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16. Abstract

This report is a compilation of research papers written by students participating in the 2015 Undergraduate Transportation Scholars Program. The 10-week summer program, now in its 25th year, provides undergraduate students in Civil Engineering the opportunity to learn about transportation engineering through participating in sponsored transportation research projects. The program design allows students to interact directly with a Texas A&M University faculty member or Texas A&M Transportation Institute researcher in developing a research proposal, conducting valid research, and documenting the research results through oral presentations and research papers.

The papers in this compendium report on the following topics: 1) Traffic Safety Issues and Commercial Motor Vehicle Crashes: A Case Study in the Eagle Ford Shale; and 2) Differences Between Familiar and Unfamiliar Drivers.

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COMPENDIUM OF STUDENT PAPERS: 2015 UNDERGRADUATE TRANSPORTATION SCHOLARS PROGRAM

Dr. David Bierling (Mentor), Ms. Michelle Anderson, Ms. Katherine Foreman, and Dr. Bradford Brimley (Mentor)

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PREFACE

The Southwest Region University Transportation Center (SWUTC), through the Transportation Scholars Program, the Texas A&M Transportation Institute (TTI) and the Zachry Department of Civil Engineering at Texas A&M University, established the Undergraduate Transportation Engineering Fellows Program in 1990. The program design allows students to interact directly with a Texas A&M University faculty member or TTI researcher in developing a research proposal, conducting valid research, and documenting the research results through oral presentations and research papers. The intent of the program is to introduce transportation engineering to students who have demonstrated outstanding academic performance, thus developing capable and qualified future transportation leaders.

In summer 2015, the following students and their faculty/staff mentors were:

STUDENTS	MENTORS
Michelle Anderson The University of Alabama at Huntsville	Dr. David Bierling
Katherine A. Foreman The University of Louisiana at Lafayette	Dr. Bradford K. Brimley

Sincere appreciation is extended to the following individuals:

- Mrs. Colleen Dau, who assisted with program administrative matters and Mrs. Barbara Lorenz in the preparation of the final compendium.

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CONTENTS

DISCLAIMER

The contents of this report reflect the view of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Traffic Safety Issues and Commercial Motor Vehicle Crashes: A Case Study in the Eagle Ford Shale

Prepared for
Undergraduate Transportation Scholars Program

by

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Michelle Anderson is a junior at The University of Alabama in Huntsville. She is expected to graduate May 2017 with a bachelor of science in civil engineering, emphasizing on structures, along with a minor in mathematics. She has been awarded the Top of the Class Award, Charger Scholars Award, Carl T. Jones Scholarship, and has been recognized on the Dean's List from spring 2013 to spring 2014.

Aside from being devoted to her studies, Michelle is an active member in many organizations, including the Society of Women Engineers, Tau Beta Pi, Charger Chasers Engineering Ambassadors, Reformed University Fellowship, and the local Volunteer Fire Department. She also holds leadership positions in the American Society of Civil Engineers, National Society of Leadership and Success, and Kappa Delta. Upon graduation, Michelle plans to pursue her career path in the Navy and continue on to graduate school. She is currently going through the process to join the Nuclear Propulsion Officer Program and will later transfer to the Civil Engineer Corps.

ACKNOWLEDGMENT

The research described in this paper was funded as independent research through the Southwestern University Transportation Center (SWUTC) and Texas A&M Transportation Institute's (TTI) Center for Transportation Safety. The research activities were conducted in support of the Undergraduate Transportation Scholars Program. The findings and recommendations included in this paper are based on the student's summer activities. The contents of this paper reflect the views of the author, who is responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official view or policies of SWUTC or TTI.

The author would like to express her appreciation to Michael Martin, Jena Prescott, and Troy Walden for their assistance and support during the course of this project. She would also like to thank Robert Wunderlich, the Director of the Center of Transportation Safety, for providing funding support for this project.

SUMMARY

Commercial motor vehicles (CMV) are important for the U.S. and Texas economies by providing a means of transportation for everyday goods. Increases in CMV traffic pose crash risks and corresponding increases in traffic delay, dangers to the environment, and delays in the provision of goods to consumers. Trucking activity has been exceptionally common in recent energy development areas, including in Texas. One of the most active shale plays in the world is the Eagle Ford Shale, producing both oil and gas. The recent expansion in energy development activity in energy production areas has led to significant increases in truck and overall traffic, as well as increases in crashes and fatalities.

The goal of the research project was to identify violations and issues associated with at-fault CMV crashes in the Eagle Ford Shale area, and identify their impacts. A sample of crash data from 2010 to 2013 for the Eagle Ford Shale was drawn for this study for three counties: Bee, Live Oak, and McMullen. Secondary data from the CRIS database were used for this project. Only crashes involving CMVs were considered. Information recorded for each vehicle unit was used to determine which vehicle was at-fault and what factors and/or charges were associated with crashes. The factors and charges were combined to create issue groups. A crash severity scale was assigned to each crash. The relationship in frequency and severity of issues was also examined across hazmat and non-hazmat loads, highways systems, and each county (Bee, Live Oak, and McMullen).

The results suggest that reported driver violations are associated more frequently than vehicle violations with at-fault CMV crashes in the study area. Lane use, speeding and following too closely, and distracted driving were the most-frequently identified issues for at-fault CMV crashes. There were no differences in relative prevalence of issues across hazmat and non-hazmat loads. Faulty evasive action was more prevalent on U.S. highways than interstates. Crashes due to driver fatigue were more frequent on U.S. highways than Farm-to-Market roads. Also, there were proportionately fewer distracted driving issues in Bee County than Live Oak County. For Bee County, there were proportionately greater vehicle load and defect issues that the other two counties. Overall, driver issues were associated with at least 80 percent of crashes, and 100 percent of fatalities for the study area.

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INTRODUCTION

Commercial motor vehicles (CMVs) play a pivotal role in the economy by transporting freight to specific, diverse locations. Trucks are a key mode of transportation for the timely distribution of perishable goods like food and other cargo including agricultural commodities, natural resources, chemicals, construction materials, household goods, etc. In 2014, according to the American Trucking Associations, trucking companies employed over 7 million people, 3.4 million as drivers. Companies moved 9.6 billion tons of freight, which accounted for 68.8 percent of all domestic freight. Overall, the trucking industry topped $700 billion in generated revenue for 2014 (*1*).

CMV traffic also poses risks including the danger of accidents, increase in traffic delay, damage to the environment through releases of hazardous materials and fuel combustion emissions, and more. The Federal Motor Carrier Safety Administration's (FMCSA) report, *Motor Carrier Safety Progress Report*, projected an overall increase in truck crashes for 2014 compared with 2013, based on crash statistics for the first six months of 2014. With more than 99,000 truck accidents reported for the first half of 2014, a 57.9 percent increase was expected if the trend were to continue (*2*). The rise in road traffic accidents continues to be a major concern for the safety of the public.

Rules, enforcement, and promotion of voluntary initiatives are three essential categories used to address driver and truck safety (*3*). According to the *Commercial Motor Vehicle Traffic Enforcement* (CMVTE) report, published by the National Highway Traffic Safety Administration (NHTSA), enforcement efforts need to increase for issues regarding moving violations, zero tolerance policy, and truck hours of service (*4*). A study by Carson found that driver, vehicle and cargo, and operating environment are characteristics that contribute to CMV safety risks (*5*). The CMVTE report estimated that 90 percent of CMV crashes happened due to the fault of the driver (*4*). While there are many factors that can contribute to any crash, driver age, personality, vehicle configuration, and adverse weather conditions are just a few examples (*5*).

Trucking activity has been especially prevalent in recent energy development areas across the United States, including in Texas. According to the South Texas Energy and Economic Roundtable (STEER), the 50 mile wide, 400 mile long and approximately 250 foot deep Eagle Ford Shale is the most active shale play in the world, producing both oil and gas. The economic impact of the shale development has fundamentally changed the region. In 2012, more than 116,000 full-time jobs were associated with the $61 billion impact (*6*). With the population growth and massive expansion in energy development, the area saw significant increases in traffic. The *Houston Chronicle* notes that accidents boomed along with drilling activity: from 2009 to 2014, fatalities in accidents that involved heavy trucks increased by 50 percent (*7*).

BACKGROUND

The section provides contextual information about trucking activity and accidents that help frame the objectives and significance of the research conducted for this study.

Characteristics

Carson organized a review of literature on large truck crash frequency and severity, focusing on contributing driver, vehicle, cargo, carrier, and operating environment characteristics to safety levels (*5*). Among the contributing characteristics identified in that review are those associated with drivers, vehicles and cargo, and operating environments (*5*). The sections below discuss these factors.

Driver Characteristics

Driver age, driving history, personality, and sensory motor abilities are some of the factors that contribute to large truck safety. The Transportation Research Board (TRB) conducted a literature review as part of a project on whether older commercial drivers posed a safety risk. The project report identified that commercial drivers over the age of 51 were least responsible for CMV crashes (*8*). Another project conducted by TRB examined factors leading to high risks for CMV drivers. Four main error categories that led to crash risk were identified in the report: violations, mistakes, inattention errors, and inexperience errors. Many of these errors are a result of driver personality, driving history (lack of experience), and sensory motor skills. Some examples include intentionally exceeding speed limits, misjudging stopping distance, failure to notice signs, and driving in too low of a gear (*9*). Carson cited Federal Highway Administration (FHWA) statistics that "roughly 22 percent of large truck fatal crashes involving more than one vehicle are speed-related" (*5*). In a report conducted by The University of Michigan Transportation Research Institute, over 64 percent of moving violations, among young drivers, were attributed to speeding and unsafe speed (*10*).

Other driver behaviors that affect traffic safety include cell phone use, aggressive driving, and drug and alcohol influence. Using a handheld phone while driving could not only result in civil penalties and driver disqualification, but also increase the chance of being involved in a crash. The chance of being involved in a safety-critical event increases by 23.2 times for CMV drivers who text while driving. The chance increases by six times for CMV drivers who dial a mobile phone while driving (*11*). Personality traits, such as dispositional anger and aggression cause people to engage in higher levels of aggressive, negative emotional, and risky driving (*12*). Carson conducted a literature review on alcohol and drug abuse among CMV drivers. In that review, alcohol and drug use statistics for truck drivers were not identified as major contributing factors in crashes; however, alcohol and drug use in large truck crashes contributed to more severe injuries and fatalities (*5*). The TRB also cited statistics collected by FMCSA and NHTSA on alcohol and illegal drug use of commercial drivers. While drug and alcohol use were not found to be major factors in crashes, drug and alcohol abusers are considered high-risk drivers (*9*).

Vehicle and Cargo Characteristics

Vehicle and cargo characteristics are important to keep in mind when reviewing large truck safety data. The vehicle's configuration, cargo body type, gross vehicle weight rating, and whether cargo is present are just a few factors that may be of concern. The *Large Truck Crash Causation Study* (LTCCS) estimates that 8,000 out of 78,000 trucks, or 10 percent, were involved in crashes nation-wide due to vehicle related factors in which truck-related violations were assigned as the critical reason for crashes (*13*). Of the associated factors, brake deficiency contributed most to crash risk, followed by tire deficiency, and overweight vehicle (*13*). Among the literature review conducted by Carson, mechanical condition and cargo characteristics were reviewed. Of single CMVs involved in crashes, 77 percent were found to have defective equipment justifying citation and 41 percent were found to have defective equipment qualifying to take the vehicle out of service. While improperly secured loads contributed to 2 percent of large truck crashes, a higher crash rate was found for CMVs carrying a load rather than being empty (*5*). The *Large Truck and Bus Crash Facts 2013* noted that 60 percent of fatal large truck crashes were truck tractors pulling a single semi-trailer. Also, single unit, two axle trucks accounted for 17.5 percent of fatal crashes and single-unit, three axle trucks contributed 10.6 percent. Trucks with the van/enclosed box cargo type accounted for 42.3 percent of fatal crashes while flatbeds presented 11.7 percent. Of trucks that were carrying hazardous materials, flammable liquids and gases counted the most for both fatal and nonfatal crashes. In hazmat truck crashes, the hazardous material release for flammable liquids in fatal crashes was 75.6 percent. Large trucks with a gross weight vehicle rating exceeding 26,000 lb had higher crash rates than those between 10,001 lb and 26,000 lb (*14*).

Operating Environment Characteristics

Other factors including weather conditions, roadway, traffic, and setting characteristics contribute to safety levels. Different light and roadway design conditions are some factors that can contribute to crashes. According to the *Large Truck and Bus Crash Facts 2007*, more accidents happen during the daylight than any other light condition. Over 80 percent of fatal, injury, and property damage accidents happened when the road surface was dry or when normal weather conditions were present. Higher crash rates were present during the weekdays than during the weekend. Also, 51.2 percent of fatal crashes happened on roads where the traffic flow was not physically divided whereas roadways with a divided median without a barrier accounted for 28.2 percent of fatal crashes (*14*). Among the literature review conducted in Carson, certain road characteristics were noted to increase truck crashes. As the degree of horizontal curvature and vertical grade increase, expected number of truck crashes also increase. Crash rates are also reported to be higher when there are either very high or very low traffic volumes (*5*).

GOALS AND OBJECTIVES

The literature reviewed above identified factors associated with drivers, vehicles, and operating environments as having significant effects on CMV traffic safety. While many factors might be considered in these categories, this study focuses on a limited set of driver, vehicle, and operating environment characteristics found in the Crash Report Information System (CRIS) data for Texas. For drivers, these factors include speed, cell phone use, aggressive driving, and drug and alcohol influence. For vehicles, these factors include inoperative equipment, failure to make repairs, and improper load securement. For operating environment, these factors include Bee Live Oak, and McMullen Counties.

The overall goal of the research project is to identify issues that contribute to at-fault commercial motor vehicle crashes in the Eagle Ford Shale and their corresponding impacts. The following measurable objectives are used to achieve this goal:

- Determine which issues contribute to at-fault commercial motor vehicle crashes.
- Assess the importance of these issues based on both frequency and severity.
- Analyze the data to understand how these issues contribute to crash risk.
- Identify the relationships between violations and at-fault commercial motor vehicle crashes.
- Describe opportunities for intervention.

The first research hypothesis examines the occurrence of driver and vehicle violations in at-fault CMV crashes. The hypothesis is that driver violations contribute more than vehicle violations to at-fault CMV crashes.

The second research hypothesis is that exceeding the speed limit, drug and alcohol use, aggressive driving, and cell phone use are important driver violations in at-fault CMV crashes. The hypothesis is that these violations will contribute the most to at-fault CMV crashes.

The third research hypothesis is that inoperative equipment, failure to make repairs, and improper load securement are important vehicle violations in at-fault CMV crashes. The hypothesis is that these violations will contribute more than other vehicle violations to at-fault CMV crashes.

DATA COLLECTION AND REVIEW

Secondary data from the CRIS database were used in this research. This database is comprised of crash data collected from the Texas Peace Officer's Crash Report. There are multiple data fields associated with these crashes including crash, vehicle, and person data, as well as outcomes such as property damage, injuries, and fatalities (*15*). Data for three counties (Bee, Live Oak, McMullen, all a part of the Eagle Ford Shale as shown in Figure 1) from 2010–2013 were extracted from the CRIS database and exported to Excel worksheets. Per Institutional Review Board requirements, personal identifier information and crash narratives were not included in the data extraction.

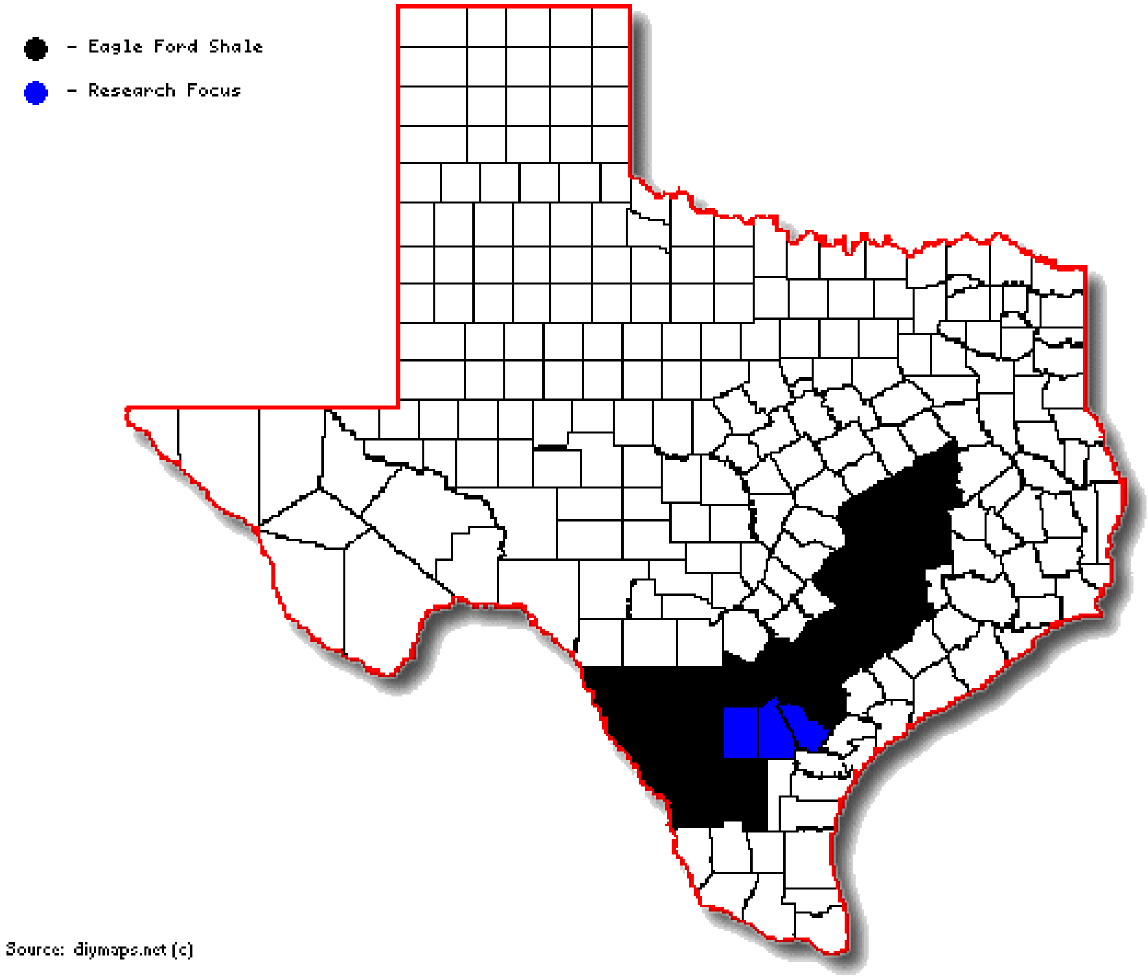

Figure 1. Eagle Ford Shale Region

A review of existing variables was conducted and certain variables related to drivers, vehicles, and operating environments were selected for analysis. Table 1 lists the variables that were utilized for the review. Each variable was assigned to a category that corresponds to the corresponding CMV characteristics. Personal identifier information and corresponding driver characteristics (age, gender, ethnicity, etc.) were not considered in this study.

Table 1. Data Variables

Category	Variables
Vehicle and Cargo	Vehicle Unit Number Vehicle Unit Description Vehicle Model Year Vehicle Make Vehicle Model Vehicle Body Style Vehicle CMV Flag Hazmat Flag CMV Carrier ID Type CMV Roadway Access CMV Vehicle Type CMV Cargo Body Style Vehicle Defect
Operating Environment	Crash Construction Zone Flag Crash Worker Present Flag Weather Condition Light Condition Road Type Intersection Related County Highway System
Other	Crash CMV Involved Flag Crash Thousand Dollar Damage Flag First Harmful Event Manner of Collision Group Manner of Collision Object Stuck Other Factor Crash Severity TTI Unit ID Vehicle Parked Flag Vehicle Hit and Run Flag Contributing Factor 1 Contributing Factor 2 Contributing Factor 3 Possible Contributing Factor 1 Possible Contributing Factor 2 Incapacitating Injuries Non-Incapacitating Injuries Possible Injuries Non-Injuries Unknown Injuries Fatalities

DATA REDUCTION AND ANALYSIS

A three county sample from counties that comprise the Eagle Ford Shale Region was used for this study: Bee, Live Oak, and McMullen Counties.

The data set was first evaluated to designate which cases were to be included in the analysis. Three variables were used to select cases: one variable was used to confirm the validity of included cases, another to identify at-fault vehicles, and a third to confirm that crash units (vehicles) were CMVs. Next, the data were reviewed to categorize contributing factors, violations, and issues associated with crashes, and assign crash severity.

Selection Variables

Case Validity

Because it is important that the cases included in the analysis are valid, the data were reviewed for consistency across information reported for crashes. A new variable, *Valid Case Flag*, was created and used to assign whether or not data were consistent for each case. The variables that were reviewed for this evaluation include:

- Person Charge.
- Contributing Factor 1.
- Contributing Factor 2.
- Contributing Factor 3.
- Possible Contributing Factor 1.
- Possible Contributing Factor 2.
- Crash Severity.
- Incapacitating Injuries.
- Non-Incapacitating Injuries.
- Possible Injuries.
- Non-Injuries.
- Unknown Injuries.
- Fatalities.

There were two cases in which the reported charge and contributing factors were not consistent. These crash IDs were designated as invalid and were not used for the analysis. Also, there were a handful of cases where injury data were not recorded for vehicle units, suggesting that the crash reports were incomplete. To validate these cases, the crash IDs associated with the units that were missing information were double checked with the data for the overall crash report. One of the variables in the original CRIS data, *Crash Severity*, indicated the overall severity for each crash. After reviewing the crash reports that were missing injury data, it was found that in some cases, a crash severity had been assigned to the vehicle unit. By assuming the crash severity assigned for these cases was correct, these cases were included in the data set. One of the fatal crashes was excluded due to missing and inconsistent information about the units involved in the crash and corresponding injury/fatality information.

At-Fault Determination

At least one unit per crash was designated as being at-fault, whether it was a CMV or another type of vehicle. The assignment of at-fault to a unit was recorded using a new dichotomous variable, *At Fault Code*, and based on the reported contributing factors, possible contributing factors, vehicle defects, and person charges. In some scenarios, more than one unit was designated to be at-fault. The process used to determine which units were found to be at-fault is explained further in Appendix A.

Commercial Motor Vehicle Designation

In the data set, there were two original variables, *CMV Flag* and *Crash CMV Involved Flag*, which indicated whether a CMV was involved in a crash. A new dichotomous variable called *CMV Check* was created to verify that each unit flagged as a CMV was correct. The data for the variable *Vehicle Body Style* were compared with data for units designated as CMVs under *CMV* Flag and *Crash CMV Involved Flag* to validate whether vehicles in each crash were commercial motor vehicles. Upon examining the data for units flagged as CMVs in the data set, some inconsistencies were found and adjusted for using the new *CMV Check* variable. Table 2 indicates how these inconsistencies were identified and adjusted for crashes involving commercial motor vehicles.

Table 2. Selected CMV Categories and CMV Verification Variables.

Vehicle Body Style	CMV Flag	CMV Check
Sport Utility Vehicle	Yes	No
Passenger Car	Yes	No
Van	Yes	No
Pickup	Yes	Yes
Pickup	No	No
Truck	Yes	Yes
Truck	No	Yes

All sport utility vehicles, vans, and passenger cars that were flagged as CMVs by the original variables were indicated as not CMVs in the *CMV Check* variable since they were not commercial motor vehicles. The pickups that were recorded as CMVs were assumed to be hot shots, and were left flagged as yes in the *CMV Check* variable. The trucks (tractors) that were coded in the original data set as not CMVs were changed to yes since they were assumed to be CMVs. Pickups that were found to originally be coded as not a CMV were left as no in the *CMV Check* variable because they were assumed to not be hot shots.

Data Classifications and Groupings

The following variables were taken into account when classifying and grouping person charges, contributing factors, and vehicle defects:

- Person Charge.
- Contributing Factor 1.
- Contributing Factor 2.
- Contributing Factor 3.
- Possible Contributing Factor 1.
- Possible Contributing Factor 2.
- Vehicle Defect.

Factor groups and charge groups were created by grouping similar concepts together. Table 3 lists the factor, charge, and issue groups used for this study. The contributing factors, possible contributing factors, and vehicle defects were combined and categorized into 17 new factor groups. The person charges were also categorized into 12 new charge groups. These groups were created as new dichotomous variables that indicated if a factor and/or charge were reported for each unit in each crash. Next, 16 new issue categories were created by combining the factor and charge categories. Factor, charge, and issue groups were assigned to each unit (vehicle) in the data set, irrespective of whether the vehicle was indicated as a CMV. Since factor and charge groups shared some of the same categories, the issues were flagged present as long as they were displayed in either the factor and/or charge group. For further information about which charges and factors were grouped together in a group, refer to Appendix B.

Table 3. Category Combination.

CATEGORY COMBINATION		
Factor Groups	**Charge Groups**	**Issue Groups**
Drug and Alcohol Influence	Drug and Alcohol Influence	Drug and Alcohol Influence
Criminal Behavior	Criminal Behavior	Criminal Behavior
	Accident Procedure	Accident Procedure
Fatigue		Fatigue
Distracted Driving		Distracted Driving
Owner/Operator*	Owner/Operator*	Owner/Operator*
Right of Way	Right of Way	Right of Way
Turning	Turning	Turning
Backing	Backing	Backing
Lane Use	Lane Use	Lane Use
Speed	Speed	Speed
Following Too Closely	Following Too Closely	Following Too Closely
Faulty Evasive Action		Faulty Evasive Action
Vehicle Load	Vehicle Load	Vehicle Load
Vehicle Defect	Vehicle Defect	Vehicle Defect
Animal		Animal
Not Applicable**		
Other (Explain in Narrative)**		

**Owner/Operator* includes issues that are the responsibility of the vehicle owner or operator such as wearing a seat belt, having a valid driver license or insurance, and maintaining vehicle inspection and registration. This convention applies to this and all subsequent tables in this report.
***Not Applicable* and *Other (Explain in Narrative)* were not created as two Issue Groups since the information provided was not sufficient for assigning a specific issue group.

Violations

Violations were examined separately from issues since not all issues were as associated with breaking the law. The original data were reviewed to determine which charges, factors, and vehicle defects were possible violations.[1] The variables that were reviewed include:

- Person Charge.
- Contributing Factor 1.
- Contributing Factor 2.
- Contributing Factor 3.
- Possible Contributing Factor 1.
- Possible Contributing Factor 2.
- Vehicle Defect.

A new variable, *Violation Flag*, was created to identify if a unit had a violation (or not) based on the associated individual charges, factors, and vehicle defects. Another variable, *CMV Violation Flag*, was created to identify only those violations flagged for commercial motor vehicles. All of the charges and most of the factors and vehicle defects were found to be violations. For further information about determination and assignment of violations, refer to Appendix C.

Crash Severity

The original CRIS data indicated the number of unknown injuries, non-injuries, possible injuries, non-incapacitating injuries, incapacitating injuries, and fatalities were linked to each unit per crash. A variable in the original CRIS data also indicated whether property damage over $1,000 resulted from a crash. Another original variable, *Crash Severity*, indicated the overall severity of each crash. However, since this crash severity only accounted for injuries and not property damage, a different severity variable, called *Crash Event Severity (Highest Impact)* was created, as described in Appendix D.

ANALYSIS

After completing the data reduction, cross tabulations and rankings were used to analyze the data. For the analysis, some issue groups were combined to help organize and display the results.

RESULTS

This section discusses the crash violations, issues, and outcomes for at-fault CMV crashes in the study area.

Table 4 lists the frequencies and percentages of driver and vehicle violations associated with at-fault CMV crashes in the study area. Driver violations accounted for approximately 92 percent of the violations in at-fault CMV crashes, while vehicle violations accounted for approximately

[1] This study uses a designation of possible violations since information about the final adjudication of assigned charges was not available. Hereafter, this study refers to these possible violations as violations.

8 percent. The data appear to support the first research hypothesis that driver violations contributed more to at-fault CMV crashes than vehicle violations.

Table 4. Driver and Vehicle Violation Frequencies for At-Fault CMV Crashes.

Violation	Frequency	Percentage of Violations
Driver • Speed • Lane Use • Distracted Driving • Faulty Evasive Action • Right of Way • Fatigue • Owner/Operator • Turning • Backing • Following Too Closely • Accident Procedure • Criminal Behavior • Drug and Alcohol Influence	492	91.96%
Vehicle • Vehicle Defect • Vehicle Load	43	8.04%

Table 5 lists the frequencies and percentages of the driver and vehicle violations associated with at-fault CMV crashes in the study area. For the second research hypothesis, occurrence of exceeding the speed limit, following too closely, drug and alcohol influence, and cell phone use were considered. Exceeding the speed limit and driving too closely were also combined as an indicator of aggressive driving violations. The data appear to support that speed and aggressive driving are frequent driver violations; however, the data do not appear to support that drug and alcohol influence and cell phone use are frequent CMV driver violations for these crashes.

For the third research hypothesis, occurrence of inoperative equipment, failure to make repairs, and improper load securement were considered. Failure to Make Repairs was not cited as a contributing factor for any of the crashes in the data set. The data appear to support that inoperative equipment is a relatively frequent vehicle violation in at-fault CMV crashes in the study area, accounting for approximately 8 percent of overall violations, and 60 percent of vehicle violations. The data also appear to support that improper load securement is an important vehicle violation, accounting for approximately 2 percent of overall violations, and 28 percent of vehicle violations. The data do not appear to support that failure to make repairs is an important vehicle violation for these crashes.

Table 5. Frequency of Certain Driver and Vehicle Violations.

Violation	Frequency	Percentage of Violations
Driver		
Speed	97	18.13%
Drug and Alcohol Influence	1	0.19%
Aggressive Driving • Speed • Following Too Closely	101	18.88%
Cell Phone Use	1	0.19%
Vehicle		
Inoperative Equipment	29	5.42%
Failure To Make Repairs	0	0.00%
Improper Load Securement	12	2.24%

The sections above discussed the occurrence of reported violations in at-fault CMV crashes in the study area. This study also examined the issues that were associated with at-fault CMV crashes. Crash issues differ from violations in that issues identify all problems associated with crashes, while violations identify cases of breaking the law.

Figure 2 illustrates the frequencies of issues that occurred in at-fault CMV crashes for three issue categories: driver, vehicle, and animal. The data appear to indicate that driver issues are more frequently associated with at-fault CMV crashes in the study area than vehicle or animal issues. The data indicate that issues related to speed and following too closely, lane use, distracted driving, and faulty evasive action were associated accounted for more than half of the issues that were identified in CMV crashes. Drug and alcohol and criminal behavior issues in at-fault CMV crashes were indicated very few times in the CRIS data for the study area.

Figure 3 illustrates the issue frequencies and corresponding severities of at-fault CMV crashes in the study area, by crash issue groupings. Only frequencies for crashes with possible injuries, non-incapacitating injuries, incapacitating injuries, and fatalities are displayed. The issue grouping for speed and following too closely was associated with largest frequency of injuries; however, this issue group in at-fault CMV crashes resulted in no fatalities in the study area. Issues related to faulty evasive action, fatigue, and right of way were associated with most of the fatalities and incapacitating injuries in at-fault CMV crashes in the study area.

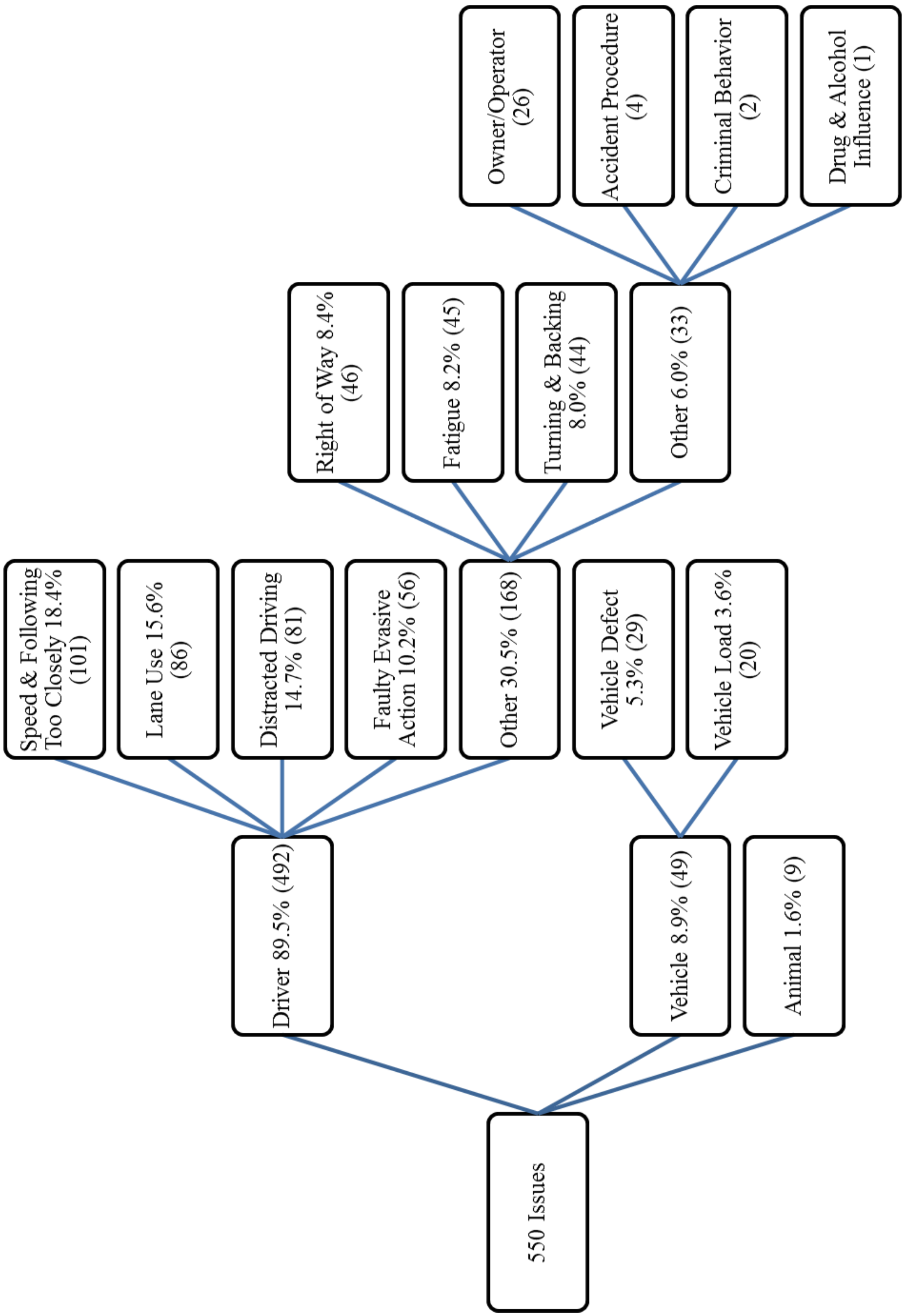

Figure 2. Issues Contributing to At-Fault CMV Crashes.

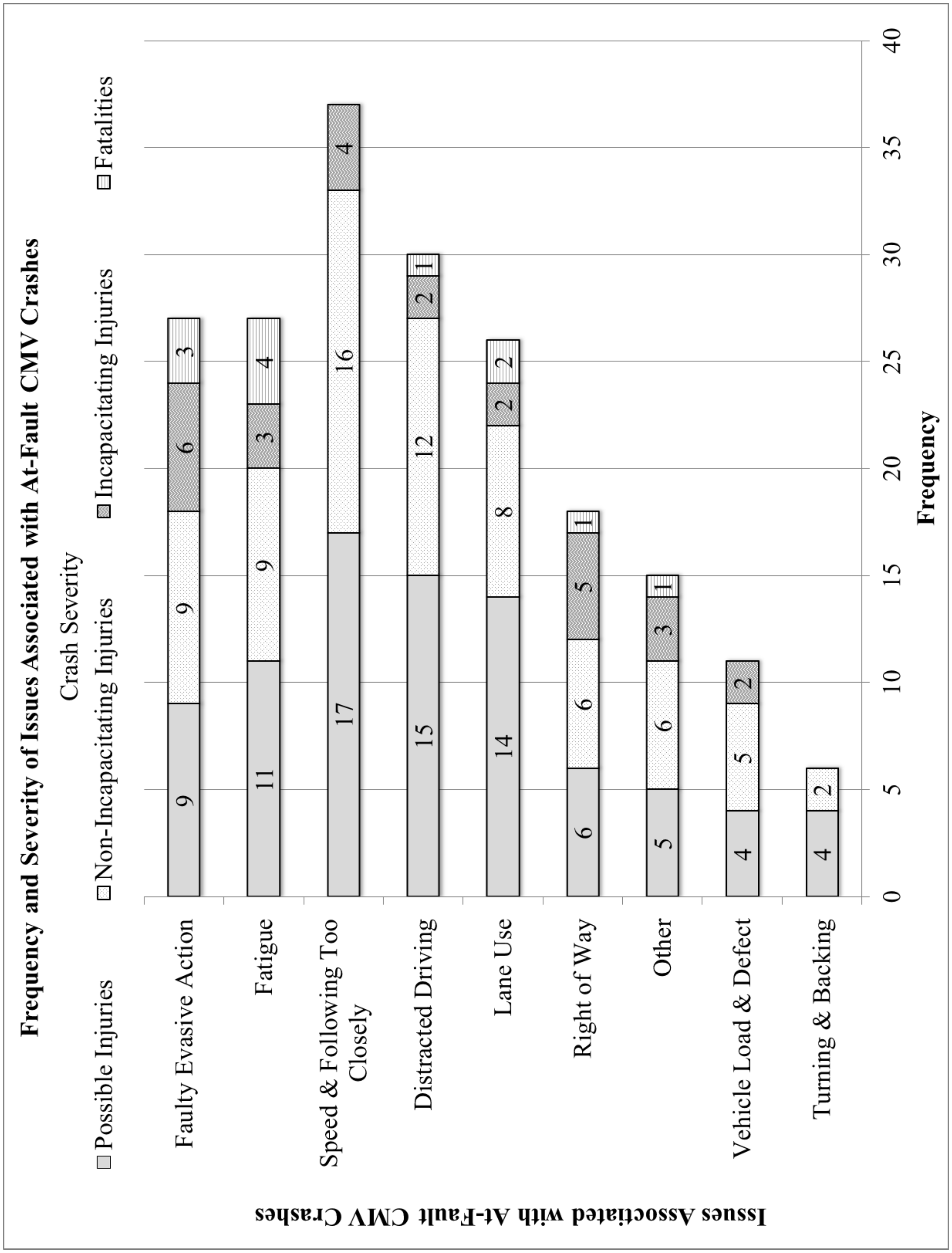

Figure 3. Frequency and Severity of Issues in At-Fault CMV Crashes.

Table 6 lists the issue frequencies and corresponding frequency ranks for non-hazmat, hazmat, and unknown hazmat loads. Based on examination of the frequencies and corresponding ranks, there do not appear to be major differences in occurrences of issues in at-fault CMV crashes in the study area involving transport of hazmat versus non-hazmat loads.

Table 6. Frequency and Rank of Issues in At-Fault CMV Crashes for Non-Hazmat, Hazmat, and Unknown Loads.

Issue	Frequency			Rank		
	Non-Hazmat	Hazmat	Unknown	Non-Hazmat	Hazmat	Unknown
Speed & Following Too Closely	90	10	1	1	1	1
Faulty Evasive Action	52	4	0	4	3	4
Fatigue	41	4	0	7	3	4
Distracted Driving	73	7	1	3	2	1
Right of Way	45	1	0	6	9	4
Lane Use	82	4	0	2	3	4
Turning & Backing	41	2	1	7	6	1
Vehicle Load & Defect	47	2	0	5	6	4
Other*	40	2	0	9	6	4

**Other* consists of issues related to drug and alcohol influence, criminal behavior, accident procedure, owner/operator, and animal. This convention applies to this and all subsequent tables in this report.

Table 7 lists the frequencies and corresponding frequency ranks for of issues by type of highway system. The issue frequencies for Business U.S. highways were lower than any other highway system. At-fault CMV crash issues involving Faulty Evasive Action appear to be proportionally more frequent on U.S. highways than interstates. Also, Fatigue on U.S. highways appears to occur proportionally more frequently and ranks higher than on Farm-to-Market roads for at-fault CMV crashes in the study area.

Table 7. Frequency and Rank of Issues in At-Fault CMV Crashes for Highway Systems.

Issue	Frequency						Rank					
	Farm-to-Mkt	Business US	State Hwy	US Hwy	Interstate	No Data	Farm-to-Mkt	Business US	State Hwy	US Hwy	Interstate	No Data
Speed & Following Too Closely	24	0	36	22	12	7	1	6	1	2	2	1
Faulty Evasive Action	18	1	12	20	4	1	3	3	7	3	7	7
Fatigue	4	0	9	19	7	6	9	6	9	4	4	3
Distracted Driving	11	0	22	30	11	7	4	6	3	1	3	1
Right of Way	10	1	10	17	5	3	5	3	8	6	6	5
Lane Use	22	2	28	15	16	3	2	1	2	8	1	5
Turning & Backing	7	2	13	15	1	6	7	1	5	8	9	3
Vehicle Load & Defect	6	1	17	19	6	0	8	3	4	4	5	8
Other	10	0	13	16	3	0	5	6	5	7	8	8

Table 8 lists the frequencies and ranks of at-fault CMV crash issues by county in the study area. Overall, the frequencies and ranks were generally consistent across the counties. One major difference appears to be for Distracted Driving in Bee and Live Oak Counties. In Live Oak County, this issue was ranked first in frequency, while in Bee County, it was ranked eighth. Also, there appears to be proportional differences in frequencies of Vehicle Load and Defect issues in Bee and Live Oak Counties.

Table 8. Frequencies and Ranks of Issues in At-Fault CMV Crashes for Bee, Live Oak, and McMullen Counties.

Issue	**Frequency**			**Rank**		
	Bee	Live Oak	McMullen	Bee	Live Oak	McMullen
Speed and Following Too Closely	19	49	33	1	1	1
Faulty Evasive Action	14	29	13	3	4	7
Fatigue	4	27	14	9	5	5
Distracted Driving	7	49	25	8	1	3
Right of Way	14	20	12	3	7	8
Lane Use	13	47	26	5	3	2
Turning and Backing	13	16	15	5	9	4
Vehicle Load and Defect	15	20	14	2	7	5
Other*	10	22	10	7	6	9

Figure 4 compares percentages of driver, vehicle, and animal issues in at-fault CMV crashes in Bee, Live Oak, and McMullen Counties. Overall, driver issues comprised over 80 percent of all issues in all three counties. There appears to be a proportionally greater percentage of vehicle issues associated with at-fault CMV crashes in Bee County than in Live Oak and McMullen Counties.

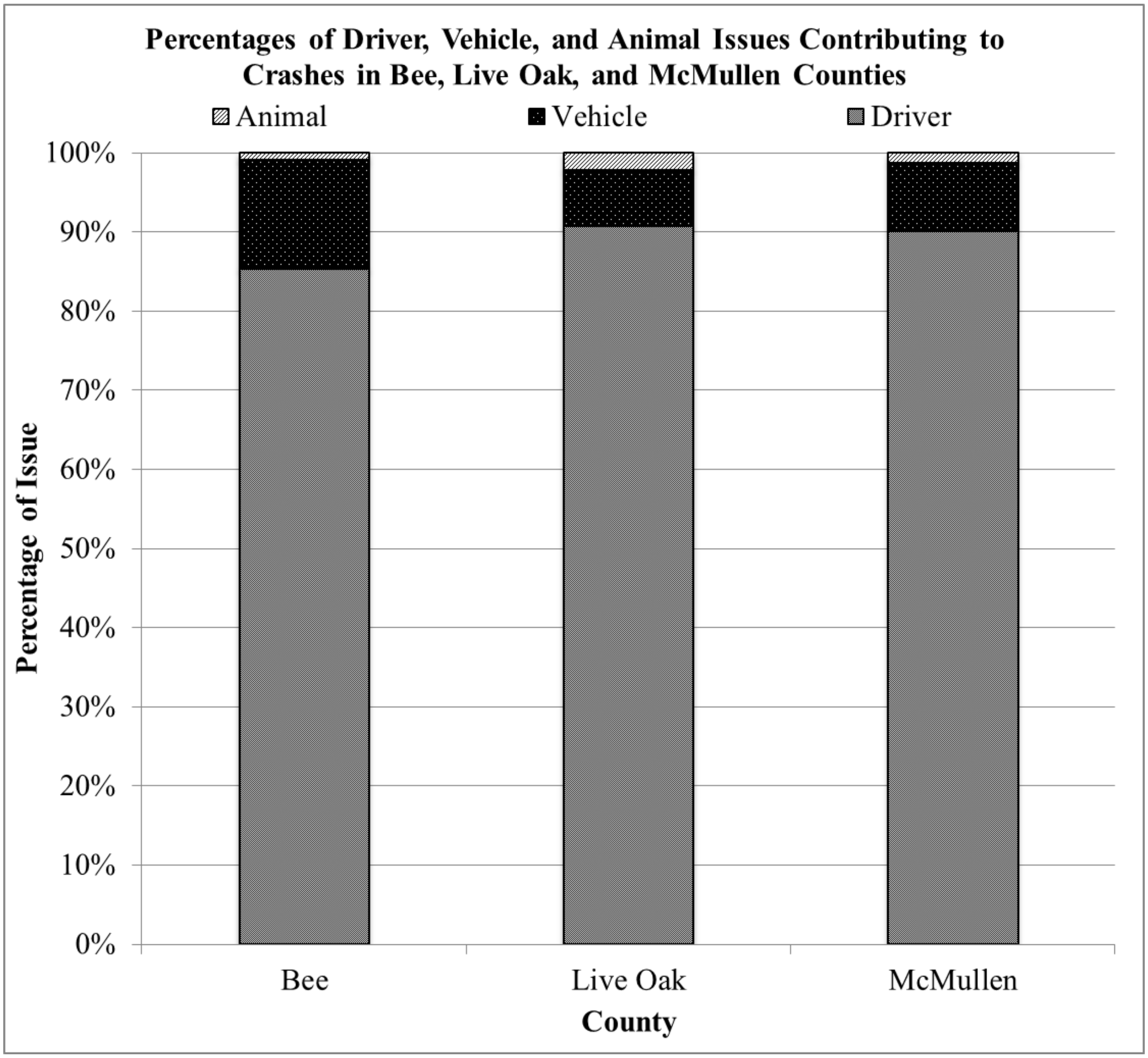

Figure 4. Percentages of Driver, Vehicle, and Animal Issues Contributing to Crashes in Bee, Live Oak, and McMullen Counties.

Figure 5 illustrates how driver, vehicle, and animal issues compare by both frequency and severity of at-fault CMV crashes. Driver issues were found to constitute at least 85 percent of all reported issues across all levels of severity, while vehicle and animal issues much smaller percentages. Driver-related issues accounted for 100 percent of the issues associated with fatalities in at-fault CMV crashes in the study area.

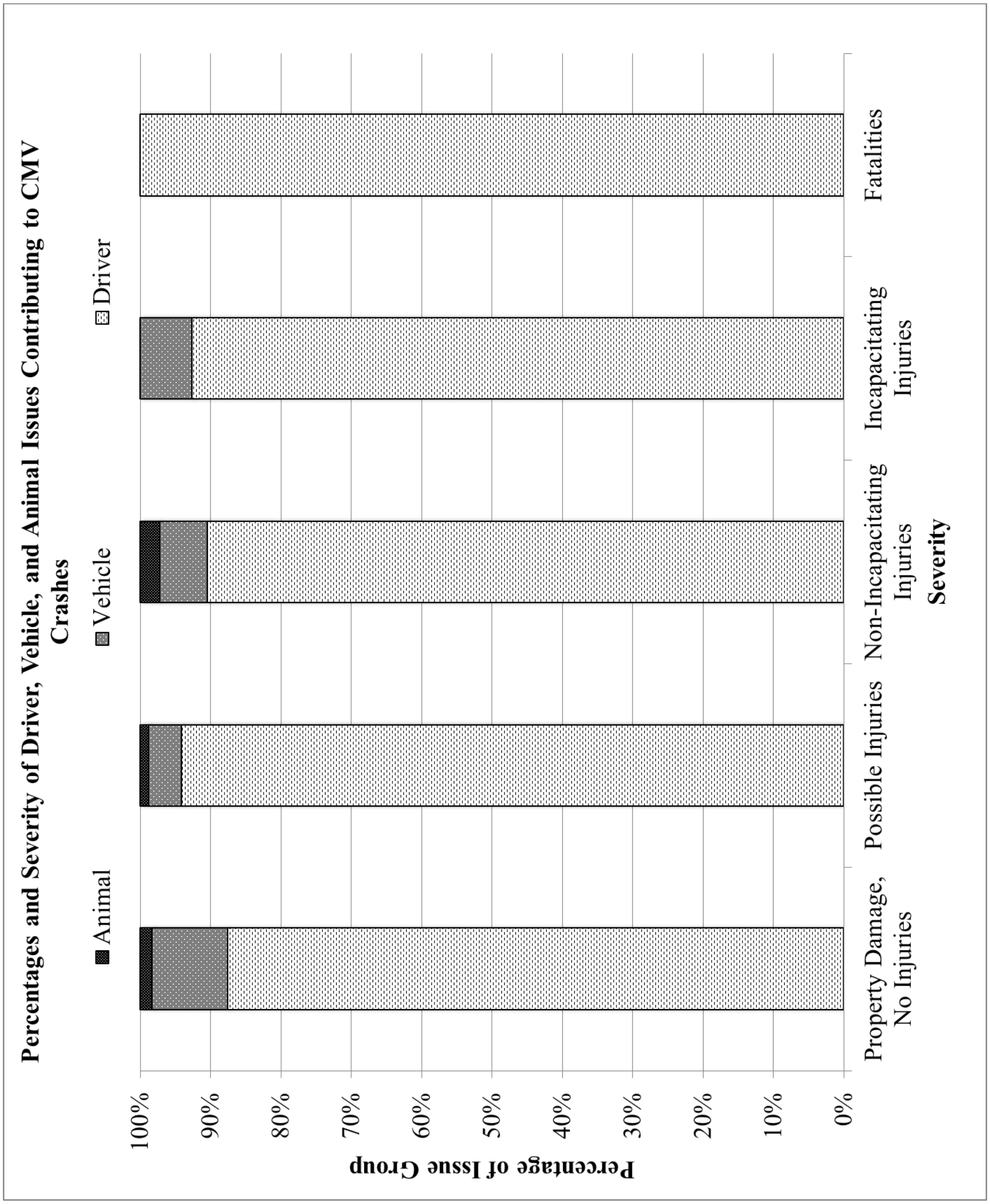

Figure 5. Percentage and Severity of Driver, Vehicle, and Animal Issues Contributing to At-Fault CMV Crashes.

Figure 6 illustrates the frequencies of at-fault CMV crash severity levels for Bee, Live Oak, and McMullen Counties. Live Oak had higher frequencies of crashes for levels of injury severity.

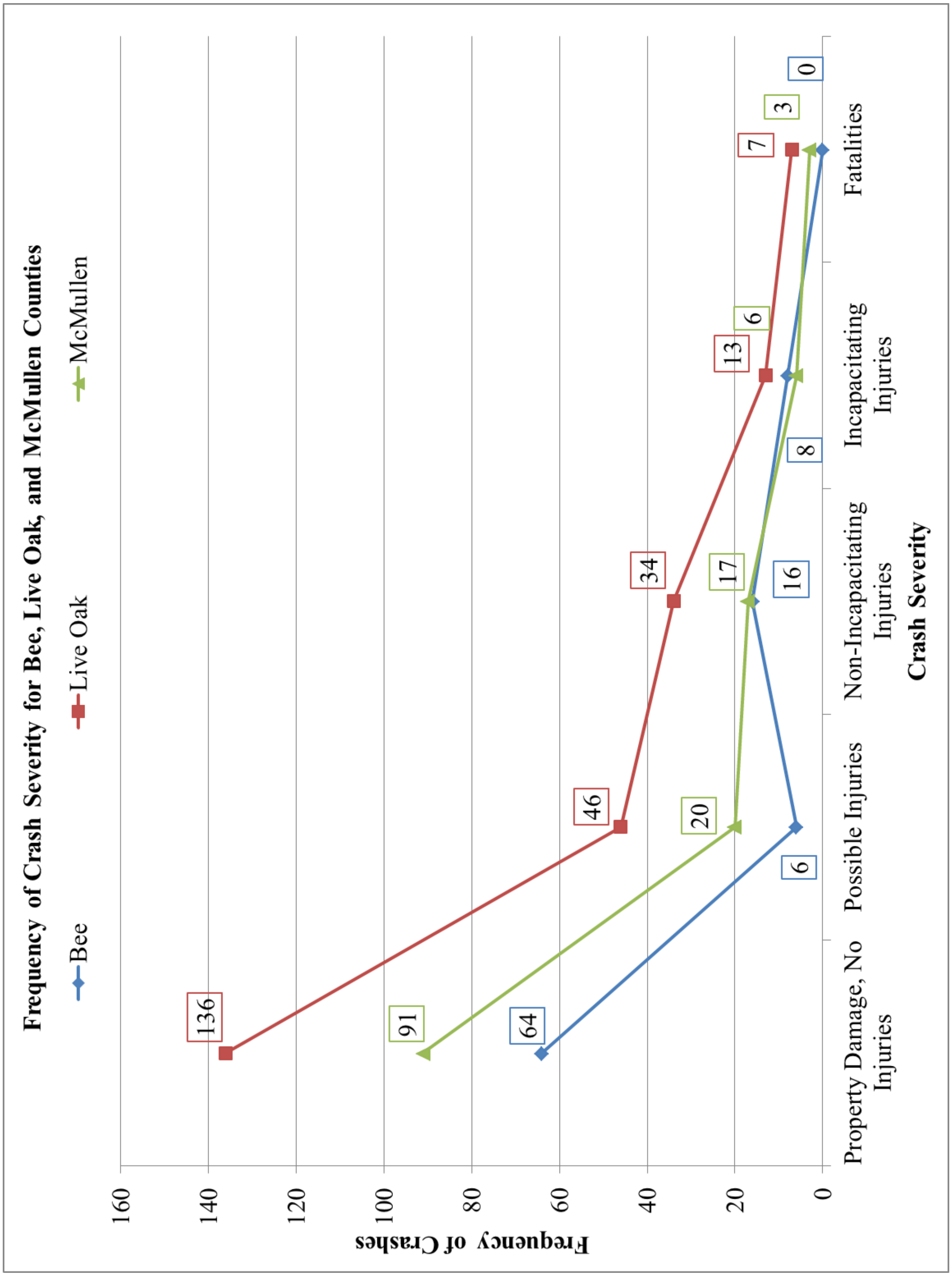

Figure 6. Frequency of Crash Severity for At-Fault CMV Crashes in Bee, Live Oak, and McMullen Counties.

DISCUSSION

Consistent with previous studies (*4*), the results of this analysis for at-fault CMV crashes in three Eagle Ford Shale counties found that 89.5 percent of CMV crashes were likely due to issues associated with the CMV driver, rather than CMV vehicle issues. At-fault CMV crashes associated with speeding resulted in more non-injuries and possible injuries than non-incapacitating and incapacitating injuries. There were no fatalities associated with speeding. Another driver issue, alcohol and drug use, was found to only be present in one case out of more than 400 cases. Alcohol and drug use was not identified as a frequently occurring contributing factor to CMV crashes in the study area.

Vehicle-related violations accounted for 8 percent of all violations associated with at-fault CMV crashes in the study area. The data appear to support that inoperative equipment and improper load securement are important vehicle violations that contribute to at-fault CMV crashes, while failure to make repairs was not directly supported to be an important vehicle violation in the study area. It can be argued that inoperative equipment is a result of failure to make repairs; however, there was an insufficient amount of data to determine if the crash resulted from a failure to make repairs.

The frequency of issues was overall lower on Business U.S. highways than any other highway system. This was expected since Business U.S. roadways are less frequently traveled by CMVs. Also, of the three counties sample in the Eagle Ford Shale, Bee County is the only county that has a Business U.S. roadway. While there are more Farm-to-Market roads in all three counties (Bee, Live Oak, McMullen) combined, fatigue appears to be more frequent on U.S. highways than Farm-to-Market road. This is reasonable since large trucks travel more frequently on larger roads like U.S. highways than Farm-to-Market roads.

CONCLUSIONS AND RECOMMENDATIONS

The findings from this research cover the impact of driver, vehicle, and other issues for at-fault CMV crashes in Bee, Live Oak, and McMullen Counties.

Driver violations were found to contribute more than vehicle violations to at-fault CMV crashes in the study area. The data appear to support that speed and aggressive driving are frequent driver violations associated with CMV crashes. The data also appear to support that inoperative equipment and improper load securement are the most frequently reported vehicle violations associated with the crashes. Drug and alcohol influence, cell phone use, and failure to make repairs were infrequent driver and vehicle violations in these crashes.

Lane use and speeding and following too closely were main issues that were associated with at-fault CMV crashes in the study area. Driver issues constituted more than 80 percent of all issues associated with the crashes. Also, driver issues accounted for 100 percent of reported fatalities for at-fault CMV crashes in the study area. Vehicle and animal issues were far less frequent.

The data were also analyzed according to hazmat and non-hazmat loads, type of highway system, and counties. Hazmat loads were found to be less frequent in crashes and crash issues appeared proportionally similar in frequencies and ranks for both hazmat and non-hazmat loads. For U.S. highways, faulty evasive action was more prevalent than on interstates. Also, crashes for which fatigue was a reported issue were more frequent on U.S. highways than on Farm-to-Market roads. Live Oak and McMullen Counties were generally similar in frequencies and ranks across issue groups. Reported vehicle load and defect issues were more proportionally more common in Bee County. Also, there were proportionally fewer distracted driving issues than in Live Oak County. Further analysis and research is recommended to determine why certain issues contribute more to at-fault CMV crashes on certain highway systems and counties.

As described in the literature review, rules, enforcement, and promotion of voluntary initiatives are three essential categories used to address driver and truck safety. Targeting inattention in driving education is one suggestion to help reduce the amount of distracted driving on roadways. A decrease in distraction could possibly contribute to fewer accidents happening due to faulty evasive action since drivers would be more aware of the roadway and driving environment. Also, training drivers to recognize objects on the roadway and proper evasive action could reduce the amount of accidents resulting from faulty evasive action. Legislators and regulators should consider whether trucking companies, instead of or in addition to truck drivers, should be penalized for inoperative equipment. Companies should also be penalized for accidents caused by fatigued drivers. Training drivers to recognize the symptoms of fatigue and ensuring there are places for CMV drivers to stop and rest and strict enforcement on logbooks may help encourage drivers not to operate their vehicles while fatigued. Also, enhancing law enforcement may help reduce the occurrence of issues associated with speeding, following too closely, and improper lane use and help contribute to reductions in at-fault CMV crashes and their associated impacts.

LIMITATIONS

Throughout the research process, many limitations prevented a greater depth of information from being obtained. The research relied on the secondary data that were reported by peace officers and maintained in the CRIS database. The data available were limited since access to all of the information in the narrative was not available. Having access to the narrative could have better informed the assignment of violations, factors, charges, and issues. There was also no access to information about adjudication of charges in assigning violations; therefore the research had to rely on the reported charges. Due to Institutional Review Board requirements, personal identifier information was not included. Without personal identifier information driver's characteristics (age, gender, race, etc.) were not able to be examined. Since the research only examined a sample of counties in the study area, further research is needed to identify the degree of how these results compare to other counties in the Eagle Ford Shale and other energy producing areas in both the United States and Texas.

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APPENDIX A: AT-FAULT DETERMINATION

This section describes the process behind determining which units were found to be at-fault for each crash in Bee, Live Oak, and McMullen Counties from 2010–2013. The following variables were considered during this process:

- Person Charge.
- Crash CMV Involved Flag.
- Weather Condition.
- Light Condition.
- Road Type.
- First Harmful Event.
- Intersection Related.
- Manner of Collision Group.
- Manner of Collision.
- Object Struck.
- Other Factor.
- County.
- Vehicle Unit.
- Vehicle Parked Flag.
- Unit CMV Flag.
- Contributing Factor 1.
- Contributing Factor 2.
- Contributing Factor 3.
- Possible Contributing Factor 1.
- Possible Contributing Factor 2.
- Vehicle Defect.

Only One Unit Involved in a Crash

Generally, when a single unit had a contributing factor, possible contributing factor, and/or vehicle defect that were anything but Not Applicable, the unit was found to be at-fault. However, if the contributing factor was described as a domestic or wild animal, the fault of the unit was coded as unknown. If the unit was found to have animal as a contributing factor along with Faulty Evasive Action, the unit was documented to be at-fault. When a contributing factor was Not Applicable but a vehicle defect was present, the unit was documented to be at-fault. If a contributing factor was Not Applicable, but there were no other contributing factors, possible contributing factors, and/or vehicle defects, other variables were examined: First Harmful Event, Other Factor, Weather Condition, and Person Charge. If the first harmful event was recorded as Overturned, Other Object, or Fixed Object, the unit was found to be at-fault.

Multiple Units Involved in a Crash

If all units had a contributing factor of Not Applicable, but one unit had a different contributing factor, possible contributing factor, and/or vehicle defect, the unit with the different factor was found to be at-fault; but if that different contributing factor and/or possible contributing factor was Other (Explain in Narrative), the charges were taken into account. Most of the time, the unit with the contributing factor of Other (Explain in Narrative) was found to be at fault in this scenario. When multiple units had contributing factors, the scenario was played out to interpret which unit may have caused the accident. Typically a contributing factor and/or possible contributing factor of Faulty Evasive Action for a unit was found to be at-fault. There were a few cases where multiple units were mutually determined to be at-fault. If a single unit was found to have a contributing factor relating to an animal while all other units did not display any factors, the units were coded as unknown. If all units had a contributing factor of either wild or domestic animal, both units were coded as unknown. When there was not a sufficient amount of details provided, typically seen when crashes involved more units, the units were coded as unknown.

APPENDIX B: FACTOR AND CHARGE GROUPS

Table 9. Specific Factors and Charges for Factor and Charge Groups

Group	Factors	Charges
Drug and Alcohol Influence	• Under influence – alcohol • Under influence – drug • Had been drinking	• DWI 1st • DWI 2nd • DUI minor • Possession of open container • Public intoxication • Intoxication assault
Criminal Behavior	• Fleeing or evading police	• Criminally negligent homicide • Obstructing highway • Evading arrest (vehicle) • Evading arrest (foot) • Theft $20,000 –$10,000
Accident Procedure		• Failed to report accident • Failed to stop and render aid • Failed to stop when involved in accident • Accident involving damage to vehicle • Leaving the scene of an accident – vehicle damage • Failed to comply with requirements on striking fixtures or lane use
Owner/Operator	• Impaired visibility (explain in narrative)	• No seat belt • Ride not secured by safety belt – driver • No motorcycle license • No driver license • Driving while license invalid • Permit unlicensed driver to drive • Violate special provisions of permit • Violated driver license restriction – no corrective lenses • Failed to maintain any commercial vehicle subject to your control • No liability insurance

Group	Factors	Charges
Owner/Operator (continued)		• No insurance • Expired proof of insurance • Failed to maintain financial responsibility • Tow unregistered trailer • Operated unregistered trailer • No annual DOT inspection • No valid inspection certificate • No valid inspection • VCO 1533 truck route
Fatigue	• Fatigued or asleep	
Distracted Driving	• Driver inattention • Distraction in vehicle • Cell/mobile phone use • Ill (explain in narrative)	
Right of Way	• Failed to yield right of way – stop sign • Failed to yield right of way – yield sign • Failed to yield right of way – open intersection • Failed to yield right of way – private drive • Disregard stop sign or light • Disregard stop and go signal • Failed to stop at proper place • Improper start from parked position	• Failed to yield right of way • Failed to yield right of way – parking lot • Failed to yield – stop intersection • Failed to yield – yield intersection • Disregard traffic signal • Disregard stop sign • Unsafe start from parked position
Turning	• Turned when unsafe • Turned improperly – cut corner on left • Turned improperly – wide right • Turned improperly – wrong lane • Failed to signal or gave wrong signal • Disregard turn marks at intersection	• Turned when unsafe • Improper turn • Turned improperly – wrong lane • Turned improperly – wide turn • Cut corner left • Failed to turn right safely • Failed to signal with turn indicator

Group	Factors	Charges
Backing	• Backed without safety	• Backed when unsafe • Back so at to interfere or without safety • Backed upon shoulder or roadway of controlled access highway
Lane Use	• Failed to pass to left safely • Failed to pass to right safely • Passed on right shoulder • Passed in no passing lane • Wrong side – not passing • Changed lane when unsafe • Wrong way – one way road • Failed to drive in single lane • Failed to give half of roadway • Disabled in traffic lane • Opened door into traffic lane • Overtake and pass insufficient clearance	• Changed lane when unsafe • Failed to pass to left safely • Failed to pass to right safely • Illegal pass on right • Wrong side of road – not passing • Wrong side of road – no passing zone • Disregard no passing zone • Failed to drive in single lane • Failed to give half of roadway • Drive on improved shoulder when prohibited • Driver open door in moving lane of traffic
Speed	• Failed to control speed • Speeding – Overlimit • Unsafe speed	• Failed to control speed • Unsafe speed
Following Too Closely	• Followed too closely	• Followed too closely
Faulty Evasive Action	• Faulty Evasive Action	
Vehicle Load	• Load not secured • Oversized vehicle or load	• Failed to secure load/ improperly secured load • Overheight
Vehicle Defect	• Defective or slick tires • Other (explain in narrative) • Defective trailer hitch	• Defective or improper coupling device • Defective parking/emergency brakes

Group	Factors	Charges
Vehicle Defect (continued)	• Defective or no vehicle brakes • Defective or no tail lamps • Defective or no turn signal lamps • Defective or no headlamps	• Brakes not maintained in good working order • Brake-hose tube damage • Defective or no turn signal lamp • Used equipment not approved (black out tail lamps)
Animal	• Animal on road – wild • Animal on road – domestic	
Not Applicable*	• Not applicable	
Other (Explain in Narrative)*	• Other explain in narrative)	
**Not Applicable* and *Other (Explain in Narrative)* were not created as Issue Groups since there was not enough information provided.		

APPENDIX C: VIOLATIONS

Each factor and charge, listed in Appendix B, were determined to either be or not a violation. All of the charges were found to be violations, while a few of the factors were found not be violations. The violations considered for this determination was not limited to moving violations but also included drug and alcohol violations, mechanical violations, etc. The following factors were recorded as not being a violation:

- Not Applicable.
- Other (Explain in Narrative).
- Ill (Explain in Narrative).
- Disabled in Traffic Lane.
- Animal on Road – Wild.
- Animal on Road – Domestic.
- Oversized Vehicle or Load.
- Vehicle Defect – Other (Explain in Narrative).

While violations may have been associated with crashes, there was an insufficient amount of data provided. All vehicle defects were considered violations expect for *Other (Explain in Narrative)* since the data were unknown.

APPENDIX D: CRASH EVENT SEVERITY SCALE

The development of a new crash severity scale from that included in the original data was based on the highest severity that occurred in each crash, irrespective of the frequencies of reported injuries or fatalities. When developing the scale, the following variables were considered:

- Crash Thousand Dollar Damage Flag.
- Crash Severity.
- Incapacitating Injuries.
- Non-Incapacitating Injuries.
- Possible Injuries.
- Non-Injuries.
- Unknown Injuries.
- Fatalities.

Table 10 represents the scale. The scale starts at a severity level of 1 because there is always an impact due to the fact a crash happened, even if at a low level of damage.

Table 10. Crash Severity Scale

Severity	Scale
Fatalities	6
Incapacitating Injuries	5
Non-Incapacitating Injuries	4
Possible Injuries	3
Property Damage (No Injuries)	2
Non-Injuries (No Property Damage)	1
Unknown Injuries	1

Differences Between Familiar and Unfamiliar Drivers

Prepared for
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Katherine is a member of the student chapters of the American Society of Civil Engineering, the Louisiana Engineering Society, and the National Society of Leadership and Success at ULL, and she is also a volunteer for Habitat for Humanity. She held an internship position at the Water Institute of the Gulf, a coastal and deltaic science and engineering research institution in Baton Rouge, Louisiana. She has also volunteered as a laboratory assistant in a concrete materials research laboratory at her university. When she is not dabbling with the various disciplines of civil engineering, you can find her running or spending time with her friends.

After graduating from ULL, Katherine hopes to pursue a master's degree in Urban Planning and apply her background in civil engineering to plan and develop resilient communities.

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The author would like to express her appreciation to her mentor Brad Brimley for his guidance throughout the duration of the project.

SUMMARY

A variety of personal and environmental factors can contribute to a driver's behavior, many of which have been extensively studied. One factor that has received less attention is a driver's familiarity with the route he or she is driving on. The purpose of this research was to investigate how driving behavior varies based on a driver's familiarity with the highway and to simultaneously investigate the incidental effect participation in a driving study has on a driver's behavior (i.e., the Hawthorne Effect). This was achieved by comparing vehicle speed data collected at seven curve sites of a rural two-lane highway from two sets of drivers: 1) drivers traveling along a familiar route and not aware of the study, and 2) drivers traveling along an unfamiliar route while consciously participating in a driving study. It was expected that familiar drivers would drive less cautiously than unfamiliar drivers and thereby operate at faster speeds. The speed of drivers at curves was the primary focus of the study.

Various statistical analyses were performed in the research, including a test of mean speeds of the familiar and unfamiliar drivers, an evaluation of the drivers' speeds while accounting for factors and interactions such as curve and time of day, and a quantification of the effect of familiarity through regression modeling. These analyses revealed that the difference in mean speeds is significant, meaning that there are characteristics of the curves which the unfamiliar drivers respond to differently than the unfamiliar drivers. The study also showed that familiarity is a significant factor when taking into account additional factors and interactions. The initial expectation of the study was supported in quantifying the effect of familiarity. The findings indicate that unfamiliar drivers generally drive slower than familiar drivers, although the effect is not the same at different locations and times of day.

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INTRODUCTION

A variety of personal and environmental factors contribute to a driver's behavior, many of which have been extensively studied. Cell phone use, for example, has been the subject of numerous driving studies in recent years, and other common physical factors like fatigue and vision have also been studied. One factor that has received less attention is a driver's familiarity with the route he or she is driving on. The purpose of this research was to investigate how driving behavior varies based on a driver's familiarity with the highway. It was expected that drivers who are familiar with the road they are traveling on would operate their vehicles at faster speeds than unfamiliar drivers, perhaps due to exercising less caution as a result of their familiarity. Identifying this relationship will provide information that may be useful for researchers and policy makers in designing future studies and promoting safe driving.

The goal of the research was to determine how a driver's familiarity with a route affects his or her driving behavior and to simultaneously investigate the incidental effect participation in a driving study has on a driver's behavior. This was achieved by comparing vehicle speed data collected from two sets of drivers on the same highway. Data from the first set of drivers were collected from pneumatic tube counters placed at several locations along the highway with a focus on sites on and near curves. Data from the second set of drivers were collected from study participants in an instrumented vehicle who were selected to participate in the study because they were unfamiliar with the highway.

BACKGROUND INFORMATION

A study conducted by Rosenbloom et al. showed that drivers who are familiar with the location they are in drive less cautiously, exhibiting more dangerous behavior while driving and committing more traffic violations than the same drivers when in less familiar locations (*1*). Another driving study designed to evaluate the effect of adding advisory speed signs to curve warning signs incorporated a local, familiar-driver control group for use as a standard with which to compare the results from the unfamiliar drivers in the study. However, results of this study were ambiguous in terms of whether driver behavior was positively or negatively affected by the driver being familiar with the route (*2*). Little additional information regarding behavioral differences between familiar and unfamiliar drivers was found in a review of the literature. Previous studies generally compared things other than speeds. Further investigation of the potential effects of driver familiarity on behavior in the present study may uncover a meaningful relationship.

Because the data collected from unfamiliar drivers were collected under conditions of a study environment, this study also provided an opportunity to investigate how normal driver behavior deviates from a driver's behavior when participating in a driving study. The effect of participation in a study has been widely studied in the field of psychology, but it has less often been a subject of concern in driving studies. The Hawthorne effect refers to the tendency to alter one's behavior and perform at a higher standard when being observed as a participant in a scientific study, relative to their behavior and performance under normal circumstances (*3*). In light of this Hawthorne effect, it was anticipated that the study would show that drivers exhibit better, more cautious driving behavior when being observed as part of a driving study. It is important that this effect is considered in all fields in which scientific studies are performed, as it could create bias in the data collected and therefore affect the interpretability and applicability of the findings.

THE DATA

The study involved two sets of data representing familiar and unfamiliar drivers. All of the data used in the study was collected on the same rural two-lane highway, Texas Farm-to-Market Road 3090 (FM 3090), shown on the map in Figure 1. The speed limit on the highway is 60 mph. The course stretched approximately 16 miles and consisted of more than 30 changes in horizontal alignment. Seven of these horizontal curves and their adjacent approach tangents were used in the analysis for the study. Table 1 gives the characteristics of each curve, and Figure 1 identifies each of the seven curves on a map. The data sets consisted of vehicle speeds in mph collected at four points of interest (POIs) for each curve, listed below and also shown in Figure 2:

- 500 feet before the point of curvature, on the tangent (TN).
- Point of curvature (PC).
- Midpoint of the curve (MP).
- Point of tangency (PT).

The next two sections describe the processes through which the familiar and unfamiliar driver data sets were collected and how the data sets were reduced and formatted for use in the study.

Table 1. Specifications of the Seven Study Curves.

Curve	Direction of Curve	Radius (ft)	Deflection (degrees)	Avg. Super-elevation (%)	Approach Tangent Distance (ft)	Posted Advisory Speed (mph)
1	Right	495	72	6.2	600	40
2	Left	365	41	5.8	490	35
3	Left	400	65	6.2	1,650	30
4	Right	390	90	8.0	2,820	30
5	Right	335	49	7.6	5,890	35
6	Left	445	90	5.7	1,300	35
7	Left	465	84	5.7	4,270	35

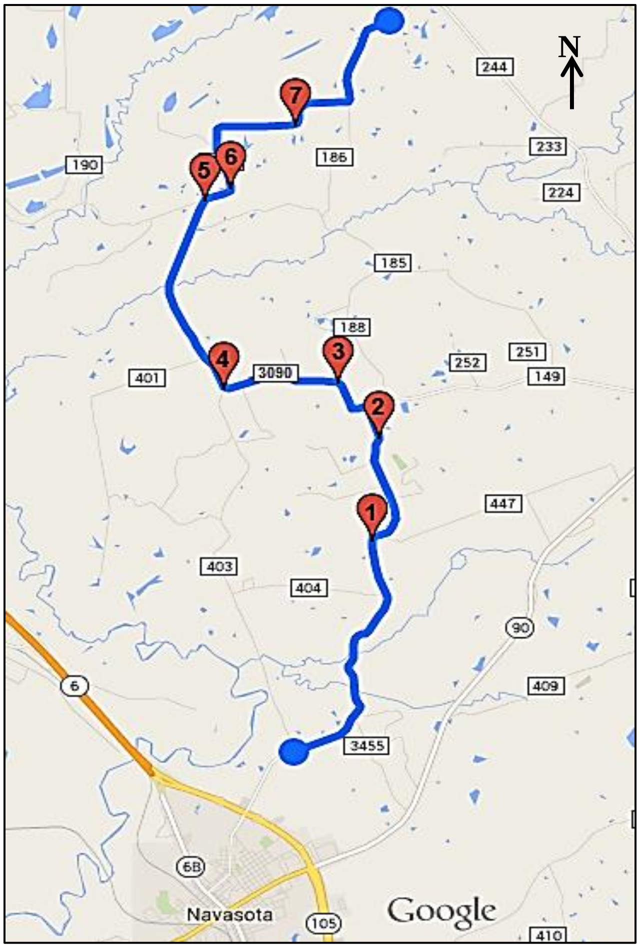

Figure 1. Map of Farm-to-Market 3090.

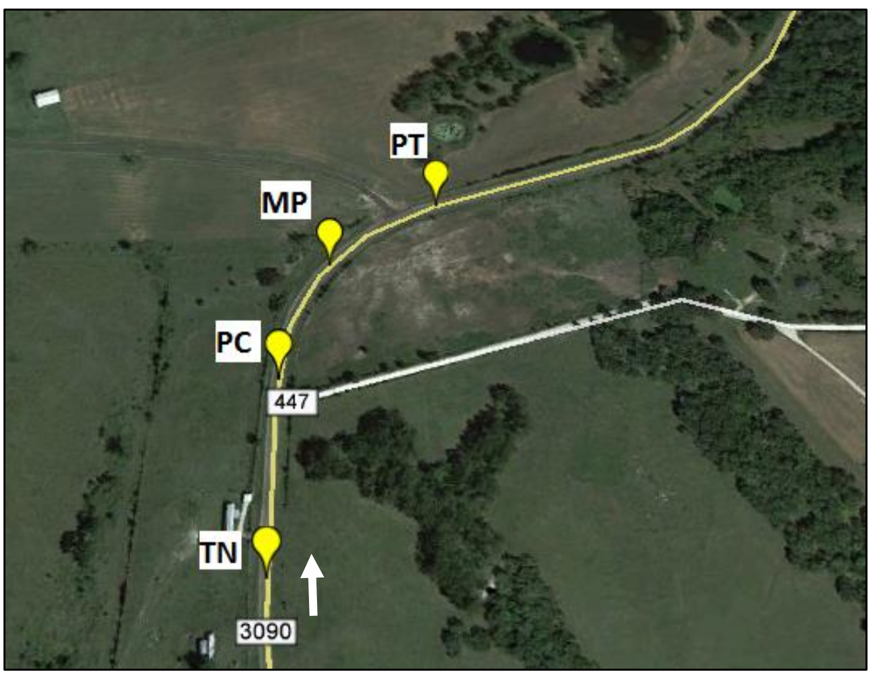

Figure 2. POIs at Curve 1 where Pneumatic Tubes Were Placed.

Familiar Drivers

FM 3090 is a rural two-lane highway that experiences low traffic volumes (<300 vehicles per day). With little traffic, it is reasonable to assume that most of the vehicles on the highway are driven by people who regularly navigate that highway. The data set consists of remotely collected observations of vehicles assumed to be driven by local drivers. The collection of this data took place over a 24-hour time period, and it involved placing pneumatic tubes attached to counter boxes across the road, as shown in Figure 3. The tubes were placed on each of the seven curves involved in the study, and placement of the tubes on each curve corresponded with the four POIs. Together, the pneumatic tubes and counter boxes collected data as each vehicle crossed over the tubes. These data included a timestamp, a vehicle’s length, speed, and the gap between vehicles.

Figure 3. Pneumatic Tubes at the Point of Curvature of Curve 16.

The data collected from the combined use of pneumatic tubes and counter boxes on the rural route were carefully processed to ensure that only observations of vehicles traveling through the entirety of the curve were used in analysis. Additional observations were also eliminated based on several parameters:

- **Vehicle type** – Vehicles that did not appear to be passenger vehicles were removed. This parameter was determined from the length of the vehicle and axle spacing.
- **Gap between vehicles** – FM 3090 is a very low-volume road where the headway between vehicles can sometimes be several minutes. To ensure that all of the data were representative of free-flowing traffic, records of vehicles following closer than 15 seconds were eliminated. A 15-second headway ensures there are more than 1,000 feet between two vehicles.
- **Vehicle speed** – Speed outliers were removed from the data set. The process used for identifying these outliers is described in the section labeled Summary of Data: Boxplots.

In addition, the data set was further organized based on time of day (i.e., day and night). Because the familiar driver data were collected remotely, personal factors about those drivers (such as age and gender) are unknown and therefore not evaluated in this study.

Unfamiliar Drivers

The second data set was originally collected for use in a study aiming to establish guidelines for the placement of Traffic Control Devices (TCDs) at curves in roads (*4*). For the purposes of the present study, those data were used to represent the behavior of unfamiliar drivers. The participants in this open-road driving study with unfamiliar drivers each drove the same test vehicle along FM 3090 with instructions to follow all traffic laws as they proceeded to the end of the highway. All participants in the driving study were known to be unfamiliar with the test route on FM 3090. Only data collected under free-flow traffic conditions were used in the study, and both day and night-time driving conditions were included. Because these unfamiliar driver data were collected in a driving study setting, several personal factors about the drivers are known; study participants' ages, vision, and gender were recorded. The test vehicle was equipped with eye-tracking cameras, a GPS receiver, and an accelerometer. However, the present study involves only the speed data collected from the GPS receiver, shown in Figure 4, since the familiar driver study also involved the collection of speed data. The GPS receiver operated at a high sampling rate, resulting in a continuous record of the vehicle's speed and position. The GPS data were reduced to values of speed at the four POIs for each curve to match the locations of the familiar driver data set.

Figure 4. GPS Receiver Used for Unfamiliar Driver Study.

The study with unfamiliar drivers included the placement of TCDs on some curves for test purposes. To maintain consistency with what the familiar drivers encountered, observations in which additional TCDs were placed were eliminated from the data set. The data set was also categorized into separate series for day and nighttime conditions.

Summary of Data: Boxplots

Box-and-whisker plots were created for each of the seven curves to visually summarize the data sets. The boxplot for Curve 1 is shown in Figure 5. Each box depicts the first quartile, median, and third quartile vehicle speeds for the familiar and unfamiliar drivers at each of the four POIs of the curve. The plots are further separated into day and night-time categories. The whiskers or error bars represent 1.5 times the Interquartile Range (IQR), the difference between the third and first quartile values. Vehicle speed observations beyond the whiskers were considered outliers and are represented by black dots on the plots. These outliers were removed from the data sets for the study analysis.

Looking at the daytime driver data in Figure 5, it can be seen that the familiar drivers tend to operate at higher speeds than the unfamiliar drivers, at least during the day. The nighttime data, however, does not appear to imply this trend. Additionally, daytime conditions resulted in more outlier data than the nighttime conditions. For both day and night-time conditions, the familiar drivers displayed a wider distribution of speeds than the unfamiliar drivers. The speed data for Curves 2–7 exhibit trends similar to that of Curve 1, though not always exactly the same. These remaining boxplots can be found in Figures 6–11 of the Appendix.

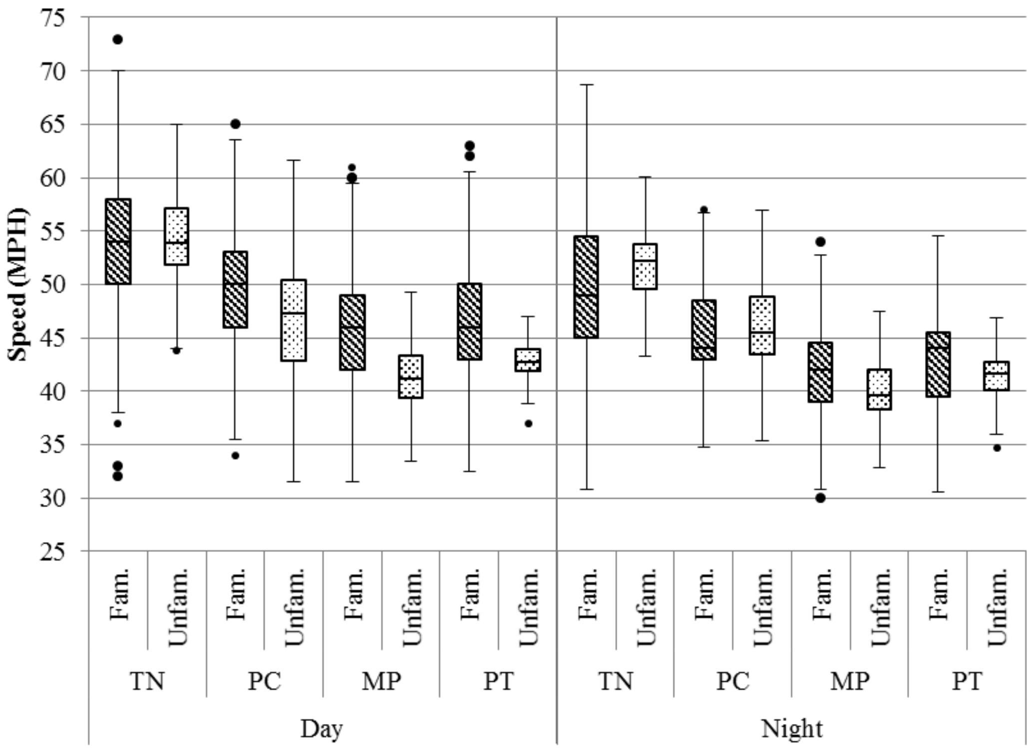

Figure 5. Summary of Data for Curve 1.

ANALYSES AND RESULTS

Several methods of statistical analysis were used to look at how the familiar driver speed observations vary from the speed observations of the unfamiliar drivers and to develop a relationship between driving speed and a driver's familiarity. Methods used included t-tests, analyses of variance, and regression modeling. Descriptions of these tests and their results are presented in the following sections.

Unequal Variance t-Tests

A t-test was used to determine whether there is a significant difference between the familiar and unfamiliar driver speeds. Because there were two populations of unequal size each with their own respective variance, the best suited t-test to analyze the data was the t-test for unequal variances. A separate unequal variance t-test was done in Excel for each of the POIs of each curve using speed in mph as the measureable variable. Additional t-tests for the change in speed between the tangent and point of curvature ate each curve were also conducted. The null hypotheses were 1) that there is no difference in mean speeds at each POI between familiar and unfamiliar drivers and 2) that there is no difference in the mean change in speed from the tangent to the point of curvature for familiar and unfamiliar drivers. If the p-value is less than 0.05, denoted in Tables 2–4 by boldface type, the null hypothesis is rejected. Table 2 shows the results of the t-tests for daytime observations, including the mean speed, variance, and number of observations for familiar and unfamiliar drivers, as well as the t-statistic and the p-value. Table 3 similarly shows the results for nighttime observations for Curves 1–3 only. Table 4 shows the results of the tests for change in speed, for both day and nighttime observations. The t-tests were not performed on nighttime observations for Curves 4–7 because the sample sizes were too small to yield reliable results.

The results of the Day t-test in Table 2 indicate that the difference in means between the familiar and unfamiliar driver speed samples is statistically significant for the majority of the individual locations. Additionally, the unfamiliar drivers had lower speeds than familiar drivers at most of the individual locations. This supports the expectation that familiar drivers would exhibit faster driving speeds than the unfamiliar drivers and therefore result in statistically significant differences in means.

The Night t-test results in Table 3 show that there is a significant difference in means between the familiar and unfamiliar driver speed samples for the majority of the curves and POIs. Almost all mean speeds of the unfamiliar drivers are lower than the mean speeds of the familiar drivers. Further, for the locations where there is a significant difference, the mean speed of the unfamiliar drivers is always lower. This supports the hypothesis that familiar driver speeds differ from unfamiliar driver speeds.

Table 4 shows the results of the t-test for the change in speed between the TN and the PC of each curve. A positive value for the mean corresponds to deceleration. The mean speed changes of the unfamiliar drivers are greater than the mean speed changes of the familiar drivers at most of the curves. This means that generally, unfamiliar drivers decelerate more in advance of curves than the familiar drivers. This is significant at four of the seven curves during the day, but at none of the curves at night.

Summary of Results for t-Tests

The results of the t-tests show that the difference in means for the familiar and unfamiliar drivers is statistically significant in many instances, for both the driver speeds and changes in speed examined. These results indicate that there may be characteristics of the curves that the unfamiliar drivers are responding to differently than the familiar drivers. The results also provide reason to look at whether there is a consistent difference between familiar and unfamiliar drivers and whether familiarity is still significant when additional factors or combinations of factors are taken in to account.

Table 2. t-Test Results for Speed of Familiar and Unfamiliar Drivers during the Day.

Curve	POI*	Familiar			Unfamiliar			t-stat.	p-value**
		Mean (mph)	Variance	Obsv.	Mean (mph)	Variance	Obsv.		
1	TN	53.9	33.7	162	54.2	12.0	18	-0.33	0.3737
1	PC	49.6	21.0	162	47.1	16.2	18	2.45	**0.0113**
1	MP	45.3	19.9	162	41.5	6.3	18	5.53	**<0.0001**
1	PT	46.0	23.3	162	43.1	3.6	18	5.03	**<0.0001**
2	TN	50.1	28.0	105	48.5	9.3	19	1.78	**0.0410**
2	PC	46.4	16.2	105	45.3	12.2	19	1.26	0.1086
2	MP	42.9	14.0	105	40.9	12.6	19	2.24	**0.0169**
2	PT	41.7	10.2	105	39.0	8.0	19	3.72	**0.0005**
3	TN	50.3	49.9	77	48.8	14.6	18	0.10	0.1026
3	PC	43.4	27.2	77	40.3	12.4	18	0.00	**0.0023**
3	MP	39.0	25.2	77	36.4	7.0	18	0.002	**0.0016**
3	PT	40.5	29.0	77	38.4	6.6	18	0.01	**0.0077**
4	TN	54.9	50.9	62	50.4	19.1	9	2.61	**0.0099**
4	PC	47.8	30.3	62	44.1	21.4	9	2.19	**0.0243**
4	MP	38.7	19.6	62	39.1	11.0	9	-0.31	0.3790
4	PT	42.7	25.2	62	40.0	1.4	9	3.59	**0.0004**
5	TN	50.0	94.2	29	56.9	18.9	8	-2.93	**0.0034**
5	PC	42.9	41.2	29	44.1	29.7	8	-0.53	0.3038
5	MP	36.8	14.1	29	38.3	18.8	8	0.20	0.2018
5	PT	40.3	20.2	29	39.7	21.4	8	0.36	0.3632
6	TN	48.6	37.4	38	50.3	20.1	19	-1.17	0.1239
6	PC	42.9	43.7	38	43.5	16.8	19	-0.42	0.3374
6	MP	38.2	17.5	38	37.5	9.7	19	0.72	0.2389
6	PT	43.6	26.4	38	42.7	8.1	19	0.82	0.2071
7	TN	54.8	35.4	24	57.1	17.3	16	-1.49	0.0727
7	PC	45.1	17.2	24	42.8	10.6	16	1.97	**0.0281**
7	MP	41.8	13.5	24	38.4	4.20	16	3.69	**0.0004**
7	PT	43.4	11.9	24	39.8	3.0	16	4.39	**<0.0001**
*The Points of Interest (POIs) are the Tangent (TN), Point of Curvature (PC), Midpoint (MP), and Point of Tangency (TN).									
**Bold indicates p < 0.05.									

Table 3. t-Test Results for Speed of Familiar and Unfamiliar Drivers at Night.

Curve	POI*	Familiar			Unfamiliar			t-stat.	p-value**
		Mean (mph)	Variance	Obsv.	Mean (mph)	Variance	Obsv.		
1	TN	50.6	30.1	12	51.9	10.3	17	-0.76	0.2278
1	PC	46.1	12.6	12	46.5	16.3	17	-0.32	0.3757
1	MP	42.5	15.2	12	40.2	7.0	17	1.80	**0.0444**
1	PT	43.6	19.2	12	41.4	3.7	17	1.62	0.0634
2	TN	50.7	30.2	26	46.4	5.5	18	3.59	**0.0005**
2	PC	46.5	19.6	26	41.3	5.9	18	4.99	**<0.0001**
2	MP	42.8	17.8	26	35.9	6.5	18	6.71	**<0.0001**
2	PT	42.1	12.3	26	34.7	6.4	18	8.16	**<0.0001**
3	TN	55.4	61.1	8	47.0	15.0	18	2.89	**0.0089**
3	PC	43.4	35.7	8	38.2	16.1	18	2.22	**0.0255**
3	MP	37.9	11.6	8	33.7	8.2	18	3.04	**0.0051**
3	PT	40.4	10.0	8	35.5	4.1	18	4.02	**0.0012**
*The Points of Interest (POIs) are the Tangent (TN), Point of Curvature (PC), Midpoint (MP), and Point of Tangency (TN).									
**Bold indicates p < 0.05.									

Table 4. t-Test Results for the Change in Speed between the TN and PC for Familiar and Unfamiliar Drivers.

Day/Night	Curve	Familiar			Unfamiliar			t-stat.	p-value*
		Mean (mph)	Variance	Obsv.	Mean (mph)	Variance	Obsv.		
Day	1	4.3	10.7	162	7.1	7.2	18	-4.10	**0.0002**
Day	2	3.6	9.2	105	3.2	6.6	19	0.64	0.2638
Day	3	6.9	13.4	77	8.5	8.5	18	-1.90	**0.0332**
Day	4	7.1	12.0	62	6.3	7.2	9	0.77	0.2285
Day	5	7.1	32.3	29	12.9	11.8	8	-3.58	**0.0010**
Day	6	5.7	9.5	38	6.8	9.8	19	-1.23	0.1143
Day	7	9.6	19.1	24	14.3	17.8	16	-3.40	**0.0009**
Night	1	4.5	17.4	12	5.4	10.1	17	-0.63	0.2690
Night	2	4.3	6.8	26	5.1	5.2	18	-1.14	0.1315
Night	3	12.0	50.3	8	8.7	9.8	18	1.26	0.1219
*Bold indicates p < 0.05.									

Analysis of Variance

A three-way Analysis of Variance (ANOVA) was used to identify significant factors that affect driver behavior by testing for differences between means. Variables tested for significance include whether the observation was during the day or at night, whether the driver was familiar or unfamiliar with the route, and the curve number. Tables 5–8 show the results of the ANOVA tests of each POI and list the before-mentioned variables as Time of Day, Familiarity, and Curve, respectively. Interactions between the three variables were also tested for significance. The measured variable in the analyses for Tables 5–8 was vehicle speed. Tables 9 and 10 similarly show the results of ANOVA tests in which the measured variable was change in speed. It was expected that all drivers would have different speeds at different curves or at a different time of day. These factors were included to account for the variability they are responsible for. The focus of this report is the effect of the type of driver. The following sections give the results of the ANOVA testing for each of the four points of interest investigated, as well as the results for the tests involving change in speed.

Tangent

The ANOVA results for the POI on the approach tangents are shown in Table 5. The results indicate that driver familiarity is a significant factor at this location. The time of day was not shown to have significance as a single factor. However, the interaction between time of day and driver familiarity was significant, and according to the F-ratio values, it had the strongest correlation with vehicle speed out of all the individual factors and interactions besides the curve itself. The interactions between the curve and driver familiarity and between the curve and time of day were also found to be significant.

Table 5. ANOVA for Speed at Tangent.

Source of Variation	Sum of Squares	DF	Mean Square	F Ratio	Significance*
Corrected Model	6,218.0	27	230.3	6.86	**<0.0001**
Curve	2,916.0	6	486.0	14.47	**<0.0001**
Time of Day	111.9	1	111.9	3.33	0.0683
Familiarity	147.5	1	147.5	4.39	**0.0364**
Curve*Time of Day	469.6	6	78.3	2.33	**0.0309**
Curve*Familiarity	519.7	6	86.6	2.58	**0.0177**
Time of Day*Familiarity	280.0	1	280.0	8.34	**0.0040**
Curve*Time of Day*Familiarity	284.0	6	47.3	1.41	0.2083
Error	24,752.4	737	33.6		
Corrected Total	30,970.3	764			
*Bold indicates p < 0.05.					

Point of Curvature

The ANOVA results for vehicle speeds at the PC of each curve, shown in Table 6, are similar to that of the approach tangent. Driver familiarity was found to be significant and carried the most weight as a factor compared to all of the other factors and interactions, while time of day was not found to be significant at all. Together, the interaction between familiarity and time of day was significant, as well as the interaction between the curve and driver familiarity. However, driver familiarity's interaction with the curve was not significant. In other words, the familiarity of drivers did not affect their behavior differently at one curve compared to another.

Table 6. ANOVA for Speed at PC.

Source of Variation	Sum of Squares	DF	Mean Square	F Ratio	Significance*
Corrected Model	6,467.0	27	239.5	10.80	**<0.0001**
Curve	1,382.1	6	230.3	10.39	**<0.0001**
Time of Day	3.7	1	3.7	0.17	0.6845
Familiarity	693.7	1	693.7	31.28	**<0.0001**
Curve*Time of Day	303.0	6	50.5	2.28	**0.0348**
Curve*Familiarity	167.8	6	28.0	1.26	0.2734
Time of Day*Familiarity	164.6	1	164.6	7.42	**0.0066**
Curve*Time of Day*Familiarity	210.7	6	35.1	1.58	0.1491
Error	16,346.4	737	22.2		
Corrected Total	22,813.5	764			
*Bold indicates p < 0.05.					

Midpoint

The ANOVA results for the midpoint of the curve are presented in Table 7. Like the results for the curve tangents, driver familiarity was a significant factor, along with the interaction between the curve and driver familiarity, between the curve and time of day, and between familiarity and the time of day. In contrast to the tangent results, however, driver familiarity was the most significant variable in relation to vehicle speed.

Table 7. ANOVA for Speed at MP.

Source of Variation	Sum of Squares	DF	Mean Square	F Ratio	Significance*
Corrected Model	8,240.3	27	305.2	19.02	**<0.0001**
Curve	1,776.6	6	296.1	18.46	**<0.0001**
Time of Day	20.3	1	20.3	1.27	0.2607
Familiarity	656.4	1	656.4	40.91	**<0.0001**
Curve*Time of Day	339.2	6	56.5	3.52	**0.0019**
Curve*Familiarity	313.9	6	52.3	3.26	**0.0036**
Time of Day*Familiarity	156.4	1	156.4	9.75	**0.0019**
Curve*Time of Day*Familiarity	313.9	6	52.3	1.91	0.0767
Error	1,1824.6	737	16.0		
Corrected Total	20,064.8	764			
*Bold indicates p < 0.05.					

Point of Tangency

The ANOVA results for the point of tangency of the curves are presented in Table 8. The significant factors and interactions are the same as those that are significant at the point of curvature. Driver familiarity was the most significant factor of all the other factors and interactions with respect to their F-ratios. Time of day was not found to be significant at all, but its interaction with familiarity was significant, as was the interaction between the curve and driver familiarity. The interaction between driver familiarity and the curve was not significant.

Table 8. ANOVA for Speed at PT.

Source of Variation	Sum of Squares	DF	Mean Square	F Ratio	Significance*
Corrected Model	6,163.9	27	228.3	13.62	**<0.0001**
Curve	1,565.6	6	260.9	15.57	**<0.0001**
Time of Day	5.0	1	5.0	0.30	0.5865
Familiarity	1,209.8	1	1209.8	72.20	**<0.0001**
Curve*Time of Day	358.4	6	59.7	3.56	**0.0017**
Curve*Familiarity	181.3	6	30.2	1.80	0.0957
Time of Day*Familiarity	239.6	1	239.6	14.30	**0.0002**
Curve*Time of Day*Familiarity	137.6	6	22.9	1.37	0.2248
Error	12,349.7	737	16.8		
Corrected Total	18,513.6	764			
*Bold indicates $p < 0.05$.					

Change in Speed

The ANOVA results for the change in speed between the tangent and the point of curvature of the curves are shown in Table 9. The results indicate that driver familiarity and the interaction between the curve and driver familiarity are significant factors. The parameter estimates generated along with the ANOVA results show that the main effect of familiarity causes unfamiliar drivers to reduce their speed by 2.1 mph more than familiar drivers between the tangent and point of curvature. The ANOVA results for the change in speed between the tangent and the midpoint of the curve are similarly shown in Table 10. The results again indicate that driver familiarity and the interaction between the curve and driver familiarity are significant. The main effect of familiarity generated along with the ANOVA shows that unfamiliar drivers reduce their speed by 2.0 mph more than familiar drivers between the tangent and the midpoint. Overall, the results of these two analyses of variance show that change in speed is affected by driver familiarity when factoring in all of the variables (i.e., curve, time of day, interactions).

Table 9. ANOVA for Change in Speed between the TN and PC.

Source of Variation	Sum of Squares	DF	Mean Square	F Ratio	Significance*
Corrected Model	5,644.8	27	209.1	16.69	**<0.0001**
Curve	1,397.4	6	232.9	18.60	**<0.0001**
Time of Day	66.3	1	66.3	5.29	**0.0217**
Familiarity	323.9	1	323.9	25.86	**<0.0001**
Curve*Time of Day	149.5	6	24.9	1.99	0.0649
Curve*Familiarity	332.9	6	55.5	4.43	**0.0002**
Time of Day*Familiarity	15.2	1	15.2	1.22	0.2706
Curve*Time of Day*Familiarity	151.9	6	25.3	2.02	0.0607
Error	9,230.2	737	12.5		
Corrected Total	14,874.4	764			
*Bold indicates p < 0.05.					

Table 10. ANOVA for Change in Speed between the TN and MP.

Source of Variation	Sum of Squares	DF	Mean Square	F Ratio	Significance*
Corrected Model	9,179.3	27	340.0	18.24	**<0.0001**
Curve	4,117.2	6	686.2	36.81	**<0.0001**
Time of Day	156.6	1	156.6	8.40	**0.0039**
Familiarity	310.0	1	310.0	16.63	**<0.0001**
Curve*Time of Day	256.7	6	42.8	2.30	**0.0334**
Curve*Familiarity	704.1	6	117.3	6.30	**<0.0001**
Time of Day*Familiarity	17.9	1	17.9	0.96	0.3279
Curve*Time of Day*Familiarity	188.2	6	31.4	1.68	0.1224
Error	13,738.6	737	18.6		
Corrected Total	22,917.9	764			
*Bold indicates p < 0.05.					

Summary of ANOVA Results

The ANOVA testing resulted in several trends that emerged for all four locations. The factor for the curve was significant for each POI, which can be attributed to differences in the characteristics of each curve, such as radius or tangent length. The time of day was not found as a significant factor at any of the locations, while driver familiarity was a significant factor at all four POIs, and it was the most significant factor at all POIs except on the approach tangent. The interaction between driver familiarity and the time of day was found significant. In other words, at all POIs, the unfamiliar drivers behave differently depending on the time of day. For example, unfamiliar drivers may drive slower than familiar drivers at night, but drive no differently during the day. The interaction between the time of day and the curve was also found significant. This means that for all POIs, drivers choose different speeds at each curve depending on the time of day. For example, drivers respond differently at night on one curve than they do at another. The interaction between driver familiarity and the curve was only significant for the approach tangents and the midpoints of the curves, meaning that, at these locations, the familiarity of the drivers affects their driving behavior differently at one curve than at another.

The ANOVA test results for change in speed showed that driver familiarity is significant when factoring in all of the variables, and so is the interaction between the curve and driver familiarity. The results also showed that unfamiliar drivers decelerate more than familiar drivers between the POIs investigated.

Regression Models

Two multivariate regression models were developed to predict vehicle speed at the point of curvature and at the midpoint of the curve based on several different parameters. In selecting the models, preference was given to the models with the simplest form (fewest variables) that still maintain a reasonable level of accuracy and significance. In most cases, the Bayes' information criterion (BIC) was smallest in the final model.

Point of Curvature

A regression model was developed to predict the vehicle speed at the PC. Table 11 shows the effects of the model parameters and their significance in the model. The regression model is given as Equation 1 and has an R^2 value of 0.73. It estimates vehicle speed (in mph) at the PC using factors for the speed on the tangent, the individual curve, the time of day, the driver's familiarity, and the interaction between the curve and speed at the tangent. The values for some of the parameters are defined in Table 12. According to the F-ratios in Table 12, the drivers' speed at the tangent holds the most weight in predicting their speed at the point of curvature. However, the focus of this study is the effect of driver familiarity. Familiarity is the second-most significant parameter according to the F-ratios. The effect of driver familiarity shown in Equation 1 indicates that under the same conditions on the same curve, unfamiliar drivers drive 1.8 mph slower than familiar drivers.

Table 11. Parameter Effect Tests for Point of Curvature Regression Model.

Parameter	F-Ratio	Prob > F
Curve	42.46	<0.0001
Time of Day	5.75	0.0168
Familiarity	46.50	<0.0001
$Speed_{TN}$	1,064.58	<0.0001
$Curve*Speed_{TN}$	5.16	<0.0001

$$Speed_{PC} = 12.6 + \beta_1 + \beta_2\left(Speed_{TN}\right) + 0.6 \times Speed_{TN} - 0.7 \times I_{Time\ of\ day} - 1.8 \times I_{Familiarity} \qquad \text{Eq. 1}$$

where

$Speed_{PC}$ = speed (mph) at the point of curvature.

β_1 = value given in Table 12.

β_2 = value given in Table 12.

$Speed_{TN}$ = speed (mph) at the tangent.
$I_{Time\ of\ day}$ = indicator for time of day (0 for day; 1 for night).
$I_{Familiarity}$ = indicator for driver familiarity (0 for familiar; 1 for unfamiliar).

Table 12. Curve Parameter Estimates for Equation 1.

Curve	β_1	β_2
1	1.9	0.012
2	1.8	0.007
3	0.1	-0.034
4	-1.9	0.036
5	1.7	-0.068
6	-13.4	0.275
7	9.8	-0.228

Midpoint

A regression model was developed to predict the vehicle speed at the MP. Table 13 shows the effects of the model parameters and their significance in the model. The regression model is given as Equation 2 and has an R^2 value of 0.85. It estimates vehicle speed (in mph) at the MP based on the speed at the PC, the individual curve, and the driver's familiarity. It also incorporates the interactions between the curve and driver familiarity, the curve and speed at the PC, and driver familiarity and speed at the PC. The values for some of the parameters are defined in Table 14 and Table 15. According to the F-ratios in Table 13, the drivers' speed at the tangent holds the most weight in predicting the speed at the midpoint. Familiarity, the focus of this study, is the second most significant parameter. The effect of driver familiarity shown in Equation 2 indicates that the speed of unfamiliar drivers at the midpoint of the curve tends to be 1.0 mph slower than that of familiar drivers.

Table 13. Parameter Effect Tests for Midpoint Regression Model.

Parameter	F-Ratio	Prob > F
Curve	59.59	<0.0001
Familiarity	25.20	<0.0001
Curve*Familiarity	9.50	<0.0001
PC	1,544.57	<0.0001
Curve*$Speed_{PC}$	14.76	<0.0001
Familiar*$Speed_{PC}$	11.58	0.0007

$$Speed_{MP} = 7.2 + \beta_1 + \beta_2\left(Speed_{PC}\right) + 0.7 \times Speed_{PC} - 1.0 \times I_{Familiarity} + (Familiarity{*}Speed_{PC}) \times I_{Familiarity} + Curve{*}Familiarity \qquad \text{Eq. 2}$$

where

$Speed_{MP}$	=	Speed (mph) at the midpoint of the curve.
β_1	=	value given in Table 14.
β_2	=	value given in Table 14.
$Speed_{PC}$	=	speed (mph) at the point of curvature.
$I_{Familiarity}$	=	indicator for driver familiarity (0 for familiar; 1 for unfamiliar).
$Familiarity{*}Speed_{PC}$	=	6.50 - 0.141 × $Speed_{PC}$ (influence of the interaction between driver familiarity and speed at the PC).
$Curve{*}Familiarity$	=	influence of the interaction between the curve and driver familiarity (from Table 15).

Table 14. Curve Parameter Estimates for Equation 2.

Curve	β_1	β_2
1	-4.4	0.130
2	-5.6	0.162
3	-5.1	0.122
4	-0.5	-0.057
5	9.7	-0.261
6	7.6	-0.183
7	-1.7	0.086

Table 15. Estimates for Interaction between Curve and Driver Familiarity.

Curve	Curve*Familiarity
1	-0.9
2	-0.9
3	-0.3
4	3.2
5	1.4
6	-1.0
7	-1.4

Summary of Model Results

Only regression models for predicting speed at the point of curvature and at the midpoint of the curve were generated. Both models support the hypothesis that the familiar drivers travel at higher speeds than the unfamiliar drivers under the conditions of the study. However, the difference between the familiar and unfamiliar driver speeds is greater at the point of curvature than it is at the midpoint of the curve. By the time the drivers reach the midpoint, their speeds are lower and have a smaller distribution (as shown in the box-plots) than at the PC, so a smaller difference attributed to unfamiliarity is not surprising.

CONCLUSION

Overall, driver behavior has been shown to be significantly affected by driver familiarity. The t-tests showed that unfamiliar drivers select speeds that are significantly different than those of familiar drivers at many locations, but there were several individual locations where that was not the case. These instances suggest that the effect of familiarity on driver speeds is inconsistent, an interpretation supported by the significant interactions between time of day and familiarity and also between curve and familiarity. Despite this inconsistency, the ANOVA tests and the regression models include factors for driver familiarity, indicating that unfamiliar drivers generally drive slower than familiar drivers, although the effect is not the same at different locations and times of day.

The results support previous studies indicating a difference in driver behavior based on familiarity, but the present study takes it a step further by quantifying this effect.
The present study ultimately identifies that unfamiliar drivers drive 1.0 or 1.8 mph slower than familiar drivers when factoring in the curve, time of day, and speed at the previous location.

Limitations

The results confirm the speculation that familiar drivers tend to drive faster than unfamiliar drivers on horizontal curves on rural, two-lane highways. A number of additional variables not included in the study could also play a part in the apparent relationship between driver familiarity and operating speed. One possible additional factor is the Hawthorne effect. It was anticipated that as a result of the Hawthorne affect, the study would show that drivers exhibit better, more cautious driving behavior when being observed as part of a driving study compared to the drivers in a natural setting. The narrow distribution of the speeds of unfamiliar drivers (as shown in the boxplots) may be an indication of the presence of this Hawthorne effect. However, it was not possible to analyze the difference in driver behavior caused by the Hawthorne effect without introducing a third data set consisting of speed observations from familiar drivers, collected in a driving study setting. The addition of such a data set would allow for better comparisons between familiar and unfamiliar drivers, as well as determine the effect of participation in a study. In addition to reducing the bias caused by the Hawthorne effect, the study could be improved upon by including characteristics of the curve such as radius, approach tangent length, deflection angle, or superelevation. This would give researchers further insight into the interaction between the curve characteristics and driver familiarity. Further limitations include not incorporating additional human factors in the analysis and only looking at one particular type of unfamiliar setting (curves on rural two-lane highways).

Recommendations

The purpose of this study was to investigate the difference in driving behavior caused by driver familiarity. The difference in the speeds of familiar and unfamiliar drivers found was not huge. Because of this difference, however, it may be advisable to incorporate driver familiarity into future studies to account for the variability it is responsible for, especially in studies looking at driver behavior. Additionally, driver familiarity may be a factor to consider when designing rural highways and planning the placement of warning signs and TCDs on these highways before changes in horizontal alignment.

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APPENDIX: DATA SUMMARY BOXPLOTS

This appendix is a continuation of the section "Summary of Data: Boxplots." Figures 6–11 contain the boxplots summarizing the speed data for curves 2–7, for both familiar and unfamiliar drivers and both day and nighttime conditions. Each boxplot shows the first quartile, median, and third quartile speed values, whiskers equivalent to 1.5 times the IQR, and black dots representing outliers, which were removed from the data sets for the analyses.

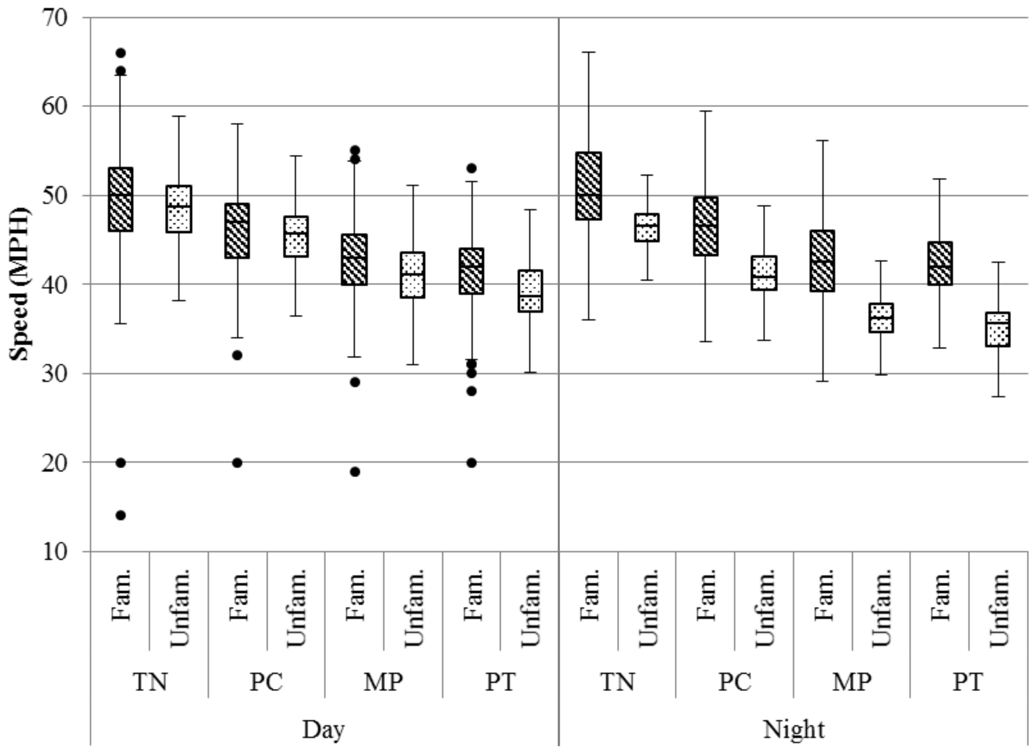

Figure 6. Summary of Data for Curve 2.

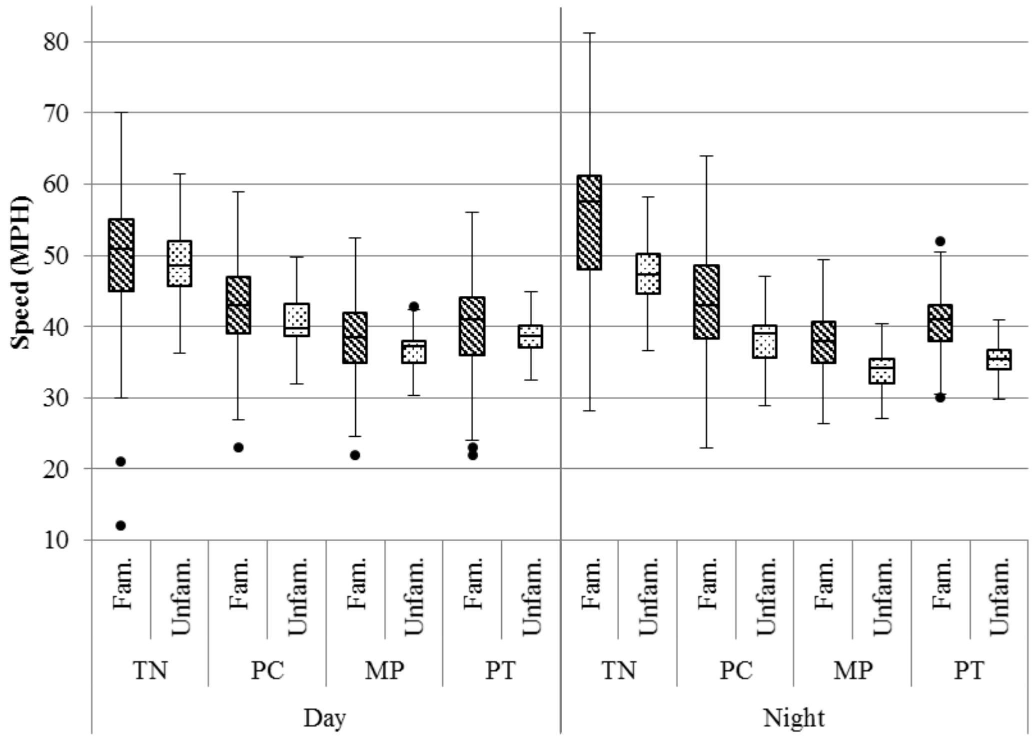

Figure 7. Summary of Data for Curve 3.

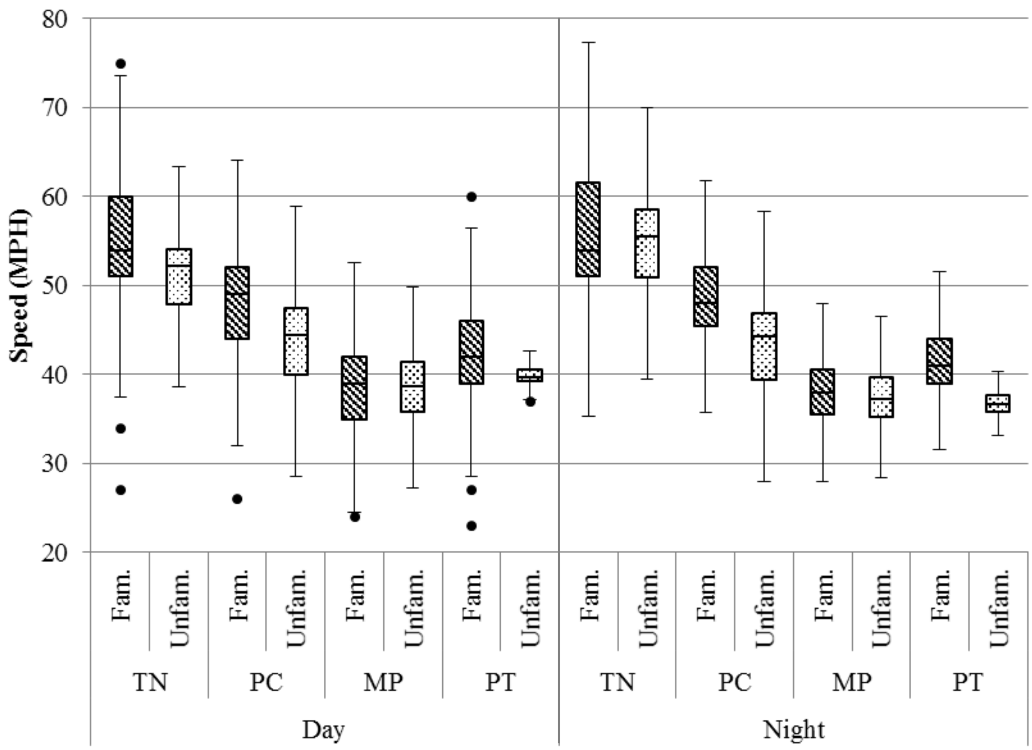

Figure 8. Summary of Data for Curve 4.

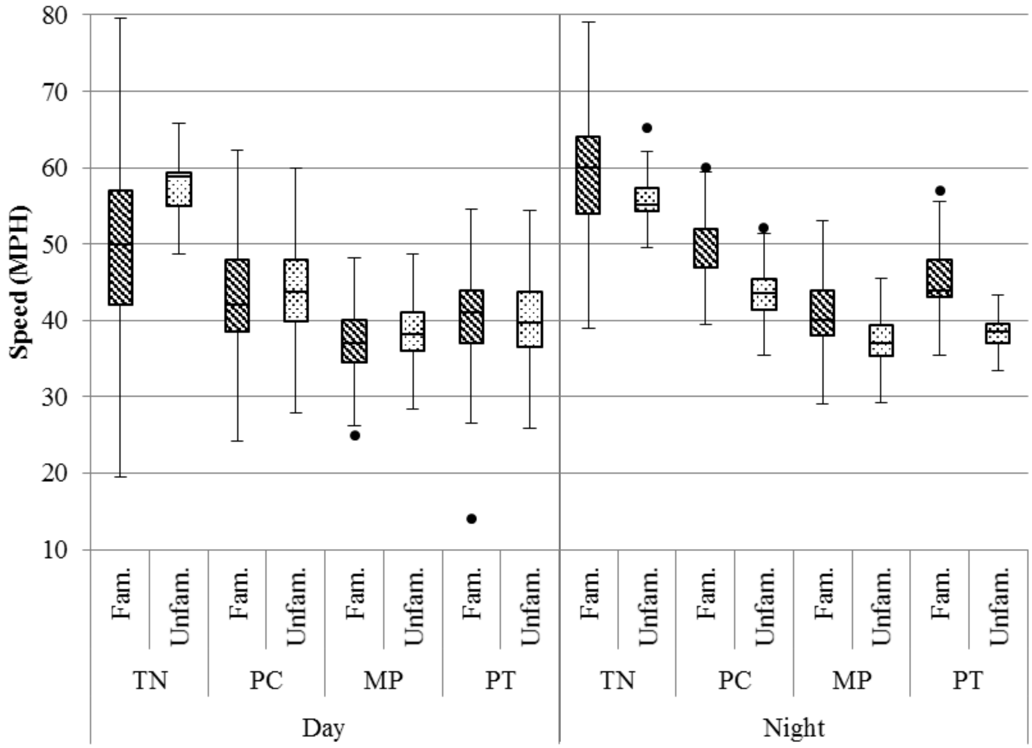

Figure 9. Summary of Data for Curve 5.

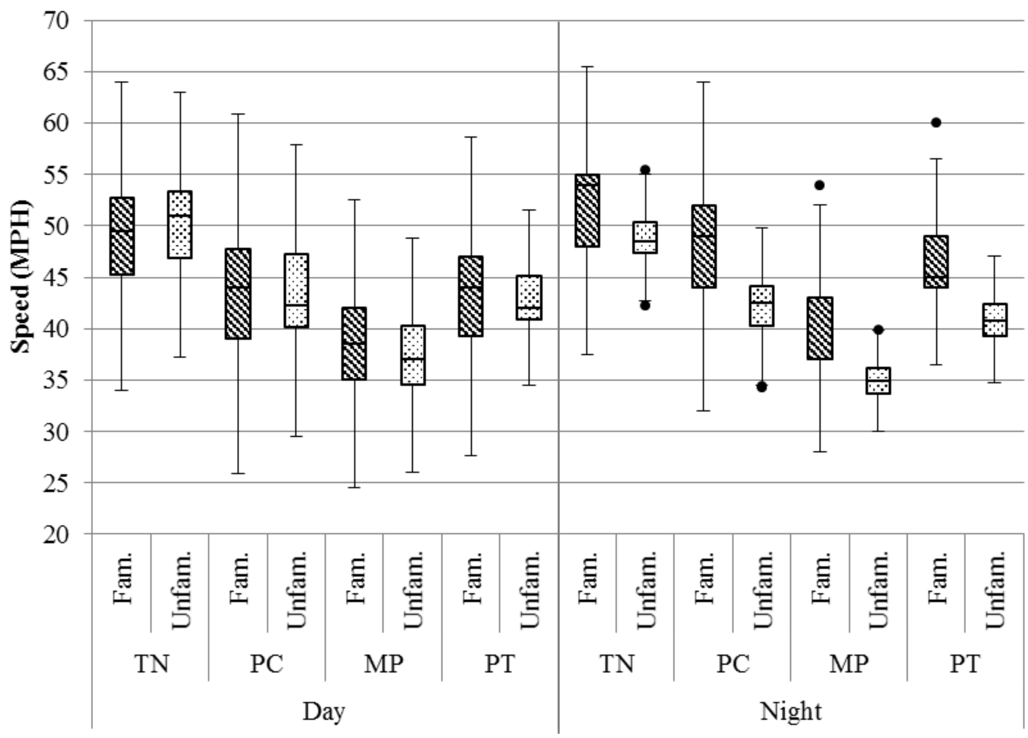

Figure 10. Summary of Data for Curve 6.

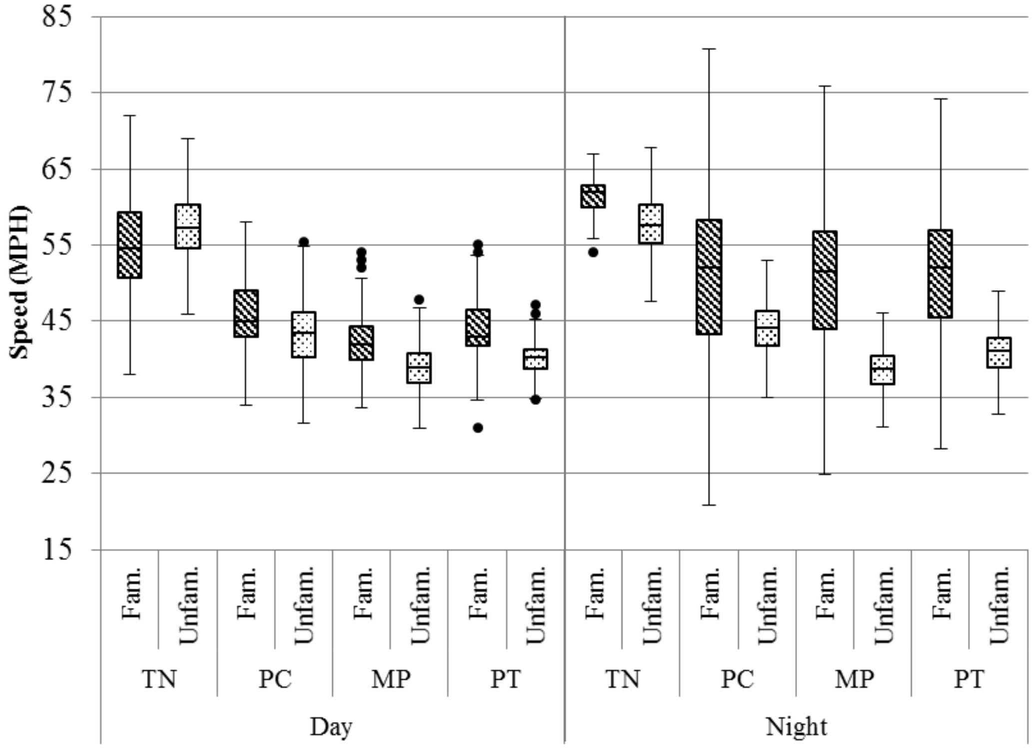

Figure 11. Summary of Data for Curve 7.