visibility conditions. The findings indicated that compared to males and young drivers (18-25 years old), females and old drivers (51 years old or more) claim to be more likely to reduce their speed in response to CMS and VSL instructions when driving in different visibility (heavy or very light fog) and traffic conditions (low or medium-high). The results also indicated that drivers who are familiar with VSL signs claim to be more likely to follow their instructions at heavy fog condition than those who are not. Concerning the type of road, the findings showed that the stated likelihood of reducing speed in response to CMS and VSL signs increases when driving on a two-lane road at adverse visibility condition compared to a freeway.

A further objective of this study was to investigate whether drivers would rely on and follow warning messages displayed on CMS/VSL signs at adverse visibility conditions. Only 37% of the respondents reported that they would reduce their speed immediately or reduce their speed and put blinkers on when encountering CMS, which advises them to reduce their speed due to reduced visibility condition, at low traffic volume while driving on a freeway. Also, it was found that only 35% of the respondents were willing to follow VSL instructions (reducing their speed to 40 mph or less) while driving on a freeway at very light fog and low traffic volume. Moreover, the results show that as the visibility distance deteriorates and traffic volume increases, drivers claim to be more likely to follow CMS/VSL instructions.

In addition, the SEM approach was used in this study to distinguish variables that affect drivers' compliance and satisfaction with advice or warning messages displayed on VSL and CMS under different traffic and visibility conditions. The findings revealed that drivers' satisfaction with VSL and CMS was the most significant variable that positively affected drivers' compliance with VSL and CMS instructions under different fog and traffic conditions followed by driver factors. This result indicates that higher satisfaction with VSL/CMS instructions and higher scores for driver factors (i.e., older age, longer driving experience, less number of traffic citations and higher usage of freeways/2-lane roads) contribute to increase drivers' compliance with advice or warning messages displayed on VSL/CMS under reduced visibility conditions. Other driver factors such as gender and education did not show significant effect on drivers' compliance with VSL/CMS.

In addition, it was found that roadway type affected drivers' behavior in response to VSL instructions only under medium and heavy fog conditions. However, roadway type did not significantly affect drivers' behavior in response to VSL under very light or light fog. The findings also indicated that roadway type affected drivers' compliance with CMS only when some vehicles are ahead. Furthermore, drivers' familiarity with VSL signs and driver factors were the significant factors affecting drivers' satisfaction with VSL/CMS advice under reduced visibility conditions.

CHAPTER 6. PREDICTING VISIBILTY RELATED CRASHES ON FREEWAYS

There is a lack of prior studies that investigated the relationship between real-time traffic flow variables and traffic crashes that occur due to reduced visibility. This chapter explores the occurrence of visibility related (VR) crashes on freeways using real-time traffic surveillance data (speed, volume and occupancy) collected from underground loop detectors (LDs) and radar sensors potentially associated with VR crash occurrence.

6.1 Data Collection and Preparation

Traffic flow data used in this study were collected from LDs and radar sensors spaced at approximately 0.5-0.8 mile for about 75 mile and 137 mile corridors of I-4 and I-95, respectively. These sensors record and archive the following traffic flow variables every 30 seconds for each lane in each direction: 1) average speed of all vehicles passing over LD or through radar sensors in 1/2 minute intervals, 2) volume (number of vehicles passing each lane over LD in 1/2 minute intervals), and 3) lane occupancy (percentage of time interval, 1/2 minute, the LD was occupied).

According to the crash database maintained by Florida Department of Transportation (FDOT), there were 2984 mainline crashes reported in the same study period and area. All crashes that occurred under the influence of alcohol and drugs were then excluded. Crashes caused by these reasons can occur under any conditions whether the visibility is low or not. Subsequently, a total of 125 VR crashes were extracted. However, due to LDs and radar data availability, only 67 VR crashes that have corresponding traffic flow data, were obtained and used in the analysis. Considering police reports, two criteria for choosing VR crashes from the crash database were considered: weather (fog or rain) and vision obstructed (inclement weather, fog or smoke).

Based on the location of each VR crash, six nearest LDs stations (three stations upstream and three stations downstream) to the crash location were identified using Geographic Information System (GIS) software. As shown in Figure 6-1, the first downstream and upstream LDs stations were named DS1 and US1, respectively. The subsequent stations in the downstream direction were labeled DS2 and DS3, respectively. Similarly, the subsequent stations in upstream direction were named US2 and US3, respectively.

Various agencies were contacted to obtain historical visibility measurements for I-4 and I-95 at the same period and study area. The aim was to determine non-crash cases at reduced visibility. Among the agencies contacted, it was found that National Climate Data Center (NCDC) provides the historical visibility data. NCDC website provides access to their database that consists of hourly weather data for many stations across the United States. Visibility measurements for the same period and study area were successfully obtained for 6 airport weather stations surrounding I-4 and I-95: Daytona Beach, Orlando Sanford, Orlando Kissimmee, Orlando Executive, Orlando International, and Melbourne.

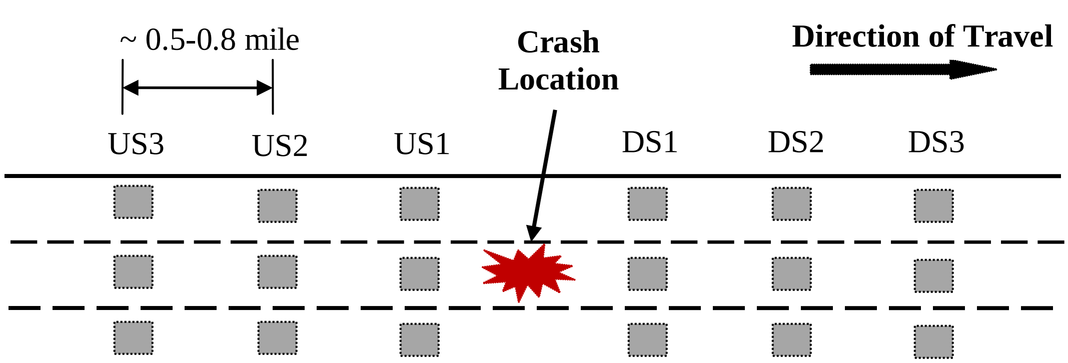


Figure 6-1: Layout of upstream and downstream LDs stations

Traffic data were then extracted for the day of every VR crashes (for 30 minutes prior to crash time) and on all corresponding non-crash cases (at reduced visibility conditions) to the day of every VR crash. For example if a VR crash occurred on February, 11, 2008 (Monday) 7:00 am, I-4 eastbound, traffic data were extracted from the nearest 3 stations upstream and 3 stations downstream of the crash location for 30 minutes prior to crash time for all Mondays of the same season in the year at the same time.

It is worth mentioning that LDs data are known to suffer from inaccuracies due to intermittent hardware problems or other errors. These errors emerge in the form of false speed, volume, and occupancy. Most of the times, the errors can be identified from the unreasonable values of traffic parameters. Thus, the first step in data preparation was to filter the traffic data for the crash and non-crash cases. In this study, all unrealistic values were eliminated from the raw 30-second data. The unrealistic values of parameters include; occupancy > 100, speed = 0 or > 100 and flow = 0 with speed > 0.

In order to determine the non-crash cases at reduced visibility, the average visibility measurements obtained from the two closest weather stations to every VR crash location were estimated for all the corresponding non-crash cases. The closest stations to every VR crash were identified using geographic information system (GIS) software. A threshold of 250 meters (about 820 feet) was selected as the criteria for determining non-crash cases at reduced visibility (Rockwell, 1997). Therefore, non-crash cases at reduced visibility were considered if the corresponding average visibility measurement obtained from the two closest weather stations to the crash location was 250 meters or less.

A stratified case control dataset consisting of traffic data corresponding to every VR crash (case) and three matched non-crash cases at also reduced visibility conditions (controls) was created. This matched sample design was created to control the effect of other confounding variables such as geometric factors, location, driver population and time of day on the freeways.

The next step was the aggregation of LDs and radar data. Since the 30-second raw data was noticed to have random noise and are difficult to work with in a modeling framework therefore, the raw data were combined into 5-minutes level to obtain averages and standard deviation for speed, volume, and occupancy.

The decision for combining the data into 5-minutes level was based on the results of prior studies. Abdel-Aty et al. (2008) demonstrated the noise reduction in speed data following the 5-min aggregation compared to 1-min aggregation. In addition, the decision to have a 5-min level of aggregation rather than a 3-min level has also been discussed in detail in one of previous studies (Pande et al. 2005). In this study, the 30-second raw data were combined into two separate levels of aggregation; 3-minutes and 5-minutes. The results indicated that 5-minute time slice would be more effective in crash prediction as it not only has higher and more significant hazard ratio but it also provides more time to analyze the data, estimate and possibly intervene to reduce the likelihood of crashes.

Thus, the 30 minutes period from which traffic flow data were collected was divided into six time slices. The interval between time of a crash and 5 minutes before was named as time slice 1; interval between 5 to 10 minutes prior to a crash time was named as time slice 2 and so on. In addition, due to high correlation coefficients that were noticed between each traffic flow variable across lanes, data were combined across lanes. Subsequently, the averages, standard deviations and coefficient of variation (standard deviation/ average) in speed, volume and occupancy were then calculated for each LDs station at the 6 time slices.

The nomenclature of traffic variables extracted from LDs stations takes the form WXYZα_β. W takes the value A, S or C for average, standard deviation or coefficient of variation, respectively, while X takes the value of S, V or O representing speed, volume or occupancy. YZα takes the value of US1, US2, US3, DS1, DS2, DS3 representing the station to which the traffic parameters belong. β takes the value of 1, 2, 3, 4, 5 or 6 which refer to the time slice. For example ASUS1_2 represents the average speed at the nearest upstream station to a crash location at time slice 2 (5-10 minutes before crash time). Also, SODS1_3 represents the standard deviation of occupancy at the nearest downstream station, at time slice 3 (10 to 15 minutes before crash time) and so on.

6.2 Identifying Significant Factors Affecting VR crashes

Random Forest (RF) is one of the most recent and promising machines learning techniques proposed by Breiman (2000), which is well known for selecting important variables from a set of variables. RF is a refinement of bagged trees. The term came from random decision forests that were first proposed by Ho (1998). The method combines Breiman's "bagging" idea and Ho's "random subspace method" to establish a collection of decision trees with controlled variations.

RF was used in this study for selecting significant flow variables affecting VR crash occurrence. The advantage of using RF instead of other data mining techniques such as traditional classification trees is that there is no need for a separate cross-validation-test data set to obtain unbiased error estimates, especially when the sample size is small (Abdel-Aty et al. 2008).

The main idea of RF is that at each tree split, a random sample of m features is selected, and only those m features are considered for splitting. Typically $m = (p)^{1/2}$, where p is the number of features. Then for each tree grown on a bootstrap sample, the error rate for observations left out of the bootstrap sample (out-of-bag) is monitored. To test whether the attempted number of trees is sufficient enough to reach relatively stable results, the plot of the out-of-bag (OOB) error rate against various tree numbers is developed. The best number of trees is that having the minimum error rate along with a constant error rate nearby. The main advantages of RF are that it usually yields high classification accuracy, and it handles missing values in the covariates efficiently (Grimm et al. 2008).

To select the important covariates affecting the binary target variable, the R package provides the mean decrease Gini “IncNodePurity” diagram. By means of the Gini Index, the quality (Node Purity) of a split for every variable (node) of a tree is measured. Every time a split of a node is made on a variable *m*, the Gini impurity criterion for the two descendent nodes is less than the parent node. Then, adding up the Gini decreases for each individual variable over all trees in the forest provides a variable importance. A higher IncNodePurity implies a higher variable importance (Kuhn et al., 2008). For detailed information regarding RF, the reader is referred to Breiman (2000); Ho (1998); Grimm (2008); and Kuhn et al. (2008).

In this study, the RF technique was conducted using the R package. Figure 6-2 shows the plot of OOB error rate against various tree numbers. Clearly, 50 trees are sufficient enough to reach relatively stable results. The purity values for every covariate are shown in Figure 6-3.

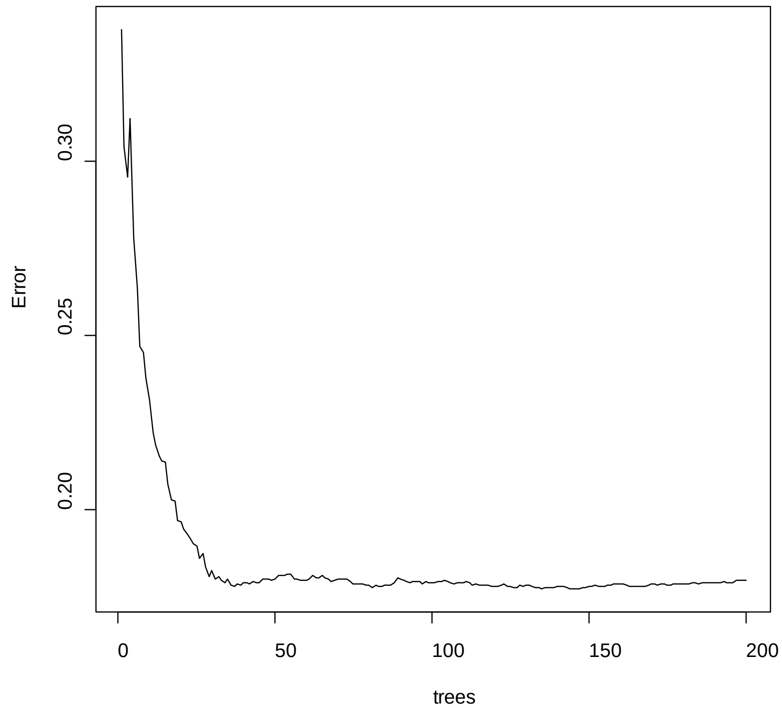


Figure 6-2: Plot of the OOB error rate against different number of trees

In order to choose the most important covariates affecting the binary target variable (VR crash versus non-crash), a cut-off purity value of “1.25” was used. This led to selecting eight important covariates. These 8 variables have higher variable importance scores than the remaining variables. These variables are average speed at stations US2, US1, DS1, DS2, average occupancy at the nearest downstream station DS1, and standard deviation of occupancy at stations US2, DS2, and DS1. These significant variables were used as inputs in the matched case-control logistic regression model.

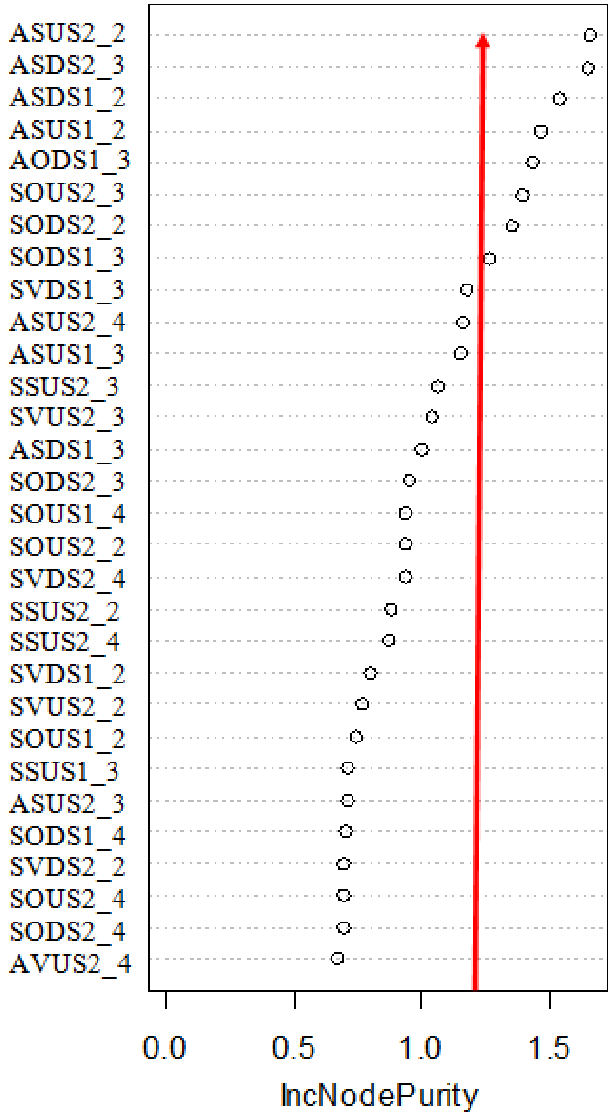


Figure 6-3: Variable importance ranking using node purity measure

6.3 Matched Crash Non-Crash Analysis

As mentioned earlier, the purpose of the proposed matched crash-non-crash analysis is to explore the effects of traffic flow variables on VR crashes while controlling for the effects of other confounding variables such as the geometric design elements of freeway sections (i.e. horizontal and vertical alignments) and crash time.

In a matched crash non-crash study, crashes are selected first. Then, for each selected crash, some non traffic flow variables associated with each crash are selected as matching factors such as location, day of the week, time of day, etc.

Using these matching factors, a total of non-crash cases (m) are then selected randomly from each subpopulation of non-crash cases. For example, for a given crash, a subpopulation of non-crash cases consist of observations on traffic flow variables obtained from the same loop detector at the same time of the day, same day of the week of crashes but over all other weeks, are recorded.

The (m+1) observations of all traffic variables for VR crashes and non-crash cases form one stratum. Within stratum, differences between VR crashes and non-crash cases regarding flow characteristic are utilized in the development of the statistical model. This procedure is conducted under the conditional likelihood of statistical theory.

Matched case-control logistic regression has been adopted in epidemiological studies. In addition, it was used in few transportation related studies such as Abdel-Aty et al. (2004). A brief description of this modeling technique is provided here.

Assume that there are N strata with 1 crash and m non-crash cases in stratum j, where j = 1, 2, 3 …… N. The probability of any observation in a stratum being a crash might be modeled by the following linear logistic regression model:

$$Logit\,\{P_j\,(X_{ij}\,)\} = \alpha_j + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \ldots\ldots\ldots\ldots\ldots + \beta_k X_{kij} \qquad (6\text{-}1)$$

Where $P_j\,(X_{ij})$ is the probability that the i^{th} observation in the j^{th} stratum being a crash; $X_{ij} = (X_{1ij}\,,$ $X_{2ij}\,, \ldots\ldots\ X_{kij})$ is the vector of k traffic flow variables; $i = 0, 1, 2 \ldots\ldots m$ and $j = 0, 1, 2 \ldots\ldots N.$

It is to be noted that the intercept term α in Equation (6-1) summarizes the effect of variables used to form strata on the crash probability and would be different across strata. A conditional likelihood is constructed to take account of the stratification in the analysis. This conditional likelihood function L (β) is independent of the intercept terms $\alpha_1, \alpha_2, \ldots\ldots\ldots, \alpha_N$ and hence, the effects of matching variables cannot be estimated. Therefore, crash probabilities cannot be estimated using Equation (6-1). However, the values of β parameters that maximize the conditional likelihood function are also the estimates of β coefficient in Equation (6-1). These estimates are log odds ratio and may be used to represent the relative risk of a VR crash.

These relative risks (named as hazard ratio in SAS) are given using SAS procedure *PHREG* (Abdel-Aty et al., 2004). Consider two observation vectors $X_{1j} = (X_{11j}, X_{21j}, X_{31j}\ldots\ldots,$ $X_{k1j})$ and $X_{2j} = (X_{12j}, X_{22j}, X_{32j}\ldots\ldots, X_{k2j})$ from the j^{th} strata on the k traffic flow variables. Thus, by substituting the two observation vectors X_{1j} and X_{2j} in Equation (6-1), the log odds ratio of VR crash occurrence due to traffic flow vector X_{1j} relative to traffic flow vector X_{2j} will have the following form:

$$log\,\left\{\frac{P\,(X_{1j}\,)\,/\,[1 - P\,(X_{1j}\,)\,]}{P\,(X_{2j}\,)\,/\,[1 - P\,(X_{2j}\,)\,]}\right\} = \sum_{i=1}^{k} \beta_i\,(X_{i1j} - X_{i2j}) \qquad (6 - 2)$$

The right hand side of Equation (6-2) is independent of α_j and can be calculated using the estimated β coefficients. Thus, the above relative log odds ratio (left hand side of Equation 6-2) may be utilized for predicting VR crashes by replacing X_{2j} with the vector of values of the traffic flow variables in the j^{th} stratum of non-crash cases under reduced visibility conditions. One may use simple average of all non-crash observations within the stratum for each variable.

Let $\bar{X}_{2j} = (\bar{X}_{12j,} \bar{X}_{22j,} \bar{X}_{32j,} \ldots\ldots\ldots, \bar{X}_{k2j,})$ denote the vector of mean values of non-crash cases of the k variables within the j^{th} stratum. Then the log odds ratio of VR crash relative to non-crash cases may be approximated by:

$$log \left\{ \frac{P\ (X_{1j}\ ) \ / \ [1 - P\ (X_{1j}\ )\ ]}{P\ (\bar{X}_{2j}\ ) \ / \ [1 - P\ (\bar{X}_{2j}\ )\ ]} \right\} = \sum_{i=1}^{k} \beta_i\ (X_{i1j} - \bar{X}_{i2j}) \qquad (6-3)$$

Therefore, log odds ratio in Equation (6-3) can be used for predicting VR crashes by establishing a threshold value that achieve the desirable crash classification accuracy.

In the following two sections, using matched case logistic regression, three different research classification hypotheses will be investigated in order to gain a comprehensive understanding of the relationship between traffic flow variables and VR crashes and how these variables differ from those highly associated with crashes that occur under clear visibility conditions (CV crashes). As shown in Figure 6-4, these three research hypotheses and the objective of each of them are:

(1) Crashes vs. non-crash cases at poor visibility condition; to investigate the effect of traffic flow factors on VR crashes while controlling for the effects of reduced visibility conditions and other confounding variables.

(2) Crashes at poor visibility conditions vs. non-crash cases at clear visibility conditions; to gain a good understanding of the traffic flow variables associated with VR crashes compared to non-crash cases at normal visibility conditions.

(3) Crashes vs. non-crash cases at clear visibility conditions; to investigate whether there are any differences between the traffic variables that are highly associated with the occurrence of VR crashes (from 1 and 2 above) and those variables that are highly correlated with CV crashes.

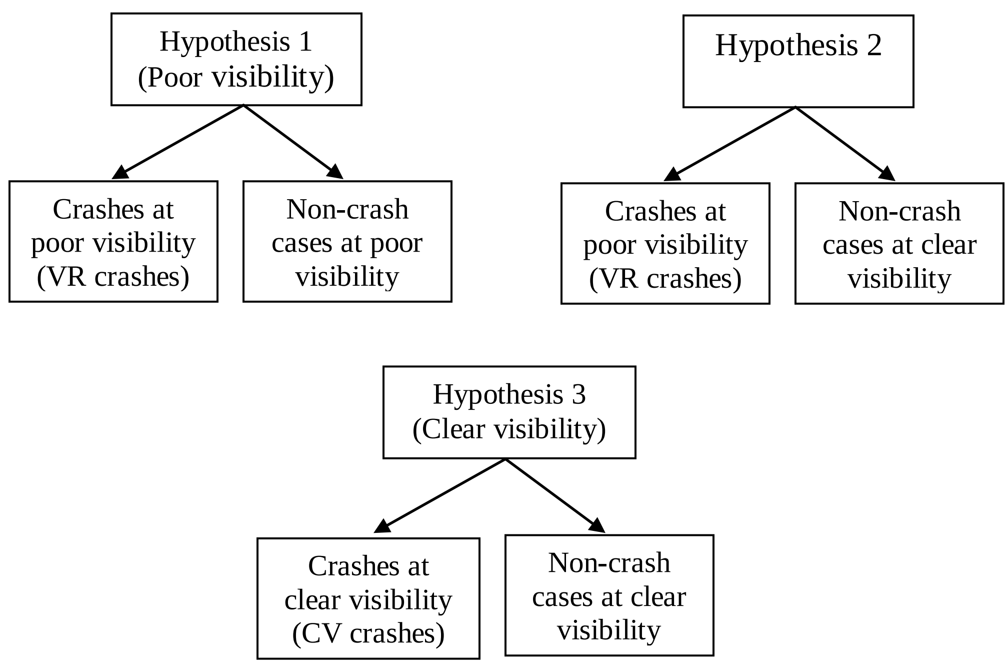


Figure 6-4: Research hypotheses examined in this chapter

6.4 Predicting VR crashes

The first research hypothesis is to compare the traffic flow variables potentially leading to VR crashes with non-crash cases at reduced visibility conditions (crashes vs. non-crash cases at poor visibility conditions).

In this regards, a total of 67 VR crashes, on I-4 and I-95 between December 2007 and March 2009, were extracted that have corresponding LDs or radar sensors data. The data of all corresponding non-crash cases (under low visibility and during the study period) were extracted. However, due to hardware problems with LDs and radar sensors, a total of only 3 non-crash cases (m) at reduced visibility were selected for every VR crash.

Varying (m) from 1 to 3, three datasets have been created which referred to as matched 1:1, 1:2, and 1:3 dataset. Each matched data set (1: m, m = 1, 2 and 3) was analyzed separately. However, no significant differences have been observed when changing m. Therefore, only the detailed description of the analysis of 1:3 matched data sets will be presented and discussed here.

In this study, SAS procedure *PHREG* was used with some modification of matched data to fit the proposed stratified conditional logistic regression model, widely known as matched case-control analysis in epidemiological studies (Abdel-Aty et al. 2004). The 8 variables obtained by RF that have been found to affect the VR crash occurrence most significantly were used as input in the model.

In addition, automatic search technique: stepwise, forward and backward were used to identify significant variables. All three search techniques resulted in three significant variables. The estimates of beta coefficients, associated summary results, and model fit statistics obtained from the final model are presented in Table 6-1.

Table 6-1: Matched case-control logistic regression estimates and goodness of fit statistics (Crashes vs. non-crash cases at poor visibility condition)

Analysis of Maximum Likelihood Estimates						
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**Chi-Square**	**Pr > ChiSq**	**Hazard Ratio**
ASUS1_2	1	0.11908	0.03799	9.8267	0.0017	1.126
ASDS1_2	1	0.12217	0.03633	11.3100	0.0008	1.130
AODS1_3	1	0.26378	0.09534	7.6558	0.0057	1.302

Model Fit Statistics		
Criterion	**Without Covariates**	**With Covariates**
-2 LOG L	185.763	125.992
AIC	185.763	131.992
SBC	185.763	142.765

The final model includes three statistically significant variables; average speed at the nearest upstream station (ASUS1_2), average speed at the nearest downstream station (ASDS1_2), all at time slice 2 (5-10 minutes before the crash). The third significant variable was average occupancy at the nearest downstream station (AODS1_3) at time slice 3 (10-15 minutes before the crash). The results indicate that higher occupancy rates downstream during 10-15 minutes before the crash coupled with an increase of the average speed downstream and upstream during 5-10 minutes before the crash increase the likelihood of VR crash occurrence in between. One explanation for these results is that as the average speed increase upstream and downstream along with an increase of occupancy downstream, drivers cannot reduce their relatively high speeds gradually or even change their traffic lanes when encountering high traffic density in poor visibility condition and hence a VR crash is likely to occur (most likely a rear-end crash).

These results imply that traffic flow indicators that may lead to VR crashes do not necessary originate at the same time slice. From the traffic operation perspective, these results could be explained as an increase in the average speed at the nearest upstream and downstream stations might lead to a VR crash only if it is coupled with pre-formed queue of vehicles at the nearest downstream station. In other words, an increase in the average occupancy should appear first (10-15 minute prior to crash time) and during this 5-minute interval, a queue of vehicles starts to build up at the nearest downstream station. Then after the queue is built up, if this is coupled with an increase in the average speed (5-10 min prior to crash time), a VR crash may occur due to this turbulent traffic conditions and the reduced visibility situation.

Using time slices 5-15 minutes before crashes may provide an opportunity for intervention to reduce crash risk in real-time and avoids any discrepancy regarding the exact time of crashes (which is ± 2 minutes of the call in reporting the crash based on previous investigation, Golob and Recker; 2001).

Note that hazard ratio corresponding to parameters estimates are shown in the last column of Table 6-1. Hazard ratio, equals the exponent of the beta coefficient, is an estimate of the expected change in the risk ratio of having a VR crash versus non-crash at reduced visibility condition per unit change in the corresponding factor (Abdel-Aty et al. 2004). For Example, a hazard ratio of 1.302 corresponding to average occupancy at the nearest downstream station, 10-15 minutes before the crash (AODS1_3) means that the risk for a VR crash increases about 1.3 times for each unit increase in the average occupancy.

As previously explained, the odds ratio in Equation (6-3) can be used to classify VR crash and non-crash cases at reduced visibility. Therefore, the mean of the three significant variables (ASUS1_2, ASDS1_2, and AODS1_3) of all three non-crash cases within each matched set were estimated. The vector X_{2j} in Equation 6-3 was then replaced by the vector of non-crash means for the j^{th} matched set. The odds ratio for each observation in the data set was then estimated by substituting the beta coefficient from Table 6-1 in Equation 6-3 where the vector X_{1j} is the actual observation in the data set. A threshold value for these ratios was then set to determine whether the location has to be flagged as a potential "VR crash". It was found that using a threshold of 1.0 for the log odds ratio, over 68% crash identification was achieved (as shown in Table 6-2).

Table 6-2: Classification results of actual and predicted VR crashes (Crashes vs. non-crash cases at poor visibility condition)

		Predicted Y		
	Frequency Percent Row Percent Col Percent	**0**	**1**	**Total**
Actual Y	**0**	131 48.88 65.17 86.18	70 26.12 34.83 60.34	201 75.00
	1	21 7.84 31.34 13.82	46 17.16 68.66 39.66	67 25.00
	Total	152 56.72	116 43.28	268 100.00

Table 6-2 indicates that the sensitivity, proportion of VR crashes that are correctly identified as VR crashes by the model, is 68.66%. Also, the specificity, proportion of non-crash cases that are correctly identified as non-crashes by the model is 65.17%. Moreover, Table 6-2 indicates that the false positive rate, ratio of observed number of non-crashes that are incorrectly classified as VR crashes to the total number of predicted VR crashes, is 60.34%. Similarly, the false negative rate, ratio of observed number of VR crashes that are incorrectly classified as non-crashes to the total number of predicted non-crashes is 13.82% (Agresti 2002). Since drivers' factors and errors are not considered in the present study, therefore 68.66% percent crash classification is considered reasonable. However, the results might need further validation with a larger sample.

The second research hypothesis is to compare crashes at poor visibility conditions vs. non-crash cases at clear visibility conditions. For each of the 67 crashes, 5 non-crash cases at clear visibility conditions (*m*) were selected randomly from all non-crash cases.

As shown in Table 6-3, the final model include three statistically significant variables; average speed at the nearest upstream station, average speed at the nearest downstream station and average occupancy at the nearest downstream station, all at time slice 2 (5-10 minutes before the crash). The results reveal that, compared to non–crash cases at clear visibility conditions, a decrease of the average speed upstream and downstream along with a decrease in the average occupancy downstream increase the risk of VR crashes.

Considering the results of the first and second research hypotheses, shown in Tables 6-1 and 6-3, the results suggest that compared to non-crash cases at reduced visibility conditions, the probability of VR crash occurrence increase when higher occupancy is observed at the nearest downstream station during 10-15 minutes before the crash coupled with an increase of the average speed upstream and downstream during 5-10 minutes prior to crash time. However, compared to non-crash cases at clear visibility conditions, lower occupancy downstream along with a decrease of the average speed downstream and upstream, all during 5-10 minutes before the crash increase the likelihood of VR crash occurrence in between. These results are logical because at low visibility conditions, drivers tend to reduce their speed compared to their speed at clear (normal) visibility conditions.

Table 6-3: Matched case-control logistic regression estimates and goodness of fit statistics (Crashes at poor visibility conditions vs. non-crash cases at clear visibility conditions)

Analysis of Maximum Likelihood Estimates						
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**Chi-Square**	**Pr > ChiSq**	**Hazard Ratio**
ASUS1_2	1	-0.38504	0.12503	9.4844	0.0021	0.680
ASDS1_2	1	-0.13679	0.04988	7.5218	0.0061	0.872
AODS1_2	1	-0.20473	0.12142	2.8431	0.0918	0.815

Model Fit Statistics		
Criterion	**Without Covariates**	**With Covariates**
-2 LOG L	92.882	40.253
AIC	92.882	46.253
SBC	92.882	52.868

6.5 Predicting CV Crashes

This section investigates whether there are any differences between the traffic variables that are highly associated with the occurrence of VR crashes and those variables that are highly correlated with CV crashes. Therefore, the third research hypothesis examined here is to compare crashes vs. non-crash cases at clear visibility conditions.

After excluding VR crashes and such crashes that occurred under the influence of drugs or alcohol, all CV crashes were extracted. A total of 255 CV crashes were extracted on I-4 that has the corresponding LDs or radar sensor data. For each of the 255 CV crashes, 5 non-crash cases at clear visibility conditions were selected randomly from all non-crash cases.

As shown in Table 6-4, the final model resulted in two significant variables: the average occupancy at the nearest downstream station (Log_{10} (AOUS1_2)) and the coefficient of variation of speed at the nearest upstream station (CSDS1_2), all at time slice 2 (5-10 minutes before the crash). It is worth mentioning that all other variables as well as using Log_{10} (CSDS1_2) was found to be statistically insignificant.

Since the coefficient of variation of speed includes the average speed as the denominator (coefficient of variation=Standard deviation / average), this indicates that the average speed is lower in crash cases. The results from this model point out that approximately one mile segment between the upstream and downstream stations experience high speed variation, high occupancy rate and lower average speed pointing to potential queue formation under turbulent speed conditions, which might be a cause for high crash possibility for a CV crash. These results are consistent with the findings of prior studies such as Abdel-Aty et al. (2004).

Considering the results of the first and third research hypothesis (shown in Table 6-1 and Table 6-4, respectively), the results suggest that traffic flow variables leading to VR crashes are slightly different from those variables leading to CV crashes. Higher occupancy observed about half a mile between the nearest upstream and downstream station increases the risk for both VR and CV crashes. In addition, an increase of the average speed observed on the same half a mile increases the probability of VR crash. On the other hand, high speed variation coupled with lower average speed observed on the same half a mile increase the likelihood of CV crashes.

Table 6-4: Matched case-control logistic regression estimates and goodness of fit statistics (Crashes vs. non-crash cases at clear visibility conditions)

Analysis of Maximum Likelihood Estimates						
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**Chi-Square**	**Pr > ChiSq**	**Hazard Ratio**
Log_{10} AOUS1_2	1	0.46431	0.13083	12.5941	0.0004	1.591
CSDS1_2	1	3.01961	1.11859	7.2872	0.0069	20.483

Model Fit Statistics		
Criterion	**Without Covariates**	**With Covariates**
-2 LOG L	906.630	890.030
AIC	906.630	894.030
SBC	906.630	901.096

6.6 Conclusions

Traffic surveillance data, collected through LDs and radar sensors on a 75 mile and 137 mile corridors of Intestate-4 and Intestate-95, respectively, between December 2007 and March 2009, were used in this study. VR crashes and historical visibility measurements were gathered for the same study area and during the same period. A total of 67 VR crashes were extracted that have corresponding LDs or radar sensors' data.

Random Forests were used in this study to indentify significant flow variables affecting VR crash occurrences. With significant variables selected by Random Forests, matched case-control logistic regression model has been estimated.

The results indicated that higher occupancy rates downstream during 10-15 minutes prior to the crash coupled with an increase of the average speed downstream and upstream 5-10 minutes before the crash increase the likelihood of VR crash occurrence in between. In addition, the results revealed that using matched case-control analysis, the log odds of VR crash occurrence may be obtained for a given value of certain traffic flow variables. The threshold value of 1.0 led to the identification of over 68% of VR crashes.

Furthermore, two more research hypotheses were investigated to improve our understanding of the relationship between traffic flow variables and VR crashes as well as how these variables differ from those variables that are associated with CV crashes. The second research hypothesis was to compare crashes at poor visibility conditions vs. non-crash cases at clear visibility conditions. The third research hypothesis was to compare crashes vs. non-crash cases at clear visibility conditions.

Considering the results of the first and second research hypotheses, it was found that compared to non-crash cases at poor visibility conditions, higher occupancy at the nearest downstream station during 10-15 minutes before the crash coupled with an increase of the average speed upstream and downstream during 5-10 minutes prior to crash time, increase the likelihood of VR crash occurrence. However, compared to non-crash cases at clear visibility conditions, lower occupancy downstream along with a decrease of the average speed downstream and upstream, all during 5-10 minutes before the crash increase the likelihood of VR crash occurrence in between.

Regarding the results of the first and third research hypothesis, the results suggest that traffic flow variables leading to VR crashes are slightly different from those variables leading to CV crashes. It was found that, higher occupancy observed about half a mile between the nearest upstream and downstream station increases the risk for both VR and CV crashes. Moreover, an increase of the average speed observed on the same half a mile increases the probability of VR crash. On the other hand, high speed variation coupled with lower average speed observed on the same half a mile increase the likelihood of CV crashes.

CHAPTER 7. PREDICTING VISIBILTY RELATED CRASHES ON EXPRESSWAYS

The emphasis in freeway management has been growing toward identifying patterns (i.e., turbulence in the traffic flow) in real-time traffic data that potentially precede traffic crashes on roadways. Additionally, in recent years, there has been a growing emphasis on employing Automatic Vehicle Identification (AVI) data for the provision of real-time travel time information to motorists within Advanced Traveler Information Systems (ATIS), (Dion and Rakha; 2006). Although, AVI system is designed primary for real-time travel time information and tolling purposes, it provides real-time traffic data (Space Mean Speeds) every one minute at stations installed on Expressways.

Numerous studies have established statistical links between freeway crash risk and traffic flow characteristics collected from subsurface loop detectors or radar sensors (LDs). However, two issues that have not explicitly been addressed in prior studies are; (1) the possibility of predicting VR crashes using traffic data collected from AVIs sensors installed on Expressways and (2) which traffic data is advantageous for predicting VR crashes; LDs or AVIs. Thus, this chapter examines the relationships between VR crash risk and real-time traffic data collected from LDs installed on two Freeways in Central Florida (I-4 and I-95) and from AVI sensors installed on two Expressways (SR 408 and SR 417). Also, it investigates which data is better for predicting VR crashes.

It is worth mentioning that there are significant differences in the nature of the collected speed data from LDs and AVIs sensors. LDs measure time-mean-speed (TMS), whereas AVIs measure space-mean-speed (SMS). TMS is defined as the arithmetic mean of the speed of vehicles passing a point during a given time interval. On the other hand, SMS is the average speed of all the vehicles traveling a given section of the road over specified time period.

Historical VR crashes and the corresponding traffic surveillance data of LDs were collected from a 75 mile and 137 mile corridors of Intestate-4 and Intestate-95 in Central Florida, respectively, between December 2007 and March 2009. In addition, historical VR crashes and the corresponding AVI traffic data were collected from two Expressways; SR 408 and SR 417 between 2007 and 2009.

Two stratified case-control datasets consisting of traffic data corresponding to every VR crash (case) and five random non-crash cases (controls) were created for both freeways and expressways under investigation. Hence, a binary classification approach may be adopted. Bayesian matched case-control logistic regression models have been estimated to achieve these goals. The purpose of using this statistical approach was to explore the effects of traffic flow variables on VR crashes while controlling for the effect of other confounding variables such as crash time (e.g., peak or off-peak time, season) and the geometric design elements of highway sections (e.g., horizontal and vertical alignments).

7.1 <u>Data Collection and Preparation</u>

7.1.1 Study Area and Parameters

Two sets of data were prepared and used in analysis presented in this Chapter; (1) Freeways LDs data and (2) Expressways AVIs data. The first dataset was collected from LDs (loop and radar detectors) sensors spaced at approximately 0.5-0.8 mile for about 75 mile and 137 mile corridors of I-4 and I-95 in Central Florida, respectively, between December 2007 and March 2009. VR crashes were gathered during the same period and at the same study area. As indicated earlier in Chapter 6, Due to LDs data availability, only 67 VR crashes that have corresponding traffic flow data, were obtained and used in the analysis.

The second dataset used in this study was collected from AVIs sensors spaced at approximately 1-1.5 mile for about 23 and 33 mile of Expressways SR408 and SR417, respectively, for three years 2007-2009. The Orlando-Orange County Expressway Authority (OOCEA) records and archives only 1-minute aggregation of space mean speed and the estimated average travel time along the defined road segments. Again, VR crashes that occurred on these Expressways during the same period were extracted. A total of 1895 mainline crashes occurred in the same study area and period were extracted. Subsequently, a total of 57 VR crashes were obtained. However, only 39 VR crashes that have corresponding traffic flow data were used in the analysis.

7.1.2 Data Preparation

Regarding the first dataset (Freeways LDs data), based on the location of each VR crash, six nearest LDs stations (three stations upstream and three stations downstream) to the crash location were identified using Geographic Information System (GIS) software. As shown in Figure 7-1, the first downstream and upstream LDs stations were named DS1 and US1, respectively. The subsequent stations in the downstream direction were labeled DS2 and DS3, respectively. Similarly, the subsequent stations in upstream direction were named US2 and US3, respectively.

Regarding the second dataset (Expressways AVIs data), based on the location of each VR crash, the crash segment (the segment in which the VR crash has occurred) in addition to six nearest segments (three segment in the upstream direction and three segment in the downstream direction) to the crash location were identified. Similar to LDs stations, the three upstream segments were named US1, US2 and US3, respectively while; the three downstream segments were named DS1, DS2 and DS3, respectively. The arrangement of LDs stations and AVIs segments is shown in Figure 7-1.

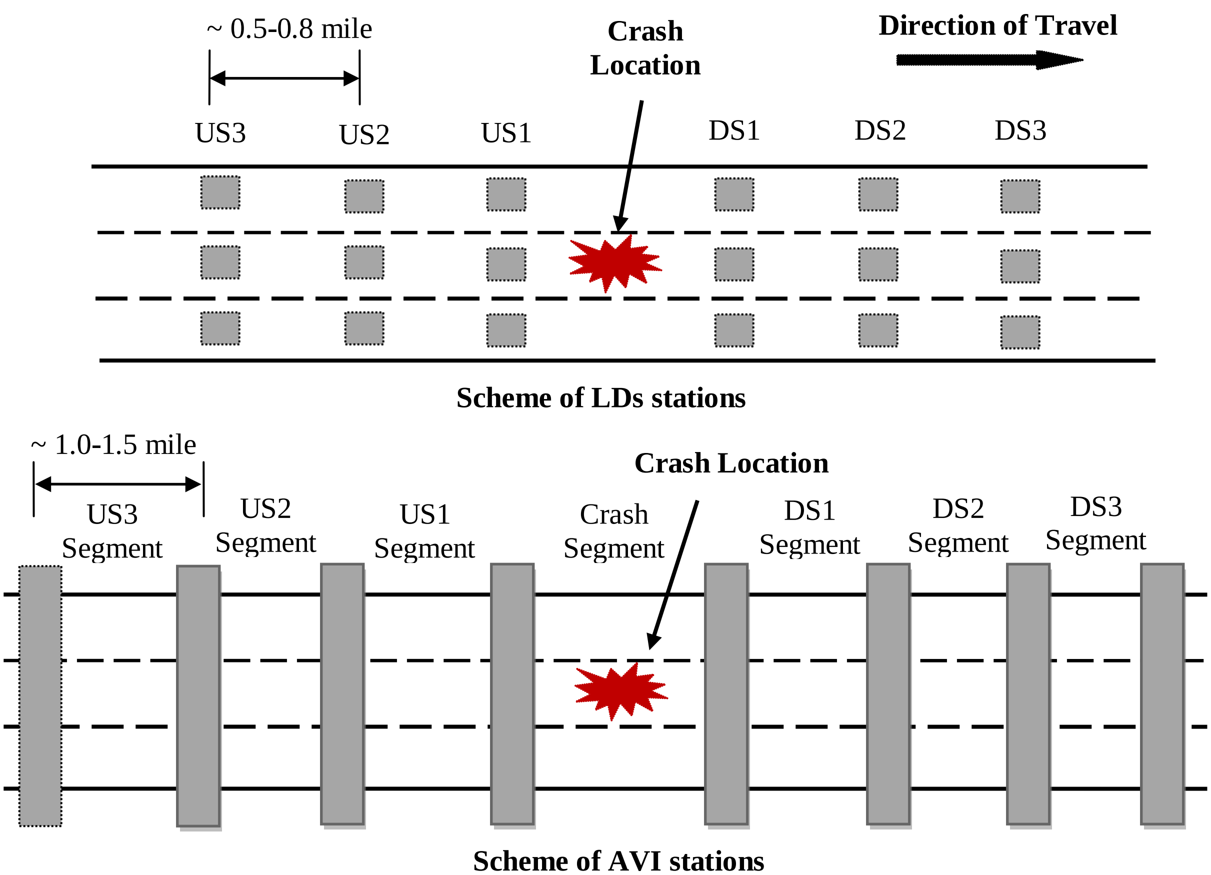


Figure 7-1: Arrangement of LDs and AVI stations

Traffic data for LDs (specifically time mean speeds) were then extracted for the day of every VR crash as follows; for example, if a VR crash occurred on January, 14, 2008 (Monday) 8:00 am, I-4 eastbound, the traffic data were extracted from 3 stations upstream and 3 stations downstream of the crash location from 7:45am to 7:55am (10 minutes window). Subsequently, five random non-crash cases were also determined for the same location and time on different

Mondays (in the same season since Central Florida experience 2 distinct seasons) where no crashes were observed within 1 hour of the original crash time. Traffic data was also extracted for these five non-crash cases during the same 10 minutes window.

The 5-minute interval prior to the crash time was disregarded for two main reasons. First, the practical application of the models that have significant variables at 0-5 minutes prior to the crash time is doubtful. If a crash time is identified correctly there would be no time for the traffic management center to analyze, react or disseminate the relevant warning information to the drivers. The second reason is to avoid any discrepancy about the exact time of crashes which is about ± 2 minutes (Golob and Recker; 2001).

The next step was the aggregation of LDs and AVIs data. As explained earlier, the raw data were combined into 5-minutes level. It is worth noting that 5-minutes of aggregation of the data are already carried out by most traffic management agencies for the travel time estimation algorithms (Pande et al. 2011). Thus, the 10-minute period for which data were collected was then divided into two time slices. The period of 5-10 minutes before the crash was named as time slice 2 while the period of 10-15 minutes prior to the crash was labeled as time slice 3. The averages, standard deviations and coefficient of variation in speed (standard deviation/ average) were then calculated for each LDs station during time slices 2 and 3.

To sum up, regarding the first dataset, a stratified case-control dataset consisting of LDs traffic data corresponding to every VR crash (case) and five randomly selected matched non-crash cases (controls) was created. Thus, the first dataset includes 402 observations (67 crashes and 335 non-crash cases).

The nomenclature of traffic variables extracted from LDs stations takes the form WXYZα_β. W takes the value A, S or C for average, standard deviation or coefficient of variation, respectively, while X takes the value of S representing speed. YZα takes the value of US1, US2, US3, DS1, DS2, DS3 representing the station to which the traffic parameters belong. β takes the value of 2 and 3 which refer to the two time slices used in the study. For example ASUS1_2 represents the average speed at the nearest upstream station to a crash location at time slice 2 (5-10 minutes before crash time).

Similarly, traffic data for AVI (space mean speeds data) were extracted for every VR crash that has occurred on Expressways (SR408 and SR417) in addition to 5 randomly non-crash cases for the same 10 minutes window mentioned above. These data were extracted for the crash segment and six nearest segments (as shown in Figure 7-1). The extracted 1-minute space-mean speeds of AVIs data were also aggregated into 5-minute aggregation level (time slices 2 and 3).

The nomenclature of AVIs variables for the six nearest segment is similar to the LDs. However, for the crash segment, the nomenclature of AVIs variables takes the form WXY_β. W takes the value A, S or C for average, standard deviation or coefficient of variation, respectively, while X takes the value of S representing speed. Y takes the value of C representing the crash segment and β takes the value of 2 or 3 representing time slices. For example, CSC_2 represents the coefficient of variation in speed of the crash segment at time slice 2.

In brief, concerning the second dataset, a stratified case-control dataset consisting of AVIs traffic data corresponding to every VR crash (case) and five randomly selected matched non-crash cases (controls) was created. Thus, the second dataset includes 234 observations (39 VR crashes and 335 non-crash cases).

It is worth noting that for each of the two datasets, by varying m (no. of controls) from 1 to 5; five datasets have been created which referred to as matched 1:1, 1:2, and 1:5 dataset. Each matched data set (1: m, m = 1, 2,… and 5) was analyzed separately. However, no significant differences have been observed when changing m. Therefore, only the detailed description of the analysis of 1:5 matched datasets is presented and discussed.

7.2 Preliminary Analysis of VR Crashes

This section presents a preliminary analysis of VR crashes used in this study. Table 7-1 summarizes the distributions of these crashes for both Freeways (I-4 & I-95) and Expressways (SR417 & SR408) under exploration. Regarding vision obstruction, 4% of the VR crashes have occurred on the freeways under investigation when vision was obstructed by fog while 96% of the VR crashes occurred when vision was obstructed due to heavy rain. In addition, 15% and 85% of the VR crashes extracted for the Expressways have occurred when vision was obstructed by fog and heavy rain, respectively.

Considering lighting conditions, the results revealed that a large percent of the VR crashes on the Freeways and Expressways under study (58.2% and 48.7%, respectively) have occurred during daylight followed by 19.4% and 23.1%, respectively that occurred at night in the absence of street light. Moreover, it was found that about half of the VR crashes, occurred on the Freeways and Expressways under investigation, were rear end crashes (about 48% and 46%, respectively). One possible explanation for this is that at reduced visibility, drivers cannot reduce their speed gradually when they suddenly encounter a relatively higher traffic density, therefore, a crash occurs and most likely rear end. In general, previous studies showed that rear-end crashes represent the highest percent on Freeways and Expressways (Pande et al. 2011, Singh 2003).

Table 7-1: Distribution of VR crashes

Factors	Categories	Freeways (I-4 & I-95)	Expressways (SR417& SR408)
		Percentages	Percentages
Roadways	I-4 / SR417	58.2 (I-4)	43.6 (SR417)
	I-95 / SR408	41.8 (I-95)	56.4 (SR408)
Vision obstruction	Fog	6.0	15.0
	Heavy rain	94.0	85.0
Lighting conditions	Daylight	58.2	48.7
	Dusk	4.5	7.7
	Dawn	6.0	5.1
	Dark (street light)	10.5	12.8
	Dark (no street light)	19.4	23.1
	Unknown	1.4	2.6
Crash type	Rear end	47.8	46.1
	Angle	17.9	10.7
	Sideswipe	7.6	30.2
	others	7.4	13.0

7.3 Methodology

A flow chart of the overall data analysis process presented in this chapter is shown in Figure 7-2. The figure shows that LDs data (time-mean speeds data) collected from freeways (I-4 & I-95) was used to predict VR crashes occurrences on Freeways using Bayesian matched case-control logistic regression approach. The final model obtained from this stage was named Model-1. This model was estimated to investigate whether or not one can predict the occurrence of VR crashes using time mean speeds only in the absence of any information regarding volume and occupancy (to be comparable to the case of AVIs data).

Subsequently, the freeways LDs data was converted from time-mean speeds into space-mean speeds. This new dataset set was also used to predict VR crash occurrence on Freeways using space-mean speed data. The model was estimated also using Bayesian matched case-control logistic regression approach and labeled Model-2. This dataset is equivalent to AVIs data and hence, the results from Model-2 were tested using the AVIs expressways data.

It is worth mentioning that Wardrop (1952) derived the relationship between the time-mean speed ($\bar{u}_T$) and space-mean speed ($\bar{u}_S$) as follows:

$$\bar{u}_T = \bar{u}_S + \frac{\sigma_S^2}{\bar{u}_S} \tag{7-1}$$

Where: σ_S^2 is the variance in vehicle speeds about the space-mean speeds. Rakha and Zhang (2005) indicated that this formulation estimates the time-mean speed from the space-mean speed, which is typically the reverse of what is required (as σ_S^2 is unknown). Therefore, they derived a modified relationship between $\bar{u}_S$ and $\bar{u}_T$ as follows:

$$\bar{u}_T = \bar{u}_S \, . \left[1 + \frac{\sigma_T^2}{\bar{u}_T \, . \, \bar{u}_T}\right] \simeq \bar{u}_S + \frac{\sigma_T^2}{\bar{u}_S} \tag{7-2}$$

Where: $\sigma^2{}_T$ is the variance in vehicle speeds about the time-mean speed. They also demonstrated that the proposed formulation, which utilizes the variance about the time-mean speed as opposed to the variance about the space-mean speed, produces an estimate error to within 0 to 1 percent. Equation [7-2] was used in the present study to estimate space-mean speeds from time-mean speeds of LDs data.

Next, AVIs data (space-mean speeds data) collected from Expressways (SR408 & SR417) was used to predict the occurrences of VR crashes on Expressways. The developed Bayesian matched case-control from this step was named Model-3. A discussion and comparison between the results of the three developed models in this study is provided in the following sections.

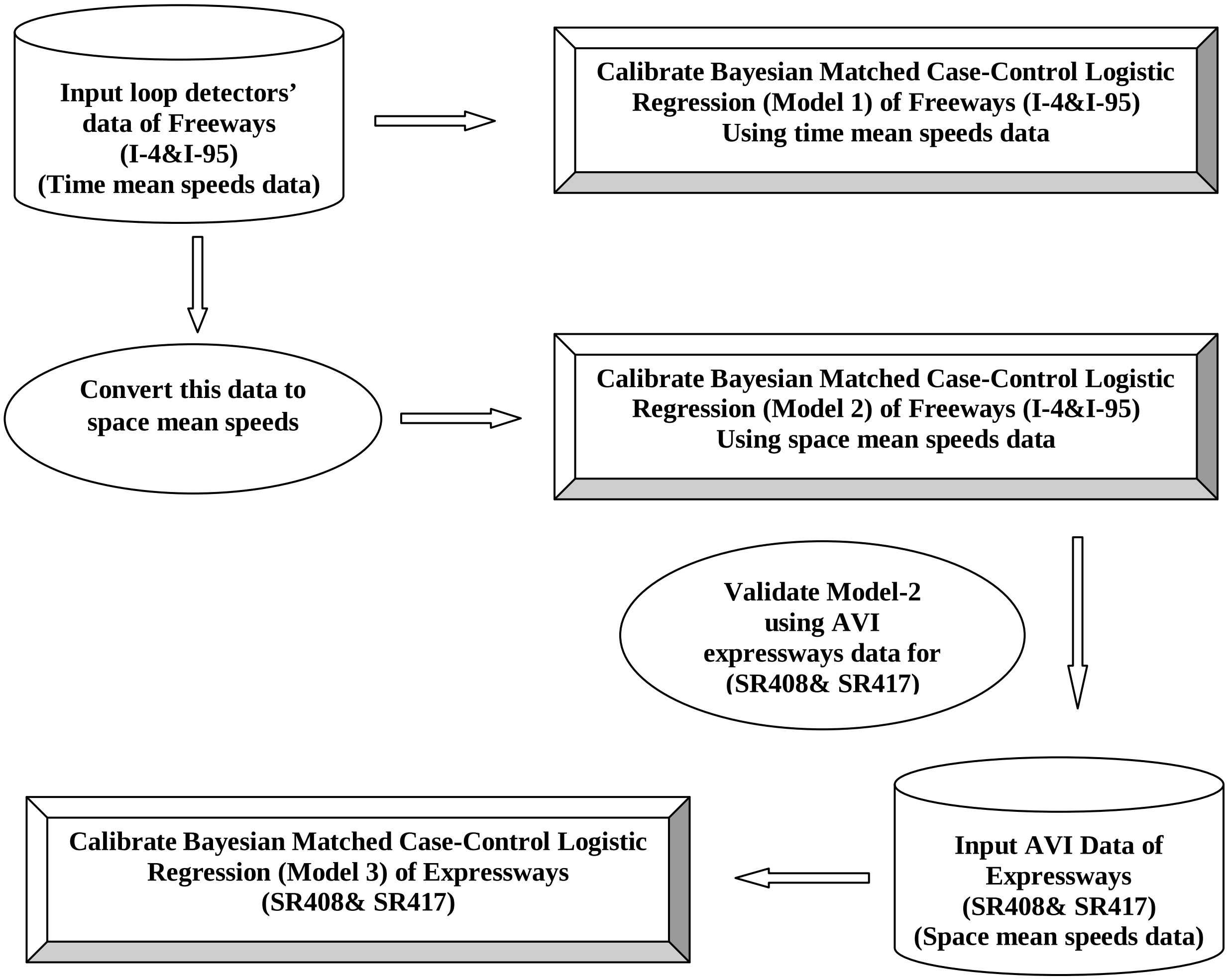


Figure 7-2: Flow chart representing the data analysis

7.4 Bayesian Matched Crash Non-Crash Analysis

As mentioned earlier, the purpose of the proposed matched crash-non-crash analysis is to explore the effects of traffic flow variables on VR crashes while controlling for the effects of other confounding variables such as crash time (e.g., peak or off-peak hours, season) and the geometric design elements of freeway/expressway sections (e.g., horizontal, vertical alignments, on-ramp and off-ramp vicinity locations, etc.). Matched case-control logistic regression using classical statistic approach has been adopted in epidemiological studies. In addition, it was used in few transportation related studies such as Abdel-Aty et al. (2004) and Hassan and Abdel-Aty (2011).

Bayesian matched case-control logistic regression approach was adopted using SAS package 9.2, procedure PHREG. This procedure provides Bayesian analysis in addition to the standard (classical) analysis they have always performed (as discussed in Chapter 6). Procedure PHREG generates a chain of posterior distribution samples by the Gibbs Sampler and provides summary statistics, convergence diagnostics and diagnostic plots for each parameter. It also uses the adaptive rejection sampling (ARS) algorithm to sample parameters sequentially from their univariate full conditional distribution (SAS Institute Inc. 2009).

The advantages of using the Bayesian approach include that (1) it provides a natural and principled way of combining prior information (if it exists) with the data, within a solid decision theoretical framework to yield a posterior belief (when new data become available, the previous posterior distribution can be used as a prior), (2) it presents full distributional profile of parameters rather than single coefficient estimates to fully account for the uncertainty associated with single parameter estimates in classical statistics, (3) it gives inferences that are exact and conditional on the data, without reliance on asymptotic approximation and hence, small sample inference proceeds in the same manner of a large sample, (Rao 2003, SAS Institute Inc. 2009).

Due to the absence of informative priors, a uniform prior distribution was assumed and used to estimate the first two models developed in this chapter. The uniform prior is a flat prior which assigns equal likelihood on all possible values of the parameter. However, the third model presented in this study were estimated twice (using uniform prior and using the results of Model-2 as informative priors) as explained in the following sections. The convergence of the generated Markov chains of all developed models was assessed by examining the trace plot, the autocorrelation function plot and the posterior density plot. It was found that, all the models have converged reasonably. The DIC, a Bayesian generalization of AIC, is used along with the classification accuracy of the three models to measure the models complexity and goodness of fit (Spiegelhalter et al. 2003).

7.5 Predicting VR crashes on Freeways Using LDs Data

7.5.1 Using Time-Mean Speed Data

As indicated earlier, to predict the real-time crash risk of VR crashes on Freeways (I-4 and I-95) using time-mean speeds' data, the first dataset was used. The first dataset includes 402 observations (67 VR crashes and 335 non-crash cases). Automatic search technique: stepwise, forward and backward were used to identify significant variables. All three search techniques resulted in two significant variables. The estimates of beta coefficients, credible interval, associated summary results; model fit statistics and classification results of actual and predicted VR Crashes obtained from the final model (Model-1) are presented in Table 7-2.

The results indicated that a decrease in the average speed at the nearest downstream station (ASDS1_2, β=-0.1409, 95%CI (-0.2010, -0.0898)) coupled with an increase in the logarithm of coefficient of variation in speed (Standard deviation/average speed) at the nearest upstream station (Log. CSUS1_2, β=0.3979, 95%CI (0.0671, 0.8536)), all at time slice 2 (5-10 minutes before the crash time) increase the risk of VR crash occurrence in between. The results from the model may imply that lower average speed at the nearest downstream station (possible due to higher occupancy) coupled with higher standard deviation in speed at the nearest upstream station, all at time slice 2 pointing to potential queue formation under turbulent speed conditions, which could be a cause for high VR crash possibility.

Note that the hazard ratio corresponding to parameters estimates are shown in Table 7-2. Hazard ratio, equals the exponent of the beta coefficient, is an estimate of the expected change in the risk ratio of having a VR crash versus non-crash cases per unit change in the corresponding factor. For example, hazard ratio of 1.53 corresponding to (Log. CSUS1_2) means that the risk of a VR crash increases about 1.5 times for each unit increase in (Log. CSUS1_2).

As previously explained, the odds ratio in Equation [6-3] can be used to classify VR crash and non-crash cases. Therefore, the mean of the two significant variables of all five non-crash cases within each matched set were estimated. The vector X_{2j} in Equation [6-3] was then replaced by the vector of non-crash means for the j^{th} matched set. The odds ratio for each observation in the data set was then estimated by substituting the beta coefficient from Table 7-2 in Equation [6-3] where the vector X_{1j} is the actual observation in the data set. A threshold value for these ratios was then set to determine whether the location has to be flagged as a potential "VR crash". Using a threshold of 1.0 for the log odds ratio, over 73% crash identification was achieved (as shown in Table 7-2). The table shows that the sensitivity, proportion of VR crashes that are correctly identified as VR crashes by the model is 73.13%. Also, the specificity, proportion of non-crashes that are correctly identified as non-crashes by the model is 60.30% (Agresti 2002).

Table 7-2: Results of Bayesian matched case-control logistic regression (Model 1) (Based on LDs data; time-mean speeds)

Parameters Estimates				
Parameter	**Mean**	**Standard Deviation**	**Credible interval**	
			2.5%	**97.5%**
ASDS1_2	-0.1409	0.0283	-0.2010	-0.0898
Log. CSUS1_2	0.3979	0.2350	0.0671	0.8536
Hazard Ratios				
Parameter	**Mean**	**Standard Deviation**	**Credible interval**	
			2.5%	**97.5%**
ASDS1_2	0.8689	0.0245	0.8179	0.9141
Log. CSUS1_2	1.5304	0.3659	0.9351	2.3481
Model Fit Statistics				
DIC				143.088
pD (Effective Number of Parameters)				1.989

Classification results of Actual and Predicted VR Crashes				
		Predicted Y		
	Frequency **Percent** **Row Percent** **Col Percent**	**0**	**1**	**Total**
Actual Y	**0**	202 50.25 60.30 91.82	133 33.08 39.70 73.08	335 83.33
	1	18 4.48 26.87 8.18	49 12.19 73.13 26.92	67 16.67
	Total	220 54.73	182 45.27	402 100.00

It is worth mentioning that this threshold may be changed to achieve desirable classification accuracy for both crashes and non-crash cases. In other words, accuracy can be easily increased by accepting higher false alarm rate and be on the conservative side. If freeway traffic turbulence is identified, even if does not lead to a crash, it would be useful to reduce turbulence and improve flow. This point could be left to implementation and the preferences of the specific traffic agency. To sum up, the predictive power of the model might be evaluated using the rate of crash misclassification or overall misclassification or some combination of the two.

7.5.2 Using Space-Mean Speed Data

As discussed previously, the first dataset (freeways LDs data) was converted from time-mean speeds into space-mean speeds. This step was done for two mean reasons. First, to calibrate a prediction model for VR crashes using a dataset that is equivalent to AVI data (named Model-2) and therefore, it might be possible to compare between the results of Model-2 and Model-3 (Expressways' VR crashes prediction model based on AVI data). Second, the results of Model-2 may be tested using the Expressways' AVI data.

Table 7-3 shows the results of the Bayesian matched case-logistic regression (Model-2) that was estimated based on Freeways' LDs data (space-mean speeds). As expected, similar to the results of Model-1, the results of Model-2 revealed that the average speed at the nearest downstream station (ASDS1_2, β=-0.1573, 95%CI (-0.2253, -0.0984)) and the logarithm of coefficient of variation in speed at the nearest upstream station (Log. CSUS1_2, β=0.4434, 95%CI (0.0926, 0.9775)), all at time slice 2 (5-10 minutes before the crash time) were found to have significant effect on VR crash risk on Freeways. As shown in Table 7-3, using a threshold of 1.0 for the log odds ratio, over 71% crash identification was achieved. Considering the results shown in Tables 7-2 and 7-3, the results indicate that Model-1 (based on time-mean speeds) is slightly better that model 2 (based on space-mean speeds) as it achieved higher classification accuracy of identifying VR crashes (73.13%) and better fit statistic (DIC=143.088 compared to DIC=156.733 of Model-2).

Table 7-3: Results of Bayesian matched case-control logistic regression (Model 2) (Based on LDs data; space-mean speeds)

Parameters Estimates				
Parameter	**Mean**	**Standard Deviation**	**Credible interval**	
			2.5%	**97.5%**
ASDS1_2	-0.1573	0.0322	-0.2253	-0.0984
Log. CSUS1_2	0.4434	0.2729	0.0926	0.9775
Hazard Ratios				
Parameter	**Mean**	**Standard Deviation**	**Credible interval**	
			2.5%	**97.5%**
ASDS1_2	0.8549	0.0274	0.7983	0.9063
Log. CSUS1_2	1.6174	0.4533	0.9116	2.6578
Model Fit Statistics				
DIC				156.733
pD (Effective Number of Parameters)				1.986

Classification results of Actual and Predicted VR Crashes				
		Predicted Y		
	Frequency **Percent** **Row Percent** **Col Percent**	**0**	**1**	**Total**
Actual Y	**0**	177 44.03 52.84 90.31	158 39.30 47.16 76.70	335 83.33
	1	19 4.73 28.36 9.69	48 11.94 71.64 23.30	67 16.67
	Total	196 48.76	206 51.24	402 100.00

Then, using the expressways AVIs data (234 observations; 39 VR crashes and 335 non-crash cases) the results of Model-2 were tested. It was found that about 64.6% and 63.1% of VR crashes and non-crash cases, respectively, were correctly identified. It can be noted that this classification accuracy (64.6%) is relatively comparable to the accuracy 71.64% obtained previously by Model-2 which may imply that Model-2 is performing well in correctly predicting the occurrences of VR crashes. One possible explanation for having relatively lower classification accuracy when using the tested dataset is the differences between LDs and AVIs arrangements (configurations). As shown in Figure 7-1, LDs sensors are spaced at approximately 0.5-0.8 mile compared to AVIs sensors that are spaced at approximately 1.0-1.5 mile.

7.6 Predicting VR crashes on Expressways Using AVIs Data

An issue that has not been addressed in prior studies is the possibility of predicting the occurrence of VR crashes using traffic data collected from AVIs sensors installed on Expressways. Therefore, using space-mean speeds data collected from Expressways SR408 and SR417 for a total of 39 VR crashes and 195 non-crash cases, a Bayesian matched case-control logistic regression model was estimated (Model-3). Table 7-4 shows the parameter estimate, hazard ratio, goodness of fit indices and classification accuracy of Model-3. The results revealed that the logarithm of coefficient of variation in speed (β=0.7588, 95%CI (0.3489, 1.2062)) at the crash segment (see Figure 7-1) during time slice 2 (5-10 minutes prior to crash time) was found to have a significant effect of VR crash risk. These results imply that lower average speed observed at a certain segment coupled with higher standard deviation in speeds at the same segment; all at time slice 2, increase the probability of VR crashes occurrences.

One may wonder if both average speed and standard deviation are significant predictors when used separately instead of combining them into coefficient of variation (standard deviation / average speed) as one variable. To address this issue, we estimated another model using these two variables however; this model showed lower accuracy in identifying VR crashes correctly. Also it showed higher DIC than the model that has Log. CSC_2 and thus we concluded that the best model is the one that has only (Log. CSC_2). No variable from the upstream or downstream segments is found to be significant. This should not be surprising since reduced visibility due to fog/smoke or heavy rain is most likely localized. As indicated earlier, the lengths of AVIs segment vary from about 1.0-1.5 mile, so it is logical to get significant variable(s) from the crash segment only.

As shown in Table 7-4, a hazard ratio of 2.19 corresponding to (Log. CSC_2) means that the risk of a VR crash increases about 2.2 times for each unit increase in (Log. CSC_2). Also the table shows that the sensitivity and the specificity of the model are 69.23% and 61.03%, respectively. As discussed earlier, due to the absence of informative priors, all the three models presented in the present study were estimated using uniform prior which is favored by many statisticians (SAS Institute Inc. 2009). However, it is worth mentioning that we re-estimated Model-3 using the results of Model-2 as informative priors (specifically, Log. coefficient of variation in speeds). Note that the datasets used to develop Model-2 and Model-3 is comparable as both of them are space-mean speeds data. It was found that the results of Model-3 had not significantly improved when using the informative priors possibly because the configurations of LDs and AVIs are different. The LDs stations are spaced approximately at 0.5-0.8 mile while the lengths of AVIs segments vary from 1-1.5 miles. Also, LDs have upstream and downstream stations only while, AVIs has crash segment in addition to the upstream and downstream segments. The results imply that it may not be advisable to use informative priors from other corridors that probably have different characteristics. Therefore, the results based on uniform prior of Model-3 are only presented here.

Table 7-4: Results of Bayesian matched case-control logistic regression (Model 3) (Based on AVI data; space mean speeds)

Parameters Estimates				
Parameter	**Mean**	**Standard Deviation**	**Credible interval 2.5%**	**Credible interval 97.5%**
Log. CSC_2	0.7588	0.2177	0.3489	1.2062
Hazard Ratios				
Parameter	**Mean**	**Standard Deviation**	**Credible interval 2.5%**	**Credible interval 97.5%**
Log. CSC_2	2.1877	0.4943	1.4174	3.3406
Model Fit Statistics				
DIC				91.122
pD (Effective Number of Parameters)				0.990
Classification results of Actual and Predicted VR Crashes				
		Predicted Y		
	Frequency **Percent** **Row Percent** **Col Percent**	**0**	**1**	**Total**
Actual Y	**0**	119 50.85 61.03 90.84	76 32.48 38.97 73.79	195 83.33
Actual Y	**1**	12 5.13 30.77 9.16	27 11.54 69.23 26.21	39 16.67
	Total	131 55.98	103 44.02	234 100.00

7.7 Conclusions

This chapter aimed at identifying patterns (i.e., turbulence in the traffic flow) in the expressway AVIs traffic data that potentially precede VR crashes. Also, it investigated which traffic data is advantageous for predicting VR crashes; data collected from LDs sensors installed on freeways or data collected from AVIs sensors installed on expressways. Statistical links between turbulent traffic conditions and VR crash occurrences were established through a detailed analysis of LDs/AVIs traffic data corresponding to VR crashes that occurred on freeways (I-4 and I-95) and on expressways (SR408 and SR417) in central Florida during the study time.

The approach adopted in this study involves developing Bayesian matched case-control logistic regression using the historical crash, LDs and AVIs data. To achieve these objectives, three models were estimated and discussed.

Historical VR crashes along with traffic data (time-mean speeds) collected from LDs on freeways were used to calibrate the first model (Model-1). The second model (Model-2) was calibrated using the same data but after converting it into space-mean speeds (to make it equivalent to AVIs data). The results of both models indicated that the average speed observed at the nearest downstream station coupled with the coefficient of variation in speed observed at the nearest upstream station, all at 5-10 minute prior to the crash time, were found to have significant effect on VR crash risk. It has been shown that Model-1 and Model-2 achieved over 73% and 71% of VR crash identification, respectively. The performance of model-2 was then tested using historical VR crashes and AVIs traffic data (space-mean speeds) collected from expressway (SR417 and SR408). It was found that about 65% of VR crashes were correctly identified. It can be noted that this classification accuracy is relatively comparable to the accuracy 71.64%

obtained previously by Model-2 which may imply that Model-2 is performing well in correctly predicting the occurrences of VR crashes, however, one possible explanation for obtaining relatively lower classification accuracy when using the tested dataset is the differences between LDs and AVIs arrangements (configurations).

Also historical VR crashes and space-mean speeds data collected from AVIs sensors located on expressways (SR417 and SR408) were used for developing prediction model of VR crashes on expressways (Model-3). The results of the model revealed that an increase in the coefficient of variation in speed at the crash segment, 5-10 minutes before the crash time increases the likelihood of VR crashes. No variables from the upstream or downstream AVIs segments were found significant possibly because the effect of fog/smoke or heavy rain is most likely localized and the longer Expressway segments. Model-3 achieved over 69% of VR crash identification.

Considering the results of Model-3 and compared to the results of Model-1 and Model-2, it can be realized that LDs data is slightly better than AVIs data regarding the prediction of VR crashes possibly due to three reasons. First, the configuration (arrangement) of LDs and AVIs sensors is different as discussed above (i.e., the distances between LDs sensors are less than the lengths of AVIs segments). Second, AVIs measures space-mean speeds by tracking the speed of vehicles through successive AVIs sensors while, LDs measures time-mean speed (spot speeds) of vehicles at certain point (LDs stations) on a roadway. Third, the AVIs sensors can only record and archive traffic data for vehicles that have AVIs tags (i.e., transponders, E-pass, etc.). It is well established that about 80% of vehicles using expressways have AVIs tags. On the other hand, LDs record and achieve traffic flow data for all vehicles travelling on the roadway.

It is worth noting that the first model presented in this chapter (based on LDs data; time-mean speed data only) achieved slightly higher classification accuracy than the first model presented in Chapter 6 (based on LDs data; speed, volume and occupancy data) possibly due to the use of Bayesian approach as it is probably more realistic than the classical statistical approach. One of the advantages of the Bayesian approach is that it accounts for the uncertainty associated with parameter(s) estimates and provides exact measures of uncertainty on the posterior distributions of these parameters and hence it overcomes the maximum likelihood methods' problem (in classical statistics) of overestimating precision because of ignoring this uncertainty (Goldstein, 2003; Rao, 2003).

CHAPTER 8. CONCLUSIONS AND RECOMMENDATIONS

This research is concerned with improving safety and drivers' behavior in poor visibility conditions. Two ways to improve safety in reduced visibility conditions are to improve drivers' behavior under such adverse weather conditions and to predict the occurrence of VR crashes using real-time traffic data collected from LDs or AVIs sensors installed on Freeways and Expressways.

This chapter presents key findings, conclusions and recommendations that were extracted from the survey-based study and from the real-time assessment of VR crash risk.

8.1 Conclusions Based on the Survey Study

Warning messages and reduced speed limits displayed on well-designed CMS and VSL signs may achieve more homogenous speeds and help to reduce accidents that may occur due to sudden onset/appearance of fog, smoke or heavy rain. Therefore, this research investigates drivers' behavior, attitudes and preferences under different traffic and fog conditions, and suggests some recommendations to improve drivers' compliance with advice displayed on CMS and VSL signs.

A multiple approach survey was designed to collect opinions and stated data from motorists in Central Florida. A total of 566 responses were used in the analysis. Conducting this survey using three approaches (handout, interactive, and online questionnaire) achieved a well representative sample (i.e., the sample was apparently broad and fairly uniform across age, gender, and education).

Several categorical data analysis techniques were applied to understand commuters' behavior at adverse visibility conditions. These methods include conditional distributions, odds' ratio, and Chi-Square tests. The results revealed that participants' response to CMS and VSL signs' instructions vary by gender, age, familiarity with CMS and VSL signs, past experience with driving at adverse visibility condition and involvement in FS/HR related crashes.

To improve our understanding of the preferences of respondents in following VSL and CMS instructions at such adverse visibility conditions, Multivariate and Bivariate Probit Models were estimated. The advantages of using BPM and MPM analysis in the present study include that the simultaneous estimation of the models would improve the coefficient estimates by accounting for the correlation between the unmeasured factors (Das et al., 2008). In addition, correlations between several equations can also be accounted for. Moreover, using MPM, all dependent and explanatory factors affecting drivers' responses to CMS and VSL signs at different traffic and visibility conditions were shown and discussed in one model framework.

The findings of MPM indicated that compared to males and young drivers (18-25 years old), females and old drivers (51 years old or more) claim to be more likely to reduce their speed in response to CMS and VSL instructions when driving in different visibility (heavy or very light fog) and traffic conditions (low or medium-high). This may imply that females and old drivers are more cautious than males and young drivers especially while driving at such adverse visibility conditions.

The results also indicated that drivers who are familiar with VSL signs claim to be more likely to follow their instructions at heavy fog condition than those who are not. One possible explanation is that drivers, who are familiar with VSL signs, usually are aware of its importance for safety and hence, they are less likely to ignore its instructions.

Concerning the type of road, the findings showed that the stated likelihood of reducing speed in response to CMS and VSL signs increases when driving on a two-lane road at adverse visibility condition compared to a freeway possibly due to the absence of a median.

A further objective of this study was to investigate whether drivers would rely on and follow warning messages displayed on CMS/VSL signs at adverse visibility conditions. Only 37% of the respondents reported that they would reduce their speed immediately or reduce their speed and put blinkers on when encountering a CMS, which advises them to reduce their speed due to reduced visibility condition, at low traffic volume while driving on a freeway. Also, it was found that only 35% of the respondents were willing to follow VSL instructions (reducing their speed to 40 mph or less) while driving on a freeway at very light fog and low traffic volume. Moreover, the results show that as the visibility distance deteriorates and traffic volume increases, drivers claim to be more likely to follow CMS/VSL instructions.

In addition, a structural equations modeling (SEM) technique was used in this study to distinguish variables that affect drivers' compliance and satisfaction with advice or warning messages displayed on VSL and CMS under different traffic and visibility conditions. The SEM models were developed and proved statistically that they have an acceptable fit. The advantages of using the SEM approach in this study were that it verified the research hypotheses, measured the degree of effect through path coefficients and analyzed both direct and indirect effects through the analysis of casual relationships between latent and manifest variables.

The findings revealed that drivers' satisfaction with VSL and CMS was the most significant variable that positively affected drivers' compliance with VSL and CMS instructions under different fog and traffic conditions followed by driver factors. This result indicates that higher satisfaction with VSL/CMS instructions and higher scores for driver factors (i.e., older age, longer driving experience, less number of traffic citations and higher usage of freeways/2-lane roads) contribute to increase drivers' compliance with advice or warning messages displayed on VSL/CMS under reduced visibility conditions.

In addition, it was found that roadway type affected drivers' behavior in response to VSL instructions only under medium and heavy fog conditions. However, roadway type did not significantly affect drivers' behavior in response to VSL under very light or light fog. The findings also indicated that roadway type affected drivers' compliance with CMS only when some vehicles are ahead. Furthermore, drivers' familiarity with VSL signs and driver factors were the significant factors affecting drivers' satisfaction with VSL/CMS advice under reduced visibility conditions.

Based on the findings of the present study, to increase drivers' compliance with advice or warning messages displayed on VSL and CMS signs, the following recommendations are suggested:

1- **Accurate and real-time detection of visibility conditions** is essential and critical to improve drivers' satisfaction and compliance with VSL/CMS instructions. In this regard, the results of the SEM models revealed that drivers' satisfaction with CMS/VSL signs was the main factor that significantly affected drivers' compliance with warning messages or advice displayed on CMS and VSL signs. Obviously, one way to improve drivers' satisfaction with CMS/VSL signs is to ensure that the signs continuously display accurate and real-time advices based on the actual visibility conditions. Numerous respondents to the current survey study reported that speed limits displayed on VSL signs cannot be relied on since fog thickness is changeable every minute, and thus, the sign would not reflect the accurate safe speed limit according to the current visibility condition. This is consistent with NHTSA (2009) which indicated that speed limits should be set carefully, taking into account environmental conditions; if not, many drivers may lose their trust in and exceed the speed limit.

2- **“Caution-fog ahead-reduce speed”** was perceived as the best warning message (selected by about 38% of respondents) that would achieve the best safety and drivers’ compliance in case of reduced visibility due to fog. Since most of CMS can display 2 pages of messages alternatively with each message containing 3 lines of up to 8 characters. Thus, the best message that can easily be displayed on CMS may be “Caution-Fog-Ahead” on the first page with "reduce-speed" on the second page.

3- **Using CMS and VSL signs together** is recommended in reduced visibility conditions. About 64% of respondents claimed that this is the best way to improve safety during such inclement weather conditions. This is logical because warning drivers about reduced visibility using CMS should be followed by informing them what they should do using VSL signs (the safe speed at each visibility condition). This could lead to accomplish more homogenous speeds in such adverse visibility conditions. This result is consistent with prior studies such as Perrin et al. (2002).

4- **Using two successive CMS signs** prior to FS zones is also recommended (reported by the majority of respondents; 83%) as it could provide drivers with another chance to read the content of the second CMS if they missed the first one (i.e., if the sign was occluded by other traffic or due to poor visibility conditions).

5- **Enforcement:** deterrence through more traffic law enforcement, especially for young and male drivers, should increase drivers’ compliance with reduced speed limits and warning messages displayed on VSL and CMS, respectively. In this regard, the results of the

MPM showed that males and young drivers claimed to be less likely to follow CMS/VSL instructions compared to female and old drivers. In addition, the findings of the SEM models indicated that drivers with more number of traffic citations are less likely to comply with CMS/VSL instructions. Thus, strict penalties for repeat offenders including increased driver's license points, license suspension or revocation, higher fines, could improve drivers' behavior in such adverse conditions.

6- **Economic Incentives:** on the other hand, incentives could promote safer behavior (for example, lower insurance premiums for drivers who were not involved in any at-fault crashes or who did not get any traffic citation within a certain period). These drivers already save money for their community by avoiding crashes and hence they deserve to be rewarded.

7- **Education or Communication Campaigns:** special education courses for young drivers in particular or aggressive drivers (i.e., drivers who have been involved in at-fault crashes due to reduced visibility or who got traffic citations due to exceeding speed limits) may be conducted to emphasize the importance of obeying VSL/CMS instructions and the strong relationship between rule violation and crash risk especially under low visibility conditions. Campaigns can be used also to increase the awareness and familiarity of drivers with VSL signs as the results of the MPM pointed out that drivers who are familiar with VSL signs are more likely to follow its instruction compared to drivers who are not familiar with it. Similarly, the results of third SEM model indicated that drivers' familiarity with VSL sign was one of the factors that significantly affected drivers' satisfaction with CMS/VSL signs.

To sum up, these recommendations might improve drivers' compliance with CMS and VSL instructions and consequently achieve more homogenous speeds in reduced visibility conditions. This may help to reduce the risk of visibility related crashes.

The limitation of this survey-based study is that the use of self-reported (stated preference) studies in examining drivers' behavior and preferences would seem to be a problem if there were a large variance between self-reported data and actual behavior. However, various prior studies (e.g., Loomis 1993; West et.al 1993; Yannis et al. 2005) reported good harmony between self-reported responses and actual ones. While actual values or percentages should be regarded with care (i.e., be more on the conservative side), the directions and indications of the results would be valid. The combined use of data from self-reported questionnaires as well as a driving simulator experiments might be recommended in future studies to address this concern.

It is also recommended to examine whether there is any difference between drivers' behavior in response to warning messages or advice displayed on the permanent changeable message signs and their responses to the portable signs in reduced visibility conditions. Finally, studying driving behavior of motorists who had been involved in visibility related crashes separately is recommended in future studies to examine the possible relationships between risky driving behavior and involvement in visibility related crashes.

8.2 Conclusions Based on Real-time assessment of VR crash Risk

The main contribution of this part is the systematic identification of relationships between historical VR crash occurrences and real-time traffic flow characteristics collected from LDs and AVIs installed on freeways and expressways, respectively. In addition, argument concerning which traffic data (LDs or AVI) is better for predicting VR crashes is also provided and discussed in this Chapter.

Real-time assessment of traffic flow characteristics may help in reducing the chances of VR crashes. This study aims at identifying traffic flow factors leading to VR crashes on freeways in order to develop a crash likelihood prediction model using real-time traffic flow variables. Thus, the first research hypothesis investigated in this part was comparing crashes vs. non-crash cases at poor visibility conditions.

Traffic surveillance data, collected from LDs and radar sensors installed on Intestate-4 and Intestate-95 were used to achieve that goal. VR crashes and historical visibility measurements were gathered for the same study area and during the same period. A total of 67 VR crashes were extracted that have corresponding LDs or radar sensors' data.

Random Forests were used to indentify significant flow variables affecting VR crash occurrences on freeways. With significant variables selected by Random Forests, matched case-control logistic regression model has been estimated. The purpose of using this statistical approach is to explore the effects of traffic flow variables on VR crashes while controlling for the effect of other confounding variables such as the geometric design elements of highway sections and crash time.

The results indicated that the average occupancy at the nearest downstream station during 10-15 minutes prior to the crash and the average speed at the nearest downstream and upstream stations at 5-10 minutes before the crash affected the likelihood of VR crash occurrence in between.

In addition, the results revealed that using matched case-control analysis, the log odds of VR crash occurrence may be obtained for a given value of certain traffic flow variables. The threshold value of 1.0 led to the identification of over 68% of VR crashes. It is worth mentioning that driver's factors and errors was not considered in the model, and therefore this identification percentage of VR crashes may be considered reasonable. Driver population might have been accounted for in the matched design, since we can assume that drivers at the same location and time of day could be comparable.

Furthermore, two more research hypotheses were investigated to improve our understanding of the relationship between traffic flow variables and VR crashes as well as how these variables differ from those variables that are associated with CV crashes. The second research hypothesis was to compare crashes at poor visibility conditions vs. non-crash cases at clear visibility conditions. The third research hypothesis was to compare crashes vs. non-crash cases at clear visibility conditions.

Considering the results of the first and second research hypotheses, it was found that compared to non-crash cases at poor visibility conditions, higher occupancy at the nearest downstream station during 10-15 minutes before the crash coupled with an increase of the average speed upstream and downstream during 5-10 minutes prior to crash time, increase the likelihood of VR crash occurrence. However, compared to non-crash cases at clear visibility conditions, lower occupancy downstream along with a decrease of the average speed downstream and upstream, all during 5-10 minutes before the crash increase the likelihood of VR crash occurrence in between.

Regarding the results of the first and third research hypothesis, the results suggest that traffic flow variables leading to VR crashes are slightly different from those variables leading to CV crashes. It was found that, higher occupancy observed about half a mile between the nearest upstream and downstream station increases the risk for both VR and CV crashes. Moreover, an increase of the average speed observed on the same half a mile increases the probability of VR crash. On the other hand, high speed variation coupled with lower average speed observed on the same half a mile increase the likelihood of CV crashes. In summary, using time slices 5-15 minutes before crashes might provide an opportunity to the appropriate traffic management centers for a proactive intervention to reduce crash risk in real-time.

Additionally, this study aimed at identifying patterns (i.e., turbulence in the traffic flow) in the expressway AVI traffic data that potentially precede VR crashes. Also, it investigated which traffic data is advantageous for predicting VR crashes; data collected from LDs sensors installed on freeways or data collected from AVI sensors installed on expressways. Statistical links between turbulent traffic conditions and VR crash occurrences were established through a detailed analysis of LDs/AVI traffic data corresponding to VR crashes that occurred on freeways (I-4 and I-95) and on expressways (SR408 and SR417) in central Florida during the study time.

The approach adopted to achieve these goals involves developing Bayesian matched case-control logistic regression. The purpose of adopting this statistical approach was to explore the effects of traffic flow variables on VR crashes while controlling for the effects of other confounding variables such as crash time and the geometric design elements of freeway/expressway sections. To achieve these objectives, three models were estimated and discussed.

Historical VR crashes along with traffic data (time-mean speeds) collected from LDs on freeways were used to calibrate the first model (Model-1). The second model (Model-2) was calibrated using the same data but after converting it into space-mean speeds (to make it equivalent to AVI data). The results of both models indicated that the average speed observed at the nearest downstream station coupled with the coefficient of variation in speed observed at the nearest upstream station, all at 5-10 minute prior to the crash time, were found to have significant effect on VR crash risk. It has been shown that Model-1 and Model-2 achieved over 73% and 71% of VR crash identification, respectively. The performance of model-2 was then tested using historical VR crashes and AVI traffic data (space-mean speeds) collected from expressway (SR417 and SR408). It was found that about 65% of VR crashes were correctly identified. It can be noted that this classification accuracy is relatively comparable to the accuracy 71.64% obtained previously by Model-2 which may imply that Model-2 is performing well in correctly predicting the occurrences of VR crashes, however, one possible explanation for obtaining relatively lower classification accuracy when using the tested dataset is the differences between LDs and AVI arrangements (configurations). LDs sensors are spaced at approximately 0.5-0.8 mile compared to AVI sensors that are spaced at approximately 1.0-1.5 mile and hence, AVI data and LDs data may not match exactly.

Also historical VR crashes and space-mean speeds data collected from AVI sensors located on expressways (SR417 and SR408) were used for developing prediction model of VR crashes on expressways (Model-3). The results of the model revealed that an increase in the coefficient of variation in speed at the crash segment, 5-10 minutes before the crash time increases the likelihood of VR crashes. No variables from the upstream or downstream AVI segments were found significant possibly because the effect of fog/smoke or heavy rain is most likely localized and due to the longer Expressway segments. Model-3 achieved over 69% of VR crash identification.

One objective of this study was to investigate which data (LDs or AVI) is advantageous for predicting VR crashes. Considering the results of Model-3 and compared to the results of Model-1 and Model-2, it can be realized that LDs data is working slightly better than AVI data regarding the prediction of VR crashes possibly due to three reasons. First, the configuration (arrangement) of LDs and AVI sensors is different as discussed above (i.e., the distances between LDs sensors are less than the lengths of AVI segments). Second, AVI measures space-mean speeds by tracking the speed of vehicles through successive AVI sensors while, LDs measures time-mean speed (spot speeds) of vehicles at certain point (LDs stations) on a roadway. Third, the AVI sensors can only record and archive traffic data for vehicles that have AVI tags (i.e., transponders, E-pass, etc.). It is well established that about 80% of vehicles using expressways have AVI tags. On the other hand, LDs record and achieve traffic flow data for all vehicles travelling on the roadway. The findings from this study led us to infer that it may be better to develop VR crash risk assessment models based on LDs traffic data. However, the main disadvantage of LDs is that it sometimes fails due to sudden hardware problems which may lead to large missing data. In this case, using AVI or Radar data might be a good alternative for predicting VR crashes.

One should remember that both systems (LDs and AVIs) are installed without safety predictive application in mind. In other words, the results of this research indicate that both systems could be used for safety applications, although there is room for improvement in the AVI system (e.g., shorten AVI segments). Given that most roadways will have either systems, this study showed that risk predictive models could be implemented in both cases for VR crash prevention.

Using the results of this research; the risk of a VR crash may be continuously assessed using real-time traffic between any two loop detectors stations on the freeway or at any AVI segment on the expressway. Software will have to be adopted to estimate significant variables and the odds ratio obtained from the models developed in this study for LDs and AVIs data. Once a potential crash location is identified in real-time based on traffic flow characteristics collected from LDs or AVIs, measures for reducing speed variability before reaching the formed queue of traffic may be implemented in order to reduce the risk of VR crashes.

Subsequently, the next logical step toward VR crash prevention is to investigate the means of notifying the drivers of the potential of a VR crash. Changeable message signs, variable speed limit signs, highway advisory radio, and information for in-vehicle navigation systems could be employed to assist drivers in these adverse conditions in real-time to reduce the risk of VR crashes. These techniques would allow more proactive intervention and help reduce the crash potential under low visibility conditions. However, prior to field application, driver behavior needs to be thoroughly examined, possibly through a driving simulator experiment. For instance, this future effort will help to precisely determine when and how far from the upstream loop detector station or AVI segment to install a variable speed limit sign and will assess the benefits of implementing such measures regarding achieving more homogenous speeds and reducing the risk of VR crashes.

Finally, it worth mentioning that the results of this study are based on reduced visibility conditions due to fog, smoke or heavy rain. However, the conclusions and recommendations that were extracted from the current study could be valid and applicable for other reduced visibility conditions (e.g., sandstorm and snow).

APPENDIX A:

SURVEY OF FREEWAYS

UCF and FDOT safety study

Objective of the survey

Researchers at **the University of Central Florida (UCF)** are currently working on a **Florida Department of Transportation (FDOT)** sponsored project intended to reduce accidents on Florida's Highways. To help us achieve this goal, we would like to invite you to complete a survey. All answers are anonymous. There are no anticipated risks or direct benefits to you if you decide to participate. There is no penalty if you decide not to participate. You can end your participation at anytime and you do not have to answer any questions that you do not want to answer. The survey will take only about 5 minutes of your time.

WOULD YOU LIKE TO PARTICIPATE IN THIS SURVEY? If yes, please begin to answer survey's questions.

Are you 18 years old or older? (Yes, No) **(if "NO" terminate survey)**

Please choose one answer only in each of the following survey's questions

Personal information:

1) What is your gender?
   a) Male   b) Female

2) Which of the following best describes your age (in years)?
   a) 18-25   b) 26-35   c) 36-50   d) 51-65   e) over 65

3) What is the highest level of education that you have completed?
   a) Graduate school or higher   b) College degree   c) Some College
   d) High School   e) Did not graduate from high school

4) How long have you had a valid driver's license?......................years

5) Number of traffic citations (i.e. Traffic rule violations) in the previous 3 years?.............

6) Have you ever been involved in any crash, while you were driving in fog/smoke, due to reduction in visibility?
   a) Yes
   b) No

7) Have you ever been involved in any crash, while you were driving in heavy rain, due to reduction in visibility?
   a) Yes
   b) No

Survey Questions:

8) Have you driven on any freeways/expressways during the last month (e.g., SR 408, SR 417, I-4, I-95)?
   a) Yes
   b) No

9) How often do you use freeways/ expressways?
   (One way trip is considered as one time)
   a) More than four times a week
   b) Two-four times a week
   c) Once a week
   d) Once in two weeks
   e) Once a month
   f) Rarely or never

A Changeable Message Sign (CMS) is an electronic traffic sign often used on roadways to provide travelers with information about special events. Such signs warn of traffic congestion, accidents, roadwork zones, and inclement weather such as fog/smoke and heavy rain.

CMS

10) Have you ever encountered CMS on a freeway/ expressway?
   a)Yes
   b) No

A Variable Speed Limit sign (VSL) is an electronically adjustable speed limit to help manage the traffic flow (vehicles) along the freeway/expressway under various traffic and environmental conditions.

VSL

11) Have you ever encountered VSL on a freeway/ expressway?
   a) Yes
   b) No

12) If you are provided with information on CMS and/or VSL that is designed to help avoid a potential accident in case of reduced visibility due to fog/smoke on a freeway/expressway, would you agree to follow the advice provided?
   a) Strongly Agree
   b) Agree
   c) Neither agree nor disagree
   d) Disagree
   e) Strongly Disagree

13) Did you encounter any reduction in visibility due to fog, smoke, or heavy rain while you were driving on a freeway/expressway?
   a) Yes
   b) No **(if "NO" skip question 14)**

14) What did you do in that situation?
   a) Did nothing
   b) Followed other vehicles' speed. If they reduced their speed then you would also reduce your speed
   c) Drove below speed limit
   d) Drove below speed limit and put blinkers on
   e) Abandoned the journey and stopped the car immediately at the right shoulder of the road

15) From your point of view, in order to warn drivers about any reduction of visibility due to Fog/smoke, what message would you most likely comply with?
   a) Fog ahead- Reduce Speed
   b) Caution-Fog ahead-Reduce speed
   c) Fog ahead-Reduce speed-fine doubled
   d) Fog ahead- Reduce Speed- Strictly enforced
   e) Caution - Reduce speed – Strictly enforced
   f) Others, please specify:…………………………………………………………...

16) It is useful to use two successive CMS prior to Fog/ smoke zones to warn drivers about any sudden reduction in visibility due to fog/smoke. This could provide drivers another chance to see the warning message on CMS if they missed the first one. Do you agree or disagree with the previous statement?
   a) Strongly Agree
   b) Agree
   c) Neither agree nor disagree
   d) Disagree
   e) Strongly Disagree

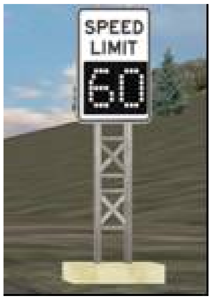
17) Do you agree or disagree that Changeable Message Signs (CMSs) are useful in warning drivers about any reduction in visibility due to fog/smoke and consequently reducing the chances of an accident?
   a) Strongly Agree
   b) Agree
   c) Neither agree nor disagree
   d) Disagree
   e) Strongly Disagree

18) Do you agree or disagree that Variable Speed Limit Signs (VSLs) are useful in reducing the number of fog related crashes by informing drivers about the safe speed limit at each visibility conditions (e.g., very light fog, light fog, medium fog, and heavy fog)?
   a) Strongly Agree
   b) Agree
   c) Neither agree nor disagree
   d) Disagree
   e) Strongly Disagree

19) From your point of view, which one of the following would improve safety during driving through fog/smoke on freeways/expressways?

a) Using CMS only
b) Using VSL sign only
c) Using CMS and VSL signs together
d) Closing the road during such adverse weather conditions.

CMS



VSL

If you were driving on a freeway at a speed of 65 mile/hour, and you encounter a CMS advising you to reduce your speed because of reduction in visibility due to Fog/smoke in order to reduce the chances of an accident. What would you do in each of the following cases?

No car leading ahead

20) a) Do nothing
b) Reduce speed immediately
c) Reduce speed after some time
d) Reduce speed and put blinkers on

car leading ahead

21) a) Do nothing
b) Reduce speed immediately
c) Reduce speed after some time
d) Follow other vehicles' speed regardless of CMS warning
e) Reduce speed and put blinkers on

If you were driving on a freeway with a speed limit of 65 mile/hour (mph), and you encounter a Variable Speed Limit (VSL) sign of 40 mile/hour (mph) in order to reduce the chances of accident that may occur because of a sudden reduction in visibility due to fog/smoke. What will you do in each of the following cases?

Note: in case you will reduce your speed (answers b or c), please specify your reduced speed in each of the following questions (questions 22 through 25)?

Very Light Fog

22) a) Do nothing
b) Reduce speed to ………..mph
(Please specify your reduced speed)
c) Put blinkers on and reduce speed to.…..mph
(Please specify your reduced speed)

Light Fog

23) a) Do nothing
b) Reduce speed to ………..mph
(Please specify your reduced speed)
c) Put blinkers on and reduce speed to.…..mph
(Please specify your reduced speed)

Medium Fog

24) a) Do nothing
b) Reduce speed to ………..mph
(Please specify your reduced speed)
c) Put blinkers on and reduce speed to.…..mph
(Please specify your reduced speed)

Heavy Fog

25) a) Do nothing
b) Reduce speed to ………..mph
(Please specify your reduced speed)
c) Put blinkers on and reduce speed to.…..mph
(Please specify your reduced speed)

Note: in case you will reduce your speed (answers c or d), please specify your reduced speed in each of the following questions (questions 26 through 29)?

Very Light Fog (some vehicles ahead)

26) a) Do nothing
  b) Follow other vehicles' speed.
  c) Reduce speed to ………..mph
   (Please specify your reduced speed)
  d) Put blinkers on and reduce speed to……mph
   (Please specify your reduced speed)

Light Fog (some vehicles ahead)

27) a) Do nothing
  b) Follow other vehicles' speed.
  c) Reduce speed to ………..mph
   (Please specify your reduced speed)
  d) Put blinkers on and reduce speed to……mph
   (Please specify your reduced speed)

Medium Fog (some vehicles ahead)

28) a) Do nothing
  b) Follow other vehicles' speed.
  c) Reduce speed to ………..mph
   (Please specify your reduced speed)
  d) Put blinkers on and reduce speed to……mph
   (Please specify your reduced speed)

Heavy Fog (some vehicles ahead)

29) a) Do nothing
  b) Follow other vehicles' speed.
  c) Reduce speed to ………..mph
   (Please specify your reduced speed)
  d) Put blinkers on and reduce speed to……mph
   (Please specify your reduced speed)

30) Suppose you encounter a sudden reduction in visibility due to fog, smoke, or heavy rain while you are driving on a freeway/expressway (as shown in the following pictures), which of the following best describe what you will do?

a) Do nothing
b) Drive below speed limit.
c) Drive below speed limit following the instructions of variable speed limit sign (VSL) and/or Changeable message sign (CMS), if they are available.
d) Follow other vehicles' speed. If they reduce their speed then you will also reduce your speed regardless of CMS and VSL warnings.
e) Drive below speed limit and put blinkers on
f) Abandon the journey and stop the car immediately at the right shoulder of the road

31) Suppose you encounter a sudden reduction in visibility due to fog, smoke, or heavy rain while you are driving on a freeway/expressway, rank the following responses from 1 to 6 where 1 is the safest action that will minimize the chance of an accident and 6 is the most dangerous action that will maximize the chance of an accident?

Responses	**Rank**
Do nothing	
Drive below speed limit.	
Drive below speed limit following the instructions of variable speed limit sign (VSL) and/or Changeable message sign (CMS), if they are available.	
Follow other vehicles' speed. If they reduce their speed then you will also reduce your speed regardless of CMS and VSL warnings.	
Drive below speed limit and put blinkers on	
Abandon the journey and stop the car immediately at the right shoulder of the road	

End of Survey
Thank you for participating in the survey!

APPENDIX B:

SURVEY OF TWO-LANE ROADS

<u>Objective of the survey</u>

Researchers at the **<u>University of Central Florida (UCF)</u>** are currently working on a **<u>Florida Department of Transportation (FDOT)</u>** sponsored project intended to reduce accidents on Florida's Highways. To help us achieve this goal, we would like to invite you to complete a survey. All answers are anonymous. There are no anticipated risks or direct benefits to you if you decide to participate. There is no penalty if you decide not to participate. You can end your participation at anytime and you do not have to answer any questions that you do not want to answer. The survey will take only about 5 minutes of your time.

WOULD YOU LIKE TO PARTICIPATE IN THIS SURVEY? If yes, please begin to answer survey's questions.

Are you 18 years old or older? (Yes, No) **(if "NO" terminate survey)**

Please choose one answer only in each of the following survey's questions

<u>Personal information:</u>

1) What is your gender?
   a) Male   b) Female

2) Which of the following best describes your age (in years)?
   a) 18-25   b) 26-35   c) 36-50   d) 51-65   e) over 65

3) What is the highest level of education that you have completed?
   a) Graduate school or higher   b) College degree   c) Some College
   d) High School   e) Did not graduate from high school

4) How long have you had a valid driver's license?......................years

5) Number of traffic citations (i.e. Traffic rule violations) in the previous 3 years?.............

6) Have you ever been involved in any crash, while you were driving in fog/smoke, due to reduction in visibility?
   a) Yes
   b) No

7) Have you ever been involved in any crash, while you were driving in heavy rain, due to reduction in visibility?
   a) Yes
   b) No

Survey Questions:

Two-lane road

8) Have you driven on any two lane roads during the last month?
   a) Yes
   b) No

9) How often do you use two lane roads?
   (One way trip is considered as one time)
   a) More than four times a week
   b) Two-four times a week
   c) Once a week
   d) Once in two weeks
   e) Once a month
   f) Rarely or never

A Changeable Message Sign (CMS) is an electronic traffic sign often used on roadways to provide travelers with information about special events. Such signs warn of traffic congestion, accidents, roadwork zones, and inclement weather such as fog/smoke and heavy rain.

CMS

10) Have you ever encountered CMS on a two lane road?
   a)Yes
   b) No

A Variable Speed Limit sign (VSL) is an electronically adjustable speed limit to help manage the traffic flow (vehicles) under various traffic and environmental conditions.

VSL

11) Have you ever encountered VSL on a two lane road?
   a) Yes
   b) No

12) If you are provided with information on CMS and/or VSL that is designed to help avoid a potential accident in case of reduced visibility due to fog/smoke on a two way-two lane road, would you agree to follow the advice provided?
   a) Strongly Agree
   b) Agree
   c) Neither agree nor disagree
   d) Disagree
   e) Strongly Disagree

13) Did you encounter any reduction in visibility due to fog, smoke, or heavy rain while you were driving on a two lane road?
   a) Yes
   b) No **(if "NO" skip question 14)**

14) What did you do in that situation?
   a) Did nothing
   b) Followed other vehicles' speed. If they reduced their speed then you would also reduce your speed
   c) Drove below speed limit
   d) Drove below speed limit and put blinkers on
   e) Abandoned the journey and stopped the car immediately at the right shoulder of the road

15) From your point of view, in order to warn drivers about any reduction of visibility due to Fog/smoke, what message would you most likely comply with?
   a) Fog ahead- Reduce Speed
   b) Caution-Fog ahead-Reduce speed
   c) Fog ahead-Reduce speed-fine doubled
   d) Fog ahead- Reduce Speed- Strictly enforced
   e) Caution - Reduce speed – Strictly enforced
   f) Others, please specify:………………………………………………………...

16) It is useful to use two successive CMS prior to Fog/ smoke zones to warn drivers about any sudden reduction in visibility due to fog/smoke. This could provide drivers another chance to see the warning message on CMS if they missed the first one. Do you agree or disagree with the previous statement?
   a) Strongly Agree
   b) Agree
   c) Neither agree nor disagree
   d) Disagree
   e) Strongly Disagree

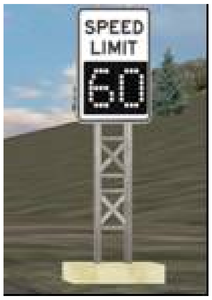
17) Do you agree or disagree that Changeable Message Signs (CMSs) are useful in warning drivers about any reduction in visibility due to fog/smoke and consequently reducing the chances of an accident?
   a) Strongly Agree
   b) Agree
   c) Neither agree nor disagree
   d) Disagree
   e) Strongly Disagree

18) Do you agree or disagree that Variable Speed Limit Signs (VSLs) are useful in reducing the number of fog related crashes by informing drivers about the safe speed limit at each visibility conditions (e.g., very light fog, light fog, medium fog, and heavy fog)?
   a) Strongly Agree
   b) Agree
   c) Neither agree nor disagree
   d) Disagree
   e) Strongly Disagree

19) From your point of view, which one of the following would improve safety during driving through fog/smoke on two lane roads?

a) Using CMS only
b) Using VSL sign only
c) Using CMS and VSL signs together
d) Closing the road during such adverse weather conditions.

CMS



VSL

If you were driving on a two lane road at a speed of 45 mile/hour (mph), and you encounter a CMS advising you to reduce your speed because of reduction in visibility due to Fog/smoke in order to reduce the chances of an accident. What would you do in each of the following cases?

No car leading ahead

car leading ahead

20) a) Do nothing
b) Reduce speed immediately
c) Reduce speed after some time
d) Reduce speed and put blinkers on

21) a) Do nothing
b) Reduce speed immediately
c) Reduce speed after some time
d) Follow other vehicles' speed regardless of CMS warning
e) Reduce speed and put blinkers on

If you were driving on a two lane road with a speed limit of 45 mile/hour (mph), and you encounter a Variable Speed Limit (VSL) of 25 mile/hour (mph) in order to reduce the chances of accident that may occur because of a sudden reduction in visibility due to fog/smoke. What will you do in each of the following cases?

Note: in case you will reduce your speed (answers b or c), please specify your reduced speed in each of the following questions (questions 22 through 25)?

Very Light Fog

22) a) Do nothing
b) Reduce speed to ………..mph
(Please specify your reduced speed)
c) Put blinkers on and reduce speed to……mph
(Please specify your reduced speed)

Light Fog

23) a) Do nothing
b) Reduce speed to ………..mph
(Please specify your reduced speed)
c) Put blinkers on and reduce speed to……mph
(Please specify your reduced speed)

Medium Fog

24) a) Do nothing
b) Reduce speed to ………..mph
(Please specify your reduced speed)
c) Put blinkers on and reduce speed to……mph
(Please specify your reduced speed)

Heavy Fog

25) a) Do nothing
b) Reduce speed to ………..mph
(Please specify your reduced speed)
c) Put blinkers on and reduce speed to……mph
(Please specify your reduced speed)

Note: in case you will reduce your speed (answers c or d), please specify your reduced speed in each of the following questions (questions 26 through 29)?

Very Light Fog (some vehicles ahead)

26) a) Do nothing
 b) Follow other vehicles' speed.
 c) Reduce speed to ………..mph
 (Please specify your reduced speed)
 d) Put blinkers on and reduce speed to……mph
 (Please specify your reduced speed)

Light Fog (some vehicles ahead)

27) a) Do nothing
 b) Follow other vehicles' speed.
 c) Reduce speed to ………..mph
 (Please specify your reduced speed)
 d) Put blinkers on and reduce speed to……mph
 (Please specify your reduced speed)

Medium Fog (some vehicles ahead)

28) a) Do nothing
 b) Follow other vehicles' speed.
 c) Reduce speed to ………..mph
 (Please specify your reduced speed)
 d) Put blinkers on and reduce speed to……mph
 (Please specify your reduced speed)

Heavy Fog (some vehicles ahead)

29) a) Do nothing
 b) Follow other vehicles' speed.
 c) Reduce speed to ………..mph
 (Please specify your reduced speed)
 d) Put blinkers on and reduce speed to……mph
 (Please specify your reduced speed)

30) Suppose you encounter a sudden reduction in visibility due to fog, smoke, or heavy rain while you are driving on a two lane road (as shown in the following pictures), which of the following best describe what you will do?

a) Do nothing
b) Drive below speed limit.
c) Drive below speed limit following the instructions of variable speed limit sign (VSL) and/or Changeable message sign (CMS), if they are available.
d) Follow other vehicles' speed. If they reduce their speed then you will also reduce your speed regardless of CMS and VSL warnings.
e) Drive below speed limit and put blinkers on
f) Abandon the journey and stop the car immediately at the right shoulder of the road

31) Suppose you encounter a sudden reduction in visibility due to fog, smoke, or heavy rain while you are driving on a two lane road, rank the following responses from 1 to 6 where 1 is the safest action that will minimize the chance of an accident and 6 is the most dangerous action that will maximize the chance of an accident?

Responses	**Rank**
Do nothing	
Drive below speed limit.	
Drive below speed limit following the instructions of variable speed limit sign (VSL) and/or Changeable message sign (CMS), if they are available.	
Follow other vehicles' speed. If they reduce their speed then you will also reduce your speed regardless of CMS and VSL warnings.	
Drive below speed limit and put blinkers on	
Abandon the journey and stop the car immediately at the right shoulder of the road	

End of Survey
Thank you for participating in the survey!

APPENDIX C:

APPROVAL OF EXEMPT HUMAN RESEARCH FROM IRB

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 Exempt Human Research

From:	**UCF Institutional Review Board #1** **FWA00000351, IRB00001138**
To:	**Mohamed A Abdel-Aty**
Date:	**September 18, 2009**

Dear Researcher:

On 9/18/2009, the IRB approved the following activity as human participant research that is exempt from regulation:

Type of Review:	Initial Review
Project Title:	Developing an Early Detection System for Reduced Visibility from Fog/Smoke and Means to Effectively and Timely Warn Drivers
Investigator:	Mohamed A Abdel-Aty
IRB Number:	SBE-09-06417
Funding Agency:	FL Department of Transportation
Grant Title:	Developing an Early Detection System for Reduced Visibility from Fog/Smoke and Means to Effectively and Timely Warn Drivers
Research ID:	16507071

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB.

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

On behalf of Joseph Bielitzki, DVM., UCF IRB Chair, this letter is signed by:

Signature applied by Janice Turchin on 09/18/2009 09:41:02 AM EDT

IRB Coordinator

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