About the MTC

The mission of the University Transportation Centers (UTC) program is to advance U.S. technology and expertise in the many disciplines comprising transportation through the mechanisms of education, research, and technology transfer at university-based centers of excellence. The Midwest Transportation Consortium (MTC) is a Tier 1 University Transportation Center that includes Iowa State University, the University of Iowa, and the University of Northern Iowa. Iowa State University, through its Institute for Transportation (InTrans), is the MTC's lead institution.

Technical Report Documentation Page

1. Report No. MTC-2007-07	**2. Government Accession No.**	**3. Recipient's Catalog No.**
4. Title and Subtitle Spatial and temporal differences in Midwestern crashes relative to national data: Public policy implications		**5. Report Date** October 2008
		6. Performing Organization Code
7. Author(s) Mahtab Ghazizadeh, Linda Ng Boyle		**8. Performing Organization Report No.**
9. Performing Organization Name and Address Human Factors and Statistical Modeling Laboratory Department of Mechanical and Industrial Engineering The University of Iowa 3131, Seamans Center for the Engineering Arts and Sciences Iowa City, Iowa, 52242		**10. Work Unit No. (TRAIS)**
		11. Contract or Grant No.
12. Sponsoring Organization Name and Address Midwest Transportation Consortium 2711 South Loop Drive, Suite 4700 Ames, IA 50010-8664		**13. Type of Report and Period Covered** Final Report
		14. Sponsoring Agency Code
15. Supplementary Notes Visit www.intrans.iastate.edu for color PDF files of this and other research reports.		

16. Abstract

The goal of this study was to explore the effects of drivers' personal characteristics and the in-car and out-car conditions associated with a car crashes on the types of crashes that drivers are most likely to be involved in.

It was hypothesized that personal and environmental characteristics surrounding a car crash will affect the types of crashes the drivers get involved in. Also, it was hypothesized that some differences in crash type patterns exist among the four Midwestern states (Iowa, Kansas, Missouri, and Nebraska) and between the Midwest and the country as a whole. The results of this study confirmed that these differences do exist.

Another goal of this study was to analyze the effect of different types of driver distractions on the crash types drivers get involved in. The results of this analysis showed that different sources of distraction lead to different types of crashes.

17. Key Words angular crashes—crash types—driver distraction—Midwestern crashes— rear-end crashes—single-vehicle crashes		**18. Distribution Statement** No restrictions.	
19. Security Classification (of this report) Unclassified.	**20. Security Classification (of this page)** Unclassified.	**21. No. of Pages** 57	**22. Price** NA

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

Spatial and Temporal Differences in Midwestern Crashes Relative to National Data: Public Policy Implications

Final Report
October 2008

Principal Investigator
Linda Ng Boyle
Assistant Professor, Department of Mechanical and Industrial Engineering
Human Factors and Statistical Modeling Laboratory, University of Iowa,

Research Assistant
Mahtab Ghazizadeh

Authors
Mahtab Ghazizadeh and Linda Ng Boyle

Sponsored by
the Midwest Transportation Consortium
a U.S. DOT Tier 1 University Transportation Center
(MTC Project 2007-07)

A report from
Midwest Transportation Consortium
Iowa State University
2711 South Loop Drive, Suite 4700
Ames, IA 50010-8664
Phone: 515-294-8103
Fax: 515-294-0467
www.mtc.iastate.edu

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

We would like to acknowledge the Midwest Transportation Consortium for the funding of this project, and Iowa Department of Transportation, Kansas Department of Transportation, Missouri Department of Transportation, and Nebraska Department of Roads for providing us with the crash data. To John Hill, whose ideas were the impetus for this project, and to the other members of the Human Factors and Statistical Lab at the University of Iowa, especially Birsen Donmez for data gathering and consolidation, and Dave Neyens and Shan Bao for their assistance and support during this project.

1. EXECUTIVE SUMMARY

The goal of this study was to explore the effects of drivers' personal characteristics and in-car and out-car conditions associated with a car crash on the types of crashes the drivers are most likely to be involved in.

It was hypothesized that personal and environmental characteristics surrounding a car crash affect the types of crashes the drivers get involved in. Also, it was hypothesized that some differences in crash type patterns exist between four Midwestern states, Iowa, Kansas, Missouri, and Nebraska, and between the Midwest and the country as a whole. We tested these hypotheses through modeling data from the four states and from the national-level General Estimates System (GES).

The crash data sets used for the analyses of crash patterns in the four Midwestern states contained data for all the crashes that had been recorded in these states during years 2001–2006. However, the GES data that will be used for the national-level analysis is sampled data. The GES obtains its data from a nationally representative probability sample that is extracted from police accident reports.

Some of the personal and environmental factors (independent variables in the models) were shown to influence the drivers' crash patterns more consistently in all four Midwestern states, whereas others affected crash types differently. Driver's gender, driver's age, rural/urban settings, and lighting conditions were the independent variables for which some similar trends were detected among all four states. Also, the interaction between driver's age and gender and the interaction between weather and lighting conditions showed some similarities in states' crash patterns.

For other variables/interaction among variables, no crash pattern was common among all four states. These variables included presence/non-presence of passengers in the car, weather conditions, and the interaction between driver's age and presence/non-presence of passengers.

For many of the variables and interactions among variables, the results for the national-level crash type analysis fully conformed to those for Midwestern states. These were the driver's gender, rural/urban settings, weather conditions, lighting conditions, interaction between driver's age and gender, and interaction between weather and lighting conditions. For the driver's age, the only difference observed between the Midwestern and national data was the odds of involvement in rear-end versus single-vehicle crashes in drivers over the age of 65. The other crash type comparison results were the same for both Midwestern and national levels.

The crash patterns at national and Midwestern levels contrasted with the presence/non-presence of passengers variable and the interaction between this variable and driver's age. In fact, the differences between national and Midwestern crash patterns were limited to the driver's age variable, the presence/non-presence of passengers variable, and the interaction between these two variables.

The analysis of the results confirms our initial hypothesis that personal and environmental conditions influence drivers' involvement in different types of crashes. Also, our hypotheses that crash patterns would be different among the four Midwestern states, and between the Midwestern region and the country as a whole were confirmed through the results of several models that we developed in this study.

In another part of this study, we focused on the effect of different types of distraction on drivers' involvement in different types of crashes. Data from the state of Missouri's vehicle crash database from 2001 to 2006 were used in this study due to the fact that Missouri was the only state that used a specific variable for distraction and a comprehensive distraction categorization.

The results of this second study show that for cell phone and passenger-related distractions, angular crashes have the highest probabilities of occurrence, whereas for electronic devices related distractions the most probable crash type is single-vehicle.

2. INTRODUCTION

2.1. Background

Research on crash data has been explored in many different ways. Police-reported crash data is a compilation of information on various factors associated with the driver (e.g., age, gender), environment (e.g., weather, lighting), roadway (e.g., rural), and traffic (e.g., signalized) for a cross-section in time. The advantage to police-reported data is that many details related to the crash can be obtained. The disadvantage is that information before and after the crash is not available. Regardless, the breadth of research that has been done in this area has provided insights into our understanding of crashes that have led to several traffic improvements. Overviews of some completed studies are presented in this section.

Previous studies looked at crash data to find meaningful relationships between driver characteristics and environmental conditions surrounding a car crash and some important aspects of car crashes and crash consequences such as crash patterns, crash severity, injury severity, etc. (Farmer, Braver, & Mitter, 1997; Hill & Boyle, 2006; Kim, Nitz, Richardson, & Li, 1995; Kockelman & Kweon, 2002; Mao et al., 1997). Several others have focused on teenage drivers and their crash patterns relative to their common driving behaviors. Some examples of the studies in this area are Neyens and Boyle (2007b), Preusser, Ferguson, and Williams (1997), Williams (2003), and Williams, Ferguson, and McCartt (2007). Also, a number of works have been written about older drivers' safety area, e.g. Chandraratna and Stamatiadis (2003), and Hing, Stamatiadis, and Aultman-Hall (2003).

A limited number of studies have focused on the effects of driver's characteristics and environmental conditions associated with the type of crashes that drivers get involved in. Each of these studies focused on a particular geographical region. For example, Ryan, Legge, and Rosman (1998) studied the crash data of Western Australia to assess the effect of driver's age on crash type, and found age related differences in crash type patterns. In another study, Richardson, Kim, Li, and Nitz (1996) used Hawaii crash data in the years 1991 and 1992, distinguishing between drivers being considered at fault by the police officers and those struck in an accident by other drivers. The authors found differences between younger and older drivers in terms of crash types that they are more likely to be involved in (where the driver was at fault). Laapotti and Keskinen (2004) analyzed accident data for several years in Finland and reported that females are more likely to be involved in accidents resulting from problems in vehicle handling and control of traffic situations, whereas males are more likely to have crashes as a result of exceeding speed limits and driving in a drunken state.

A number of studies examined the likelihood of a driver's involvement in a specific crash type as influenced by lighting and weather conditions. Khattak, Kantor, and Council (1998) used data from the Highway Safety Information System database between the years 1990 to 1995, for limited-access roadways in North Carolina State. They reported that adverse weather increases the chance of certain crash types versus other crash types. Golob & Recker (2003) studied the effect of traffic flow, light, and weather conditions on the types of crashes that occur, using data from freeways in Southern California. Within their conclusions, the authors reported that collisions with an object and multiple vehicle collisions are more likely on wet roads, whereas rear-end collisions are more likely on dry roads during daylight.

The effects of other in-car and out-car parameters on crash types have been studied as well. Tavris, Kuhn, and Layde (2001b) focused on injuries caused by motor vehicle crashes using data from Wisconsin's Office of Health Care Information. They found that the presence of passengers in a car can reduce the risk of loss-of-control crashes. Wang, Hasselberg, Wu, and Laflamme (2008) analyzed crash data from the Chaoyang District of Beijing, China for a one-year period, to study the relationship between road type and crash injury patterns. In terms of crash types, they found special crash patterns for some rural areas.

2.2. Problem Statement

The goal of this study was to explore the effects of drivers' personal characteristics and in-car and out-car conditions associated with car crashes on the types of crashes that drivers are most likely to be involved in. This study was conducted across four Midwestern states: Iowa, Kansas, Missouri, and Nebraska.

Analyzing data from these four Midwestern states will enable us to gain some valuable insights into the crash patterns in this region and also allow us to compare the four states in terms of the patterns observed in their car crashes. Utilizing data from multiple states will highlight the effects of past policy decisions on automobile crashes across states with similar driving populations. The findings of this study will help identify where gaps in the crash data exist and how we can make better policies tailored to the Midwest.

Also, because the final step of this study will be to compare crash patterns at the Midwestern and national levels, a better understanding of the specific characteristics of Midwestern states' car crashes will be gained.

We hypothesize that the personal and environmental characteristics surrounding a car crash will affect the types of crashes the drivers get involved in. We also hypothesize that some differences in crash type patterns exist among the four Midwestern states and between the Midwest and the country as a whole. We tested these hypotheses through modeling data from the four states and using sampled data from the national-level car crashes.

3. METHOD

3.1. Crash Type Analysis

Prior to the analytical modeling of the four states crashes, we first had to gain some overall insight into the properties of the data and determine the factors that should be included in the model. Through this initial analysis, we tried to capture the crash types that have the highest odds of occurrence based on the data.

3.1.1. Four States Crash Type Data Summary

We calculated the frequencies of each crash type occurrence and sorted the data from the four states based on the frequencies observed in the years 2001 to 2006 for each state and for the combined data from all the states. The results are presented in Table 1.

Table 1. Summary of crash type frequencies

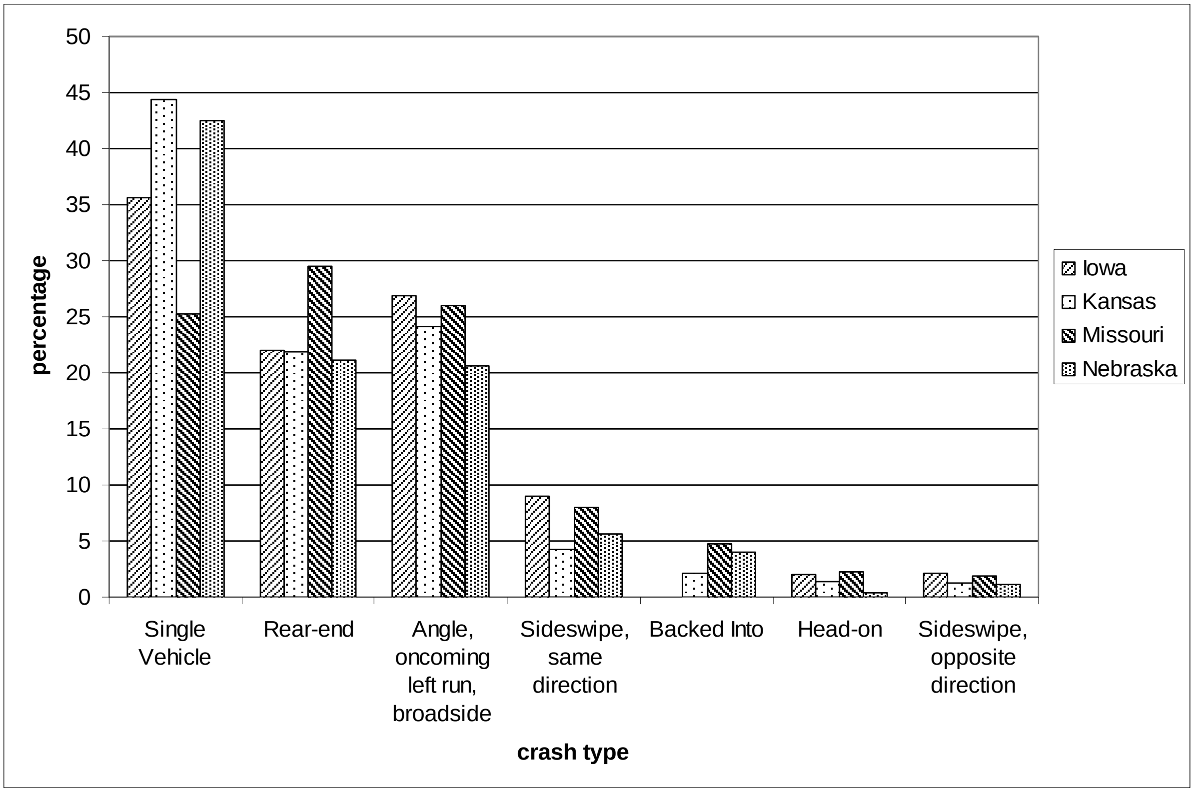
Crash type	State								All States	
	Iowa		Kansas		Missouri		Nebraska			
	Number	%	Number	%	Number	%	Number	%	Total	%
Single-vehicle	124,588	35.64	195,657	44.42	273,235	25.28	153,286	42.51	746,766	33.47
Rear-end	76,987	22.02	96,324	21.87	319,368	29.55	76,234	21.14	568,913	25.50
Angle, oncoming left run, broadside	94,101	26.92	106,506	24.18	280,876	25.99	74,346	20.61	555,829	24.91
Sideswipe, same direction	31,534	9.01	18,732	4.25	86,663	8.02	20,065	5.57	156,994	7.04
Backed Into	-	-	9,423	2.14	50,807	4.7	14,394	3.99	74,624	3.34
Head-on	6,865	1.96	6,088	1.38	24,294	2.25	1,350	0.37	38,597	1.73
Sideswipe, opposite direction	7,304	2.09	5,368	1.22	19,585	1.82	4,115	1.14	36,372	1.63
Other	-	-	1,894	0.43	22,541	2.08	-	-	24,435	1.10
Left-turn leaving	-	-	-	-	-	-	14,065	3.9	14,065	0.63
Unknown	4,331	1.24	439	0.1	3,433	0.32	200	0.05	8,403	0.38
Not Reported	3,906	1.12	-	-	-	-	-	-	3,906	0.18
Not Applicable	-	-	-	-	-	-	2,527	0.7	2,527	0.11
Total	349,616	100	440,431	100	1,080,802	100	360,582	100	2,231,431	100

Highlights denote the highest proportions of crashes.
- indicates that the corresponding category is not available in this state.

The crash types with the highest frequencies are single-vehicle crashes, rear-end crashes, and angular crashes (in the order of frequencies in the four-state data). Our study focused on these three major crash types, as they cover more than 83 percent of all crashes in the four states, and thus will be worthwhile to study closely.

3.1.2. Comparison of Four States Based on Crash Types

We further compared the frequencies of the crashes with the highest ranks (ranks 1 to 7) in the four states. Figure 1 shows the results of this comparison. As is apparent in Table 1, the three crash types with the highest frequencies in each state and in the overall four states are single-vehicle, rear-end, and angular crashes. Thus, we narrowed down our analysis to comparisons among the odds of occurrence of these major crash types.



*Backing not considered as a major crash type in Iowa

Figure 1. Comparison among the states for major crash types

3.2. Data

Data for this study was obtained from the four states' departments of transportation (i.e. Iowa Department of Transportation, Kansas Department of Transportation, Missouri Department of Transportation, and Nebraska Department of Roads). Each of the four data packages contained data sets for crashes in the years 2001 to 2006 in their related states. The data needed to go through different procedures in order to become usable for our study, including data cleaning, data integration, and data consolidation.

Data sets obtained from the four states' departments of transportation can be analyzed in several levels of detail (i.e., crash-level, driver-level, occupant-level, etc.), depending on the application and goal of the analysis to be done. In this study, our goal was to analyze the effects of different personal and environmental factors on the types of crashes the drivers are most likely to be involved in. In Section 3.1, we used crash-level data sets to find the crash types with the largest frequencies. In order to do our study on the effects of driver's characteristics on crash types, we needed to analyze driver-level data. Table 2 contains the sizes of the four data sets that was used in our analyses, listed under the driver-level data set size column. Note that for each state and for the total four-state data, these numbers are greater than the crash-level data set sizes, which are the sum of major-type crashes derived directly from Table 1). This is due to the fact that the number of drivers involved in a car crash may be greater than one.

Table 2. States data set sizes at driver level

State	Driver-level data set size	Crash-level data set size
Iowa	392,579	295,676
Kansas	619,480	398,487
Missouri	1,389,585	873,479
Nebraska	426,154	303,866
Total	2,827,798	1,871,508

3.3. Crash Type Classification

Crash type classifications were slightly different among the four states. However, the differences were not substantial and were mostly associated with labeling the same crash types differently. The two main differences were related to "backing into," which was not considered as a crash type in Iowa, and "left-turn leaving," which was only considered as a crash type in Nebraska. Fortunately, these issues did not change the outcomes of crash type analysis, because the "backing into" category comprised less than five percent of crash data for each state and all states as a whole, as Table 1 shows. Also, "left-turn leaving" was the type of crash for less than four percent of Nebraska crashes. Therefore, these incompatibilities did not change the configuration of the crash type frequencies and the conclusions made from the data.

The three major crash types based on the crash type frequencies study, discussed in Section 3.1, were used in the models: single-vehicle crashes, rear-end crashes, and angular crashes. We tried to build models that predicted the odds of driver's involvement in each of these crash types versus the other two, i.e., rear-end versus single-vehicle crashes, angular versus single-vehicle crashes, and rear-end versus angular crashes for different settings of independent variables that will be discussed in Section 3.4.

3.4. Independent Variables

We had four data sets for crash records from the four states. These data sets shared some properties, but were not entirely compatible. In some cases, they did not all include the same attributes, and in the many cases that they did, the categories for these attributes were not the same. However, all data sets included the variables needed for our analysis. In cases where the required variables were not available, they were obtained from corresponding sources, such as the different states' departments of transportation, in the course of analysis (e.g., rural/urban variable for Iowa and Missouri).

New data sets were built for each of the states to include the variables proven in the literature to be important for this analysis. These variables also needed to be grouped into specific categories suggested by the literature. We have summarized the variables that were used in the analysis and their corresponding variables in each of the states' data sets in Table 3. Also, we have added descriptions of the variables where needed. For our national-level analysis, a comparison of data from the Midwestern states and national crash patterns, Section 5.7 we will use General Estimates System (GES) data. The data are a part of the National Highway Automotive Sampling System (NASS). GES data provide a stratified sample of crashes and are weighted to represent national crash patterns. In Table 3, we have included the variables used from this data set.

Variables included in the multinomial logit model have been shown to influence the crash types drivers become involved in (Golob & Recker, 2003; Khattak et al., 1998; Laapotti & Keskinen, 2004; Massie, Campbell, & Williams, 1995; Richardson et al., 1996; Ryan et al., 1998; Tavris et al., 2001b; Wang et al., 2008). These variables include driver's characteristics (e.g., age and gender) and environmental conditions, including in-car (e.g., presence or non-presence of passengers) and out-car conditions (e.g., rural versus urban setting, weather and lighting conditions).

The categories used to classify the variables were also based on the results of similar studies in the literature (Engstrom, Gregerson, Granstrom, & Nyberg, 2008; Hill & Boyle, 2006; Khattak et al., 1998; Laapotti & Keskinen, 2004; Massie et al., 1995; Richardson et al., 1996; Tavris et al., 2001b; Wang et al., 2008) (Table 3). The population of drivers was divided into three age groups: (1) drivers aged less than 25, (2) drivers aged between 25 and 65, and (3) drivers aged more than 65. Adverse weather was defined as the presence of snow, rain, fog, or sleet. Lighting conditions were categorized into daylight and non-daylight (i.e., dawn, dusk, dark with no street lights, dark with street lights on, and dark with street lights off).

3.5. Sampling Strategies for Each Data Set

The crash data sets used for the analyses of crash patterns in the four Midwestern states of Iowa, Kansas, Missouri, and Nebraska contained data for all the crashes that had been recorded in these states during the years 20012006. However, the GES data used for the national-level analysis, Section 5.7, is sampled data. The GES obtains its data from a nationally representative probability sample that is extracted from police accident reports (PARs). The sampling from PARs is accomplished in three stages: (1) sampling of geographic areas that provide the primary sampling units (PSUs), (2) sampling of police jurisdiction with each PSU, and (3) selection of crashes within the sampled police jurisdictions (NHTSA, 2005). In this study, we analyzed the sampled national crash data of the exact years for which we analyzed Midwestern states' crashes, i.e., the years 2001 to 2006.

Table 3. Variables used in the analyses and their corresponding variables in each state's data set

Variable	Variable Type	Variable values	Iowa Variable Name	Kansas Variable Name	Missouri Variable Name	Nebraska Variable Name	GES variable Name	Description
Driver's gender	independent	male, female	DriverGen	Gender	Sex	Drivers_Sex	SEX_H	-
Driver's age	independent	less than 25, between 25 and 65, more than 65	DriverAge	Age	Date_Of_Birth: Converted to age	Drivers_Birth_Year, Drivers_Birth_Month, Drivers_Birth_Day	AGE_H	Drivers were grouped into 3 categories based on their age.
Number of Occupants (in each vehicle)	independent	one, more than one	Occupants	Nbr_Of_ Occupants	HP_Person_No: Converted to number of occupants	Occupant_Number: Converted to number of occupants	OCC_INVL (for year 2001), NUMOCCS (for 2002-2006)	We classified the cars based on the number of occupants per vehicle into two categories as mentioned. The vehicles with more than 6 occupants were excluded from the analysis (less than 0.26% of data).
Rural/ Urban	independent	rural, urban	RuralUrban	Function_ C	Urban_Rural_Class: "Urbanized" was merged into "Urban"	Population_Group	LAND_USE	-
Weather condition	independent	adverse, normal	Weather1	Weather_ Conditions	Weather_cond_1	Weather_condition_1	WEATHR_I	Weather condition was classified into two categories: adverse (rain, snow, sleet or fog), and normal.
Lighting condition	independent	daylight, non-daylight	Light	Light_ Conditions	Light_condition	Light_condition	LGTCON_I	Lighting condition was classified into two categories: daylight, and non-daylight (dusk, dawn, dark, etc.).
Crash type	dependent	Single-vehicle, rear-end, angular	CrCoManner, Vehicles	Collision_W_Other_ Veh, Nbr_Of_Veh	Two_Veh_Analysis, No_Of_Vehicles	Direction, Total_vehicles	MANCOL_I	Only single-vehicle, rear-end, and angular crashes were included in the analysis. So, we excluded the other crash types from data used in the analysis.

4. ANALYSIS TECHNIQUE

4.1. Multinomial Logit Model to Calculate Crash Type Contrasts

A multinomial logit model was used for the data analysis due to the discrete nature of the response variable, i.e., crash type. The main objective of building a multinomial logit model is to estimate a function that determines outcome probabilities (Washington, Karlaftis, & Mannering, 2003). The analysis was done in Statistical Analysis System (SAS) version 9.1 using the CATMOD procedure (PROC CATMOD) (Allison, 1999). The CATMOD procedure is used to estimate the odds that the dependent variable will be in one of its categories in comparison to another category. Therefore, for this study we used this procedure to compare the three pairs of crash types: (1) rear-end crashes compared to single-vehicle crashes, (2) angular crashes compared to single-vehicle crashes, and (3) rear-end crashes compared to angular crashes, for each of the independent variables.

Multinomial logit models are used to model events with multiple unordered outcomes (Borooah, 2001). In the crash type analysis domain, for a problem with M types of crashes (j = 1, …, M), the chances that the ith driver (i = 1, …, N) is involved in the jth type of crash is represented as U_{ij}. Suppose that U_{ij} is a linear function of R factors, and the values of the these R variables, representing the characteristics of the ith driver, are X_{ir}, r =1, …, R. U_{ij} is calculated by Equation 1, where β_{jr} is the coefficient associated with the rth characteristic (r = 1, …, R) for the jth crash type.

$$U_{ij} = \sum_{r=1}^{R} \beta_{jr} X_{ir} + \varepsilon_{ij} = Z_{ij} + \varepsilon_{ij} \tag{1}$$

It is shown that if the error terms ε_{ij} (j = 1, …, M) are independently and identically distributed with Weibull distribution $F(\varepsilon_{ij}) = \exp[\exp(-\varepsilon_{ij})]$, then

$$\Pr(Y_i = m) = \frac{\exp(Z_{im})}{\sum_{j=1}^{M} \exp(Z_{ij})} \tag{2}$$

In Equation 2, Y_i is a random variable whose value (j = 1, …, M) indicates the type of crash driver i gets involved in. The multinomial model is defined by Equation 3.

$$Z_{ij} = \sum_{r=1}^{R} \beta_{jr} X_{ir} \tag{3}$$

Since the probabilities $\Pr(Y_i = j)$ sum to 1 ($\sum_{j=1}^{M} \Pr(Y_i = j) = 1$), only M – 1 of the probabilities can be determined independently. Thus, the model of Equation 3 is indeterminate, as it is a system of M equations. This problem is solved by setting β_{jr} = 0, r = 1, …, R. Under this normalization Z_{i1} = 0, and so from Equation 2

$$\Pr(Y_i = 1) = \frac{1}{1 + \sum_{j=2}^{M} \exp(Z_{ij})} \tag{4a}$$

$$\Pr(Y_i = m) = \frac{\exp(Z_{im})}{1 + \sum_{j=2}^{M} \exp(Z_{ij})}, m = 2, \ldots, M. \tag{4b}$$

As a result of the normalization, the probabilities are uniquely determined by Equations 4a and 4b. From Equations 4a and 4b, the logarithm of the ratio of the probability of the crash type *m* ($j = m$) to crash type *k* ($j = k$) is

$$\log\left(\frac{\Pr(Y_i = m)}{\Pr(Y_i = k)}\right) = \sum_{r=1}^{R} (\beta_{mr} - \beta_{kr}) X_{ir} = Z_{im} - Z_{ik} \tag{5}$$

PROC CATMOD in SAS outputs comparisons between the odds of different crash types (i.e., rear-end, angular, and single-vehicle crashes) in the form of Equation 5. These values are included in all parameter estimate tables in the results section, Section 5, under the "estimate" column. The exponentiation of these values allows us to obtain the probability ratios for each pair of crash types. In reference to Equation 5, wherever the logarithmic ratio estimate is positive, the exponent of this estimate gives a value more than one, and thus the odds of crash type *m* are more than crash type *k*. On the other hand, where the estimate is negative, the exponent of this estimate will give a value less than one, and the odds of crash type *m* are less than crash type *k*. This is the rationale behind interpretation of PROC CATMOD results.

The output of the CATMOD procedure only shows two out of the three crash type contrasts (e.g., rear-end crash versus single-vehicle crash and angular crash versus single-vehicle crash). However, the third contrast, the rear-end crash versus angular crash, can easily be calculated by subtracting the second contrast from the first one. All three of the contrasts are included in the tables throughout Section 5 to provide the reader with a complete collection of results.

4.2. Modeling Procedure

Figure 2 shows the steps that were taken in data modeling. First, we built models at state level, i.e., separate models for the states of Iowa, Kansas, Missouri, and Nebraska. Then we compared the outcomes of these models (e.g., the crash patterns in each state). We also built a model using the four-state crash data to compare the states in a more effective way. Our final two steps were to model crash data at the Midwestern and national levels and compare the results of the two models.

The independent variables entered into the model, as discussed in Section 3.4, were the driver's age, driver's gender, presence/non-presence of passengers, rural versus urban setting, weather condition, and lighting condition. Some interactions between these variables were also put into the model, i.e., interaction between driver's gender and age, driver's age and presence/non-presence of passengers, and weather and lighting conditions.

Using the presence/non-presence of passengers variable is another way to look at the number of occupants. Non-presence of passengers corresponds to "1" for the number of occupants, where the driver is the only occupant, while the presence of passengers corresponds to "more than 1" for the number of occupants. While the number of occupants in the car is easier to obtain from the data in practice, the presence/non-presence of the passengers variable is more meaningful from the interpretation point-of-view and thus was opted in model results presentation.

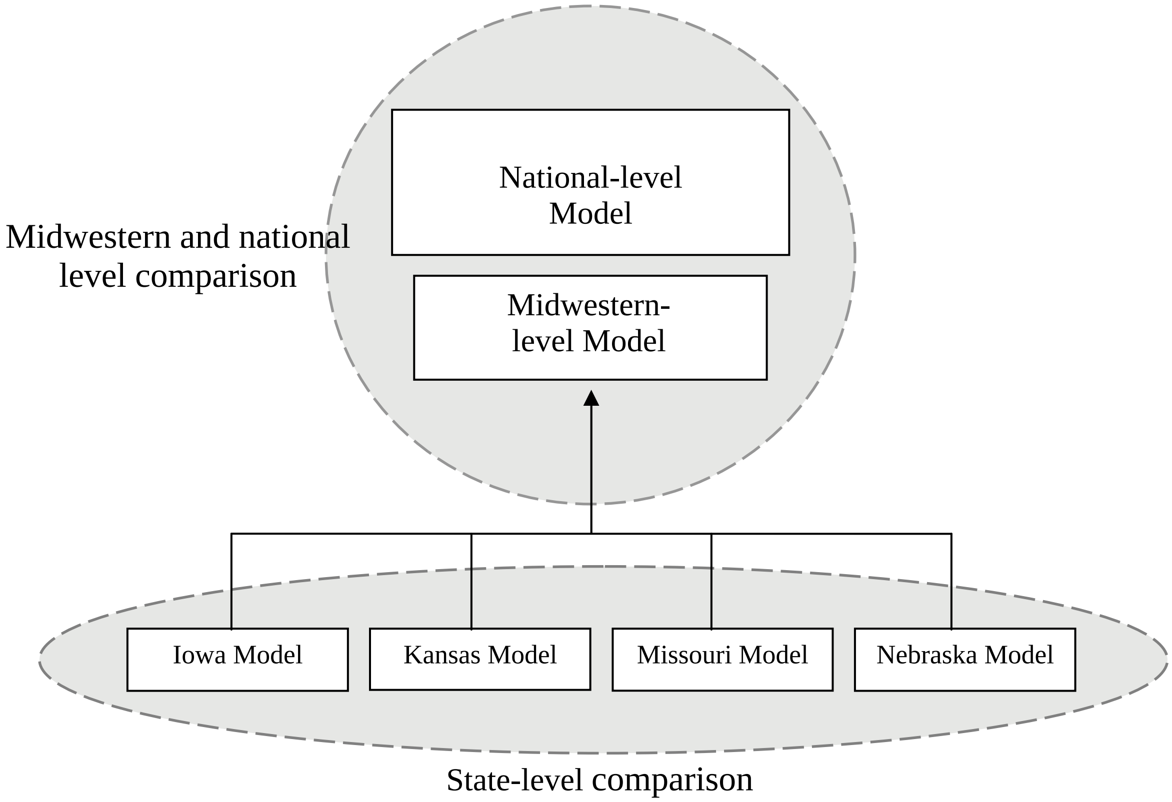


Figure 2. A schematic view of the relationship between models developed on state, Midwestern, and national levels

An important point to be considered in interpreting the results of this study is that the analyses were performed on crash data and that the findings are in terms of relative likelihood of involvement in a type of crash, given that a crash has occurred. Therefore, the results do not predict the odds of a driver in certain personal and environmental conditions becoming involved in a certain type of crash. Instead, the results show the relative likelihood of different crash types for people in different conditions.

5. RESULTS

In this section, we present the results of the models that we built for each of the four states. In each of the models' result tables, we have parameter estimates for each of the three types of crashes versus the two others. With the exponents of these coefficient estimates for each independent variable, we obtain the comparison between the odds that a certain category of that variable will fall into one of the dependent variable categories versus another category or categories of the independent variable (e.g., male drivers). As an example, for the driver's gender variable, the odds of involvement of a female driver in a rear-end crash versus a single-vehicle crash in comparison with a male driver is calculated by finding the exponent of the corresponding coefficient estimate.

We chose a significance level of 0.001 due to the large data set sizes we had to deal with. Setting a smaller level could lead to finding misleading significant differences. In order to communicate the results more efficiently, we omitted the Chi-squares for insignificant contrasts and replaced them with n.s. (no significance). Therefore, any Chi-square presented in the table has a *p*-value smaller than the significance level (0.001), and the corresponding contrast is significant.

The results for the four states are presented in the following four sections: State of Iowa, State of Kansas, State of Missouri, and State of Nebraska, sections 5.1 through 5.4

5.1. State of Iowa

The results of the model for the Iowa data are shown in Table 4. For each independent variable, a contrast between categories is included in the table, and the variables that are set as the base of the comparison (by CATMOD procedure) are calculated for each of the three crash type contrasts. For variables with two categories (e.g., weather condition), contrast estimates (labeled as "estimate") reflect the contrast between the category listed in the table and the other category, which is treated as the reference category (e.g., adverse weather versus normal weather). The reference category is not listed in the table. However, we should note that for variables with more than two categories (e.g., driver's age), the contrast estimates are not calculated in comparison with the omitted category (Allison, 1999). Instead, they are overall estimates for all of the variable categories.

In Table 4, we can observe that female drivers are more likely to have rear-end and angular crashes than single-vehicle crashes. Also, for this group of drivers, a higher likelihood of having an angular crash versus a rear-end crash is observed.

Drivers between the ages of 25 and 65 are more likely to have rear-end crashes when compared to single-vehicle and angular crashes. The odds of having a single-vehicle crash are greater than for an angular crash for this age group. For drivers over the age of 65, the odds of being involved in an angular crash are greater than a single-vehicle or a rear-end crash. However, no significant difference between the odds of having rear-end and single-vehicle crashes was detected for this group of drivers.

We also put the interaction between driver's age and gender in the model. Based on the results, female drivers between the ages of 25 and 65 are more likely to have single-vehicle and rear-end crashes than angular crashes. For this group of drivers, no significant difference was detected between the odds of having rear-end and single-vehicle crashes. For female drivers over the age of 65, the odds of being involved in a single-vehicle or an angular crash are greater than for a rear-end crash. No significant difference was observed between angular and single-vehicle crashes for this group.

For drivers with passengers in their cars, the odds of involvement in a rear-end or an angular crash are greater than for a single-vehicle crash. There is no significant contrast between rear-end and angular crashes for this group.

No significant contrast between different types of crashes was found for drivers between the ages of 25 and 65 with passengers present in their cars. However, drivers older than 65 with passengers are more likely to have rear-end crashes than single-vehicle or angular crashes. There is no significant contrast between angular and single-vehicle crashes for this group.

In rural settings, drivers are more likely to be involved in single-vehicle crashes than rear-end and angular crashes. Also, the odds of having a rear-end crash are greater than for an angular crash for rural settings.

In adverse weather conditions, the likelihood of being involved in a rear-end or a single-vehicle crash is more than for an angular crash. No significant contrast between rear-end and single-vehicle crashes is observed.

In non-daylight lighting conditions, drivers are more likely to be involved in single-vehicle crashes than rear-end and angular crashes. No significant difference is observed between rear-end and angular crashes for these poor lighting conditions.

When both adverse weather and non-daylight conditions are present, the odds of having rear-end or angular crashes are greater than for single vehicle crashes. Also, for this weather and lighting condition combination, the likelihood of being involved in an angular crash is more than for a rear-end crash.

Table 4. Parameter estimates from the multinomial logit model for the State of Iowa

Variable	Rear-end crash vs. single-vehicle crash			Angular crash vs. single-vehicle crash			Rear-end crash vs. angular crash		
	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square
Intercept	-0.0943	0.0107	77.43	0.0171	0.0105	n.s.	-0.1115	0.00910	150.05
Female driver	0.0496	0.00775	40.99	0.0973	0.00741	172.41	-0.0477	0.00510	87.47
Driver’s age between 25 and 65	0.0769	0.00964	63.56	-0.1049	0.00936	125.44	0.1818	0.00638	812.21
Driver’s age more than 65	0.0496	0.0155	n.s.	0.4283	0.0148	838.43	-0.3786	0.00981	1490.53
Female driver between the ages of 25 and 65	-0.00766	0.00872	n.s.	-0.0466	0.00843	30.55	0.0389	0.00586	44.21
Female driver over the age of 65	-0.0708	0.0140	25.45	-0.00053	0.0133	n.s.	-0.0702	0.00896	61.49
Passenger(s) present in the car	0.1196	0.00827	208.91	0.1116	0.00798	195.34	0.00800	0.00550	n.s.
Driver between the ages of 25 and 65 with passenger(s) present in the car	0.0258	0.00941	n.s.	0.0300	0.00916	n.s.	-0.00420	0.00634	n.s.
Driver over the age of 65 with Passenger(s) present in the car	0.0770	0.0150	26.43	0.0276	0.0143	n.s.	0.0494	0.00970	25.97
Rural setting	-1.2883	0.00568	51372.22	-1.4460	0.00584	61299.25	0.1577	0.00585	727.11
Adverse weather condition	0.0232	0.00797	n.s.	-0.0406	0.00804	25.47	0.0638	0.00684	87.01
No daylight	-0.7427	0.00801	8599.85	-0.7316	0.00809	8185.23	-0.0111	0.00685	n.s.
Adverse weather and no daylight	0.1769	0.00796	493.29	0.2160	0.00804	722.66	-0.0391	0.00684	32.77

Note: n.s. indicates no significance found at level of 0.001.

5.2. State of Kansas

The model results for the state of Kansas are summarized in Table 5. Interpretation of the results has been done based on the same criteria used for the state of Iowa model. The main findings for the Kansas model are explained in the following paragraphs.

In this state, female drivers are shown to be more likely to have rear-end and angular crashes than single-vehicle crashes. In the comparison between rear-end and angular crashes, female drivers are more likely to have angular crashes.

For drivers between the ages of 25 and 65, the odds of involvement in rear-end crashes are more than for single-vehicle and angular crashes. The drivers in this age group are more likely to be involved in single-vehicle crashes than angular crashes. These results are totally similar to the corresponding results for the state of Iowa in Section 5.1. The results observed for drivers over the age of 65 contrast entirely with the results that we reported for drivers between the ages of 25 and 65. For this age group, the likelihood of involvement in single-vehicle and angular crashes is more than rear-end crashes. The odds of having an angular crash are greater than for a single-vehicle crash for these drivers.

The interaction between driver's age and gender reveals some interesting patterns. These patterns are similar to those from the state of Iowa. For female drivers between the ages of 25 and 65, no significant contrast is detected between rear-end and single-vehicle crashes. These drivers are more likely to have single-vehicle and rear-end crashes than angular crashes. For female drivers over the age of65, the odds of being involved in a single-vehicle or an angular crash is more than for a rear-end crash. There is no significant difference between the odds of having angular and single-vehicle crashes for this group of drivers.

The results for presence of passengers in the car are similar to those from Iowa as well, as noted in Section 5.1. Drivers with passengers in their cars are more likely to have a rear-end or an angular crash than a single-vehicle crash. No significant difference was observed between rear-end and angular crashes for this group of drivers.

For drivers between the ages of 25 and 65 with passengers present in their cars, no significant contrast was detected between the three types of crashes. These results are similar to those obtained from the model for Iowa as well. Drivers over the age of 65 with passengers in their cars are more likely to have rear-end crashes than single-vehicle and angular crashes. There is no significant difference between angular and single-vehicle crashes for this group of drivers.

In rural settings, drivers are more likely to have single-vehicle crashes than rear-end and angular crashes. The likelihood of being involved in an angular crash is more than for a rear-end crash in these settings.

Drivers driving in adverse weather conditions are more likely to have rear-end crashes than single-vehicle and angular crashes. No significant difference was detected between angular and single-vehicle crashes in adverse weather conditions.

In non-daylight driving situations, the odds of involvement in a single-vehicle crash are greater than for a rear-end or angular crash. In these poor lighting conditions, drivers are more likely to be involved in an angular crash than a rear-end crash.

In the presence of adverse weather and non-daylight conditions, drivers are more likely to have rear-end and angular crashes than single-vehicle crashes. No significant contrast was found between the odds of involvement in rear-end and angular crashes in combinations of these weather and lighting conditions.

Table 5. Parameter estimates from the multinomial logit model for the State of Kansas

Variable	Rear-end crash vs. single-vehicle crash			Angular crash vs. single-vehicle crash			Rear-end crash vs. angular crash		
	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square
Intercept	-0.1855	0.00793	547.07	-0.1411	0.00756	348.10	-0.0444	0.00750	35.07
Female driver	0.1030	0.00578	317.41	0.1316	0.00522	635.97	-0.0286	0.00463	38.20
Driver's age between 25 and 65	0.1206	0.00705	292.49	-0.1257	0.00652	371.48	0.2463	0.00573	1847.35
Driver's age more than 65	-0.1599	0.0117	185.84	0.2878	0.0105	748.91	-0.4478	0.00931	2314.74
Female driver between the ages of 25 and 65	0.0209	0.00643	n.s.	-0.0294	0.00592	24.68	0.0503	0.00521	93.32
Female driver over the age of 65	-0.0833	0.0106	61.59	-0.0186	0.00942	n.s.	-0.0648	0.00838	59.77
Passenger(s) present in the car	0.0713	0.00622	131.40	0.0787	0.00567	192.42	-0.00736	0.00506	n.s.
Driver between the ages of 25 and 65 with passenger(s) present in the car	-0.00933	0.00692	n.s.	0.00775	0.00642	n.s.	-0.0171	0.00570	n.s.
Driver over the age of 65 with Passenger(s) present in the car	0.0583	0.0114	25.97	-0.00858	0.0103	n.s.	0.0669	0.00921	52.75
Rural setting	-1.3285	0.00736	32545.96	-1.2139	0.00749	26280.59	-0.1146	0.00835	188.19
Adverse weather condition	0.0488	0.00528	85.42	-0.00536	0.00519	n.s.	0.0541	0.00535	102.27
No daylight	-0.8113	0.00530	23461.79	-0.7177	0.00521	19004.68	-0.0936	0.00537	303.93
Adverse weather and no daylight	0.1436	0.00527	741.79	0.1519	0.00519	856.99	-0.00827	0.00535	n.s.

Note*:* n.s. indicates no significance found at level of 0.001.

5.3. State of Missouri

The results obtained from the model built for the state of Missouri are shown in Table 6. Again, we will use the contrast estimate sign as the criterion for determining how different crash types compare with different variables.

Female drivers in the state of Missouri, in comparison to male drivers, are more likely to have rear-end and angular crashes than single-vehicle crashes . The likelihood of being involved in an angular crash is more than a rear-end crash for female drivers.

For drivers between the ages of 25 and 65, the odds of involvement in rear-end crashes are greater than for single-vehicle and angular crashes. This group of drivers is more likely to have single-vehicle crashes than angular crashes. These results are completely in agreement with those obtained from the same age group in the states of Iowa and Kansas, Sections 5.1 and 5.2. Drivers over the age of 65 are more likely to be involved in rear-end and angular crashes than single-vehicle crashes. The likelihood of having an angular crash is more than a rear-end crash for this group of drivers.

Female drivers between the ages of 25 and 65 are more likely to have rear-end crashes than single-vehicle or angular crashes. No significant difference was observed between the odds of being involved in angular crashes and single-vehicle crashes for this group of drivers. For female drivers over the age of 65, the odds of involvement in a single-vehicle crash are greater than for a rear-end or an angular crash. These drivers are more likely to have angular crashes than rear-end crashes.

With the presence of passengers in the car, drivers are more likely to be involved in single-vehicle crashes than rear-end or angular crashes. These results are completely in contrast to what was observed for the states of Iowa and Kansas. Also, this group of drivers is more likely to have angular crashes than rear-end crashes. This contrast was insignificant for the states of Iowa and Kansas.

Contrary to the results we found for the states of Iowa and Kansas, the contrast between different crash types for drivers between the ages of 25 and 65 who have passengers present in their cars is significant for the state of Missouri. For this group of drivers, the likelihood of having a rear-end or an angular crash is more than for a single-vehicle crash. These drivers are more likely to have a rear-end crash than an angular crash. Drivers over the age of 65 with passengers in their cars are more likely to have single-vehicle and rear-end crashes when compared with angular crashes.

Drivers driving in rural settings are more likely to have single-vehicle crashes than rear-end or angular crashes. These drivers are more likely to be involved in rear-end crashes than angular crashes. The results obtained regarding rural/urban settings for Missouri are similar to those we observed for Iowa.

In adverse weather conditions, drivers are more likely to have single-vehicle crashes than rear-end or angular crashes. The odds of being involved in a rear-end crash are greater than for an angular crash in these weather conditions.

In non-daylight conditions, the likelihood of being involved in a single-vehicle crash is more than for a rear-end or an angular crash. The odds of involvement in an angular crash are greater than for a rear-end crash in these lighting conditions.

When drivers are dealing with both adverse weather and non-daylight conditions, they are more likely to be involved in a rear-end or an angular crash than a single-vehicle crash. In these driving situations, the odds of involvement in an angular crash are greater than for a rear-end crash. These results are all similar to those we previously obtained for the same weather and lighting conditions combination in the state of Iowa.

Table 2. Parameter estimates from the multinomial logit model for the State of Missouri

Variable	Rear-end crash vs. single-vehicle crash			Angular crash vs. single-vehicle crash			Rear-end crash vs. angular crash		
	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square
Intercept	0.0192	0.00767	n.s.	0.2618	0.00727	1297.29	-0.2427	0.00639	1442.25
Female driver	0.1063	0.00417	650.37	0.1357	0.00410	1095.62	-0.0294	0.00247	141.93
Driver's age between 25 and 65	0.1155	0.00787	215.70	-0.0605	0.00749	65.25	0.1760	0.00631	778.90
Driver's age more than 65	0.2089	0.0126	276.37	0.4264	0.0119	1294.54	-0.2175	0.00965	508.19
Female driver between the ages of 25 and 65	0.0475	0.00465	104.33	-0.00230	0.00460	n.s.	0.0498	0.00284	308.26
Female driver over the age of 65	-0.0940	0.00760	152.95	-0.0411	0.00744	30.50	-0.0529	0.00427	154.00
Passenger(s) present in the car	-0.5287	0.00686	5942.79	-0.3748	0.00647	3357.08	-0.1539	0.00550	781.59
Driver between the ages of 25 and 65 with passenger(s) present in the car	0.1142	0.00777	215.83	0.0910	0.00740	151.14	0.0232	0.00629	13.59
Driver over the age of 65 with Passenger(s) present in the car	-0.0226	0.0124	n.s.	-0.0849	0.0117	53.11	0.0623	0.00961	42.05
Rural setting	-0.9981	0.00397	63177.37	-1.0650	0.00400	71045.72	0.0669	0.00361	343.06
Adverse weather condition	-0.1711	0.00397	1853.82	-0.1890	0.00398	2254.11	0.0179	0.00347	26.62
No daylight	-0.6711	0.00400	28148.64	-0.5313	0.00400	17603.75	-0.1398	0.00348	1611.14
Adverse weather and no daylight	0.0738	0.00397	345.12	0.1211	0.00398	925.60	-0.0473	0.00347	185.22

Note: n.s. indicates no significance found at level of 0.001.

19

5.4. State of Nebraska

The results obtained from the Nebraska model are summarized in Table 7. We used the same criterion, the contrast estimate sign, for the interpretation of these results.

For female drivers in the state of Nebraska, the odds of being involved in a rear-end or an angular crash are greater than for a single-vehicle crash, when compared with male drivers. No significant contrast was observed between rear-end and angular crashes for this group of drivers.

Drivers between the ages of 25 and 65 are more likely to have rear-end and angular crashes than single-vehicle crashes. For these drivers, the odds of being involved in a rear-end crash are greater than for an angular crash. Drivers over the age of 65 are more likely to have single-vehicle and angular crashes than rear-end crashes. For this age group, the likelihood of involvement in an angular crash is more than for a single-vehicle crash. The results observed for drivers over 65 are similar to those we reported for the same age group in the state of Kansas, Section 5.2.

Looking at the results of the interaction between driver's age and gender, we find some interesting significant contrasts between different crash types. For female drivers between the ages of 25 and 65, the odds of involvement in a rear-end crash are greater than for a single-vehicle or an angular crash. For this group of drivers, no significant contrast between angular and single-vehicle crashes was observed. Female drivers over the age of 65 are more likely to be involved in a single-vehicle crash than a rear-end or an angular crash. They are more likely to have angular crashes than rear-end crashes. All the results observed for the interaction between age and gender for the state of Nebraska are similar to those we found for the state of Missouri, Section 5.3.

In the presence of passengers, drivers are more likely to have rear-end and angular crashes than single-vehicle crashes. No significant difference between the odds of being involved in rear-end and angular crashes was detected. These results are the same as the results that we found for the states of Iowa and Kansas, Sections 5.1 and 5.2.

For drivers between the ages of 25 and 65 with passengers present in their cars, the odds of involvement in a rear-end crash are greater than for an angular crash. For this group of drivers, no other significant contrast was observed. For drivers over the age of 65 with passengers in their cars, none of the three crash types was different from the other two in terms of the odds of occurrence.

In rural settings in Nebraska, drivers are more likely to be involved in single-vehicle crashes than rear-end and angular crashes. These contrasts are shown to be valid for all the four states. Also, for rural settings in Nebraska, the odds of involvement in angular crashes are more than rear-end crashes. We found the same pattern for Kansas in Section 5.2.

In adverse weather conditions, the likelihood of being involved in a rear-end or an angular crash is more than a single-vehicle crash. Drivers in these weather conditions are more likely to have angular crashes than rear-end crashes. These results are completely in contrast with the results we observed for the state of Missouri.

In non-daylight conditions, drivers are more likely to be involved in single-vehicle crashes than rear-end or angular crashes. This pattern is valid for all four states, which are shown in the Sections 5.1, 5.2, and 5.3 for patterns observed in states of Iowa, Kansas, and Missouri. In these lighting conditions, the odds of involvement in angular crashes are greater than for rear-end crashes. This was the same for the states of Kansas and Missouri.

In adverse weather and non-daylight conditions in Nebraska, the likelihood of being involved in rear-end and angular crashes is greater than for single-vehicle crashes. Drivers in these driving situations are more likely to have angular crashes than rear-end crashes. These results are similar to those we had previously found for the states of Iowa and Missouri.

Table 7. Parameter estimates from the multinomial logit model for the State of Nebraska

Variable	Rear-end crash vs. single-vehicle crash			Angular crash vs. single-vehicle crash			Rear-end crash vs. angular crash		
	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square
Intercept	-0.3598	0.00952	1429.05	-0.2283	0.00917	620.24	-0.1315	0.00911	208.49
Female driver	0.0475	0.00601	62.38	0.0575	0.00572	100.90	-0.00997	0.00497	n.s.
Driver’s age between 25 and 65	0.2315	0.00764	917.78	0.0275	0.00738	13.92	0.2040	0.00621	1080.08
Driver’s age more than 65	-0.2741	0.0122	502.58	0.0794	0.0114	48.36	-0.3535	0.00987	1282.87
Female driver between the ages of 25 and 65	0.0503	0.00689	53.29	0.00759	0.00666	n.s.	0.0427	0.00569	56.35
Female driver over the age of 65	-0.1665	0.0107	241.22	-0.0969	0.0100	93.77	-0.0695	0.00882	62.17
Passenger(s) present in the car	0.0896	0.00665	181.51	0.0842	0.00633	176.66	0.00545	0.00543	n.s.
Driver between the ages of 25 and 65 with passenger(s) present in the car	0.0209	0.00753	n.s.	0.000059	0.00729	n.s.	0.0208	0.00616	11.40
Driver over the age of 65 with Passenger(s) present in the car	0.0207	0.0120	n.s.	0.0290	0.0113	n.s.	-0.00833	0.00975	n.s.
Rural setting	-1.0340	0.00530	38113.31	-0.9588	0.00524	33505.68	-0.0752	0.00595	160.02
Adverse weather condition	0.0579	0.00732	62.58	0.0809	0.00733	122.00	-0.0230	0.00671	11.74
No daylight	-0.5778	0.00733	6219.61	-0.5492	0.00733	5618.28	-0.0286	0.00672	18.11
Adverse weather and no daylight	0.0361	0.00732	24.38	0.0619	0.00732	71.64	-0.0258	0.00670	14.82

Note: n.s. indicates no significance found at level of 0.001.

5.5. Common Findings Among All Four States

After modeling data from all four states, we did an analysis to explore the similarities among the observed patterns. Although we already mentioned some of the similarities in the patterns for the four states, as we explained the results of our analyses, it seems worthwhile to have a closer look at these similarities. We were particularly interested to find the patterns that are shared among all four states. These patterns are listed here in groups of the variables that they relate to. This listing includes six of the variables or interactions between variables:

- Driver's gender:
  - Female drivers are more likely to have rear-end crashes than single-vehicle crashes (in comparison to male drivers). They are also more likely to have angular crashes than single-vehicle crashes.

- Driver's age:
  - For drivers between the ages of 25 and 65, the odds of being involved in a rear-end crash are greater than for a single-vehicle or an angular crash.
  - For drivers over the age of 65, the odds of involvement in an angular crash are greater than for a rear-end or a single-vehicle crash.

- Interaction between driver's age and gender:
  - For female drivers between the ages of 25 and 65, the likelihood of being involved in a rear-end crash is greater than for an angular crash.
  - For female drivers over the age of 65, the odds of being involved in an angular crash are greater than for a rear-end crash.

- Rural/urban settings:
  - In a rural setting, the likelihood of being involved in a single-vehicle crash is greater than for a rear-end or an angular crash (in comparison to an urban setting).

- Lighting condition:
  - In non-daylight conditions, drivers are more likely to be involved in a single-vehicle crash than a rear-end or an angular crash.

- Interaction between weather and lighting conditions:
  - In the presence of simultaneous adverse weather and non-daylight conditions, the odds of being involved in a rear-end or an angular crash are greater than for a single-vehicle crash.

While all of the patterns we found in the four separate state models in Sections 5.1 through 5.4 are important and informative, the patterns that are shared among all the states are of greater importance. These common findings are repeatedly confirmed through different states' data models, and are more widely applicable. Also, common patterns are valid among all four states whereas other patterns are only valid in the state/states where they were observed.

5.6. Model of all Midwestern States

5.6.1. Model Development

In our analysis, we modeled each state's data separately, i.e., we ran our model four times, once on each of the state's data. This strategy was helpful, since it provided us with valuable findings about each single state's crash type patterns. For each state, we obtained results that are only valid in that state. Thus, the results are applicable in their corresponding state and not in all four Midwestern states we studied. This approach also gave us the opportunity to compare the results from different states and find interesting similarities and dissimilarities among the observed patterns.

The results we found for the different states, discussed in Sections 5.1 through 5.4, were not fully compatible. For some variables, interactions between variables, or their categories, results observed from different states contrasted with other states. Thus, we were unable to present coherent results for the whole four-state region in some cases. We tried to mention similarities and contrasts, but in order to have a more effective comparison among the four states, we needed to have a single model and a data set that included data for all four states.

We merged data from the four states into one single data set and ran our model on this consolidated data. The four-state data set contained 2,827,798 records, as shown in Table 2. The records were labeled by the state in which the crash had occurred. The new model included all of the independent variables we controlled in the single-state models, as described in the analysis technique section, Section 4. The new model also had a state variable, i.e., state where the crash occurred. This new variable was entered into the model in order for the model to control different states' characteristics. The model also included the interactions between state and driver's gender, and state and driver's age, to capture the differences among the different states' population groups more effectively.

For the state variable, the state of Nebraska was treated as the reference category, and was thus omitted from the results. Contrast estimates for Nebraska can be easily calculated through the other three states' estimates; these four must sum up to one for each crash type comparison for each variable. We included the state of Nebraska's contrast estimates in the table to make it easier for the reader to comprehend.

5.6.2 Results

The results of the four-state model are shown in Table 8. Note that the patterns that were shared among all the four states' models, shown in Section 5.5, are also observed in the results of the all-states data model.

Drivers involved in car crashes in the state of Iowa are more likely to have single-vehicle or angular crashes than rear-end crashes. They are also more likely to have angular crashes than single-vehicle crashes. In Kansas, the odds of being involved in a single-vehicle crash are greater than for a rear-end or an angular crash. Drivers are more likely to be involved in a rear-end crash than an angular crash. For drivers in Missouri, the likelihood of involvement in rear-end and angular crashes is more than for single-vehicle crashes. Drivers are more likely to have rear-end crashes than angular crashes in Missouri. In Nebraska, drivers are more likely to be involved in single-vehicle crashes than rear-end and angular crashes. They are more likely to have angular crashes than rear-end crashes. As we can see, no two states show completely similar results.

Female drivers, in comparison to male drivers, are more likely to have rear-end and angular crashes than single-vehicle crashes. In a comparison between rear-end and angular crashes, the odds of being involved in angular crashes are greater for this group of drivers.

Female drivers in Iowa are more likely to have single-vehicle or angular crashes than rear-end crashes. No significant contrast between angular and single-vehicle crashes was observed for them. The patterns observed for female drivers in Kansas and Missouri are similar. In these two states, the likelihood of being involved in rear-end and angular crashes is more than for single-vehicle crashes for female drivers. There is no significant difference between rear-end and angular crashes. In Nebraska, female drivers are more likely to be involved in single-vehicle crashes than rear-end and angular crashes. They are more likely to have rear-end crashes than angular crashes.

For drivers between the ages of 25 and 65, the odds of involvement in rear-end crashes are greater than for single-vehicle and angular crashes. These drivers are more likely to have single-vehicle crashes than angular crashes. Drivers over 65 are more likely to have single-vehicle and angular crashes than rear-end crashes. They are more likely to have angular crashes than single-vehicle crashes. As we can see, the patterns observed for drivers over 65 contrast completely with those for drivers between the ages of 25 and 65.

Drivers between the ages of 25 and 65 in Iowa are more likely to be involved in single-vehicle crashes than rear-end or angular crashes. No significant contrast between rear-end and angular crashes was detected. For drivers over 65 in Iowa, the likelihood of being involved in rear-end and angular crashes is more than for single-vehicle crashes. The odds of having angular crashes are greater than for rear-end crashes for this group of drivers. We see a lot of differences when comparing these results to those we found for the age group variable in Iowa, discussed in Section 5.1. This is due to the fact that in the four-state model, we compared crashes in Iowa to crashes in the three other states. This differs from the Iowa model, as our analysis was limited to Iowa. The same was observed for the other three states.

In Kansas, drivers between the ages of 25 and 65 are more likely to have single-vehicle and rear-end crashes than angular crashes. There is no significant contrast between rear-end and single-vehicle crashes. For drivers over the age of 65 in Kansas, the odds of being involved in a single-vehicle or an angular crash are greater than for a rear-end crash. No significant difference was observed between angular and single-vehicle crashes.

Drivers between the ages of 25 and 65 in Missouri are more likely to be involved in single-vehicle crashes than rear-end and angular crashes. The odds of involvement in angular crashes are greater than for rear-end crashes for this group. Drivers over the age of 65 in Missouri have an opposite pattern. They are more likely to be involved in rear-end and angular crashes than single-vehicle crashes. The likelihood of having a rear-end crash is more than for an angular crash for these drivers.

In Nebraska, drivers between the ages of 25 and 65 and drivers over 65 have different crash type patterns. For the former group, the odds of involvement in rear-end and angular crashes are greater than for single-vehicle crashes, while for the latter the opposite was observed. Drivers over 65 are more likely to have single-vehicle crashes than rear-end and angular crashes. No significant difference between rear-end and angular crashes was detected for either of the two driver groups.

For female drivers between the ages of 25 and 65, the odds of being involved in rear-end crashes are greater than for single-vehicle crashes, and the odds of involvement in single-vehicle crashes are greater than for angular crashes. This group of drivers is more likely to have rear-end crashes than angular crashes. Female drivers over 65 are more likely to be involved in rear-end crashes than single-vehicle crashes, single-vehicle crashes than angular crashes, and angular crashes than rear-end crashes.

In the presence of passengers, the odds of involvement in a single-vehicle crash are greater than for a rear-end or an angular crash. In these situations, drivers are more likely to have angular crashes than rear-end crashes.

Drivers between the ages of 25 and 65 with passengers in their cars are more likely to be involved in rear-end or angular crashes than single-vehicle crashes. There is no significant contrast between rear-end and angular crashes for these drivers. For drivers over 65 with passengers in their cars, the odds of involvement in rear-end crashes are greater than for single-vehicle and angular crashes. No significant difference between angular and single-vehicle crashes was observed.

In rural settings, drivers are more likely to be involved in a single-vehicle crash than a rear-end or an angular crash, in comparison to urban settings. The odds of involvement in rear-end crashes are greater than for angular crashes in these settings.

In adverse weather conditions, the likelihood of having a single-vehicle crash is more than for a rear-end or an angular crash. Drivers in these weather conditions are more likely to have rear-end crashes than angular crashes.

When driving in non-daylight conditions, drivers are more likely to be involved in single-vehicle crashes than rear-end or angular crashes. In these lighting conditions, the odds of having an angular crash are greater than for a rear-end crash.

When both adverse weather and non-daylight conditions are present, the likelihood of being involved in a rear-end or an angular crash is more than a single-vehicle crash. In these situations, drivers are more likely to have an angular crash than a rear-end crash.

Table 8. Parameter estimates from the multinomial logit model for four states combined data

Variable	Rear-end crash vs. single-vehicle crash			Angular crash vs. single-vehicle crash			Rear-end crash vs. angular crash		
	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square
Intercept	-0.1397	0.00417	1125.07	0.1472	0.00393	1404.26	-0.2869	0.00354	6555.21
Driving in Iowa	-0.1647	0.00596	764.18	0.1854	0.00558	1104.46	-0.3501	0.00427	6723.30
Driving in Kansas	-0.0429	0.00538	63.53	-0.3039	0.00507	3587.57	0.2610	0.00428	3720.97
Driving in Missouri	0.6499	0.00429	22931.08	0.4584	0.00413	12289.07	0.1916	0.00293	4278.46
Driving in Nebraska	-0.4424	0.00538	6748.22	-0.3399	0.00514	4373.43	-0.1025	0.00422	589.81
Female driver	0.0760	0.00283	720.67	0.1064	0.00270	1550.30	-0.0304	0.00203	224.59
Female driver in Iowa	-0.0367	0.00409	80.63	-0.00763	0.00397	n.s.	-0.0291	0.00315	85.65
Female driver in Kansas	0.0261	0.00327	63.39	0.0220	0.00323	46.53	0.00403	0.00275	n.s.
Female driver in Missouri	0.0244	0.00283	74.52	0.0226	0.00282	64.07	0.00179	0.00210	n.s.
Female driver in Nebraska	-0.0137	0.00378	13.15	-0.0370	0.00377	96.15	0.0233	0.00304	58.75
Driver’s age between 25 and 65	0.1259	0.00391	1037.88	-0.0738	0.00370	397.39	0.1997	0.00299	4458.75
Driver’s age more than 65	-0.0608	0.00634	92.04	0.2989	0.00587	2596.85	-0.3598	0.00472	5805.73
Driver in Iowa between the ages of 25 and 65	-0.0500	0.00656	58.16	-0.0396	0.00617	41.19	-0.0104	0.00479	n.s.
Driver in Iowa over the age of 65	0.0456	0.0105	18.89	0.0813	0.00964	71.15	-0.0358	0.00733	23.83
Driver in Kansas between the ages of 25 and 65	-0.00045	0.00543	n.s.	-0.0583	0.00509	131.24	0.0579	0.00440	173.34
Driver in Kansas over the age of 65	-0.1040	0.00886	137.70	0.00189	0.00803	n.s.	-0.1059	0.00696	231.17
Driver in Missouri between 25 and 65	-0.0722	0.00476	229.91	-0.0292	0.00463	39.82	-0.0430	0.00335	165.01

Table 8. Parameter estimates from the multinomial logit model for four states combined data

Variable	Rear-end crash vs. single-vehicle crash			Angular crash vs. single-vehicle crash			Rear-end crash vs. angular crash		
	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square
Driver in Missouri over the age of 65	0.3090	0.00767	1622.33	0.1864	0.00732	648.11	0.1227	0.00510	577.42
Driver in Nebraska between the ages of 25 and 65	0.1227	0.00592	429.96	0.1271	0.00569	499.74	-0.00445	0.00471	n.s.
Driver in Nebraska over the age of 65	-0.2506	0.00926	732.43	-0.2696	0.00863	975.10	0.0190	0.00726	n.s.
Female driver between the ages of 25 and 65	0.0373	0.00303	151.07	-0.0103	0.00294	12.31	0.0476	0.00212	505.66
Female driver over the age of 65	0.1046	0.00489	457.09	-0.0439	0.00465	89.18	-0.0607	0.00324	349.80
Passenger(s) present in the car	-0.0518	0.00345	226.03	-0.0154	0.00324	22.49	-0.0364	0.00264	190.27
Driver between the ages of 25 and 65 with passenger(s) present in the car	0.0335	0.00388	74.23	0.0313	0.00370	71.60	0.00214	0.00301	n.s.
Driver over the age of 65 with passenger(s) present in the car	0.0271	0.00628	18.64	-0.00971	0.00585	n.s.	0.0368	0.00472	60.92
Rural setting	-1.1224	0.00286	153616.0	-1.2469	0.00289	185709.8	0.1244	0.00288	1868.68
Adverse weather condition	-0.0501	0.00272	338.53	-0.0736	0.00271	734.48	0.0235	0.00248	89.17
No daylight	-0.7102	0.00273	67565.45	-0.6156	0.00272	51133.94	-0.0946	0.00249	1445.74
Adverse weather and no daylight	0.0937	0.00272	1186.06	0.1322	0.00271	2376.23	-0.0385	0.00248	240.36

Note: n.s. indicates no significance found at level of 0.001.

5.7. Comparison Between the Four Midwestern States' and National-Level Crash Patterns

Now that we have built models for each of the four states and compared them in a single model, it would be beneficial to compare the four-state crash patterns to the patterns observed in national crash data.

5.7.1. Model Development

Data from the GES were used for the national-level analysis. We used data for the same years as analyzed at the four-state level, i.e., from the years 2001 to 2006 (NHTSA, 2008). The GES data is a part of the National Highway Automotive Sampling System (NASS) from the NHTSA. The GES data is a stratified sample of crashes and is weighted to represent national crash patterns.

For modeling the national-level data, we used the same model as the one we had developed in Section 4. The independent variables were driver's age, driver's gender, presence/non-presence of passengers, rural versus urban, weather condition, and lighting condition. The interactions used in the model were driver's gender and age, driver's age and presence/non-presence of passengers, and weather and lighting conditions' interactions.

For the four-state analysis, the same consolidated data set used in the model of all Midwestern states, Section 5.6, was used. The model that was developed here was different from the one we used in Section 5.6.1 due to the different goals we had in the two analyses. In Section 5.6, we sought to compare the four states to each other. As such, we included a "state" variable in the model. However, we considered the four Midwestern states as a whole in this model. We did not intend to emphasize the distinctions between them. Instead, we tried to compare the whole Midwestern area to the country in terms of crash type patterns. Therefore, the model we used here for the four-state data was the same as the model we developed in Section 4, where the state variable was excluded from the model. The interactions between this variable and the other variables were excluded as well.

5.7.2. Results

The results from the national-level model and the Midwestern level model are shown in Table 9 and Table 10, respectively. These results are similar to a great extent. However, there are some points of distinction for certain variables. We will discuss the results from national-level data (GES) and compare them to the results from Midwestern states' data. We will also summarize the differences between the national and Midwestern crash type patterns in Section 5.7.3.

At the national level, female drivers are more likely to have rear-end and angular crashes than single-vehicle crashes in comparison to male drivers. They are more likely to have angular crashes than rear-end crashes. These results are completely compatible with those observed for female drivers at the Midwestern level, shown in Table 10.

For drivers between the ages of 25 and 65, the likelihood of being involved in a rear-end crash is more than for a single-vehicle crash. This group of drivers is more likely to have single-vehicle and rear-end crashes than angular crashes. These results are similar to the results found at the Midwestern level. At the national level, drivers over 65 are more likely to have rear-end and angular crashes that single-vehicle crashes. The odds of being involved in angular crashes are greater than for rear-end crashes for this group of drivers. The comparison between rear-end and single-vehicle crashes shows the opposite pattern of what we see for the Midwestern level, where the odds of involvement in a single-vehicle crash are greater than for a rear-end crash. The other two crash type comparisons yield similar results at the national level.

For female drivers between the ages of 25 and 65, the odds of involvement in rear-end crashes are greater than for single-vehicle and angular crashes. No significant contrast between angular and single-vehicle crashes was observed. These patterns completely agree with those observed at the Midwestern level. Female drivers over the age of 65 are more likely to have single-vehicle crashes than rear-end or angular crashes at the national level. They are also more likely to be involved in angular crashes than rear-end crashes. These patterns are the same as the patterns found at the Midwestern level.

Drivers with passengers in their cars are more likely to be involved in rear-end and angular crashes than single-vehicle crashes. No significant contrast between rear-end and angular crashes was observed for this group of drivers at the national level. The patterns found for the Midwestern level are completely different. At the Midwestern level, drivers with passengers present in their cars are more likely to have single-vehicle crashes than rear-end and angular crashes. The odds of involvement in angular crashes are more than for rear-end crashes for these drivers at the Midwestern level.

The interaction between driver’s age and presence/non-presence of passengers in the car reveals a lot of differences between national-and Midwestern-level patterns. At the national level, drivers between the ages of 25 and 65 with passengers in their cars are more likely to be involved in single-vehicle crashes than rear-end and angular crashes. This group of drivers is more likely to have angular crashes than rear-end crashes. In contrast, the same group of drivers in Midwestern states is more likely to have rear-end and angular crashes than single-vehicle crashes. They are more likely to have rear-end crashes than angular crashes. For drivers over 65 with passengers in their cars, the odds of involvement in rear-end and angular crashes are greater than for single-vehicle crashes at the national level. This group of drivers is more likely to have rear-end crashes than angular crashes. The results from the Midwestern level are completely different. At this level, drivers over 65 with passengers in the car are more likely to have single-vehicle crashes than rear-end and angular crashes. There is no significant difference between rear-end and angular crashes for these drivers.

In rural settings, drivers are more likely to be involved in single-vehicle crashes than rear-end and angular crashes. The odds of involvement in rear-end crashes are greater than for angular crashes. These results are shared between the national- and Midwestern- level models.

While driving under adverse weather conditions, drivers are more likely to be involved in single-vehicle crashes than rear-end and angular crashes at the national level. They are more likely to have a rear-end crash than an angular crash. The same patterns are observed at the Midwestern level.

At the national level, in non-daylight driving conditions, the odds of involvement in single-vehicle crashes are greater than for rear-end and angular crashes. In these poor lighting conditions, drivers are more likely to be involved in angular crashes than rear-end crashes. These results are similar to those observed at the Midwestern level.

When both adverse weather and non-daylight conditions are present, drivers are more likely to be involved in rear-end and angular crashes than single-vehicle crashes. The odds of involvement in angular crashes are greater than for rear-end crashes in these conditions. The national- and Midwestern-level models share these patterns.

5.7.3. Differences Between National- and Midwestern-level Crash Patterns

Although we discussed the differences observed between the national- and Midwestern-level crash patterns as we were proceeding through the results obtained in Section 5.7.2, it seems helpful to summarize these contrasts in order to find the major points of difference. We organize these differences based on the variables/interaction between the variables they are related to and the specific driver groups to which the differences are observed:

- Driver's age:
  - Drivers over the age of 65
    - Comparison between rear-end and single-vehicle crashes: At the national level, drivers are more likely to be involved in rear-end crashes than single-vehicle crashes, whereas at the Midwestern level the opposite is observed.
- Presence/non-presence of passengers in the car:
  - Passengers present in the car
    - Comparison between rear-end and single-vehicle crashes: At the national level, the odds of involvement in rear-end crashes are greater than for single-vehicle crashes. The opposite holds for Midwestern states.
    - Comparison between angular and single-vehicle crashes: At the national level, drivers in this group are more likely to be involved in angular crashes than single-vehicle crashes. For Midwestern states, the opposite was observed.
    - Comparison between rear-end and angular crashes: No significant contrast was observed at national level. However, the odds of involvement in angular crashes are greater than for rear-end crashes at the Midwestern level.
- Interaction between age and presence/non-presence of passengers in the car:
  - Drivers between the ages of 25 and 65 with passengers in their cars
    - Comparison between rear-end and single-vehicle crashes: At the national level, the odds of involvement in single-vehicle crashes are greater than for rear-end crashes. The opposite is observed at the Midwestern level.

- Comparison between angular and single-vehicle crashes: At the national level, these drivers are more likely to be involved in single-vehicle crashes than angular crashes. The opposite holds for the Midwestern level.

- Comparison between rear-end and angular crashes: At the national level, drivers in this group are more likely to be involved in angular crashes than rear-end crashes. At the Midwestern level, the opposite pattern was found.

- Drivers over the age of 65 with passengers in their cars

  - Comparison between rear-end and single-vehicle crashes: At the national level, the odds of involvement in rear-end crashes are greater than for single-vehicle crashes, while in Midwestern states the opposite holds.

  - Comparison between angular and single-vehicle crashes: At the national level, drivers in these conditions are more likely to have angular crashes than single-vehicle crashes. The opposite was observed at the Midwestern states level.

  - Comparison between rear-end and angular crashes: At the national level, drivers are more likely to be involved in rear-end crashes than angular crashes. However, no significant contrast between these crash types was detected at the Midwestern level.

As we can see through these comparisons, the differences between the national and Midwestern levels are confined to driver's age, presence/non-presence of passengers, and the interaction between these two variables.

Table 9. Parameter estimates from the multinomial logit model for national (GES) crash data

Variable	Rear-end crash vs. single-vehicle crash			Angular crash vs. single-vehicle crash			Rear-end crash vs. angular crash		
	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square
Intercept	0.5666	0.00103	299990.8	0.6829	0.00101	459066.2	-0.1163	0.000733	25150.24
Female driver	0.1309	0.000758	29814.03	0.1481	0.000725	41746.95	-0.0172	0.000514	1123.49
Driver’s age between 25 and 65	0.1322	0.00101	17089.05	-0.0957	0.000986	9432.74	0.2279	0.000631	130591.5
Driver’s age more than 65	0.0941	0.00177	2831.82	0.4669	0.00171	74932.95	-0.3727	0.00104	129510.3
Female driver between the ages of 25 and 65	0.0327	0.000831	1545.37	0.00259	0.000803	n.s.	0.0301	0.000571	2773.60
Female driver over the age of 65	-0.1163	0.00140	6880.98	-0.0791	0.00133	3541.58	-0.0372	0.000924	1623.73
Passenger(s) present in the car	0.1670	0.000919	33035.49	0.1683	0.000891	35704.75	-0.00131	0.000563	n.s.
Driver between the ages of 25 and 65 with passenger(s) present in the car	-0.0590	0.000991	3545.02	-0.0313	0.000967	1049.99	-0.0277	0.000625	1966.24
Driver over the age of 65 with passenger(s) present in the car	0.2009	0.00174	13388.94	0.1269	0.00168	5731.49	0.0740	0.00102	5246.09
Rural setting	-0.0992	0.000479	42933.59	-0.1148	0.000483	56507.08	0.0156	0.000377	1713.69
Adverse weather condition	-0.0943	0.000596	24990.10	-0.1368	0.000602	51705.49	0.0425	0.000547	6034.79
No daylight	-0.6123	0.000598	1046821	-0.5005	0.000604	687228.4	-0.1118	0.000549	41521.76
Adverse weather and no daylight	0.0960	0.000596	25942.45	0.1152	0.000601	36718.43	-0.0192	0.000547	1232.13

Note: n.s. indicates no significance found at level of 0.001.

Table 10. Parameter estimates from the multinomial logit model for Midwestern crash data

Variable	Rear-end crash vs. single-vehicle crash			Angular crash vs. single-vehicle crash			Rear-end crash vs. angular crash		
	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square	Estimate	Standard Error	Chi-Square
Intercept	-0.0307	0.00398	59.54	0.1648	0.00378	1896.20	-0.1955	0.00342	3264.08
Female driver	0.0810	0.00265	935.30	0.1132	0.00255	1971.29	-0.0323	0.00184	309.37
Driver’s age between 25 and 65	0.1195	0.00375	1014.52	-0.0783	0.00358	479.82	0.1979	0.00287	4754.75
Driver’s age more than 65	-0.0310	0.00610	25.76	0.3075	0.00568	2926.32	-0.3385	0.00453	5591.95
Female driver between the ages of 25 and 65	0.0463	0.00298	241.85	-0.00358	0.00290	n.s.	0.0499	0.00210	563.39
Female driver over the age of 65	-0.1188	0.00479	614.88	-0.0533	0.00457	135.75	-0.0655	0.00322	414.52
Passenger(s) present in the car	-0.2092	0.00327	4092.98	-0.1247	0.00308	1638.37	-0.0845	0.00250	1137.95
Driver between the ages of with passenger(s) present in the car	0.0481	0.00369	169.83	0.0320	0.00352	82.57	0.0161	0.00285	31.80
Driver over the age of 65 with passenger(s) present in the car	-0.0431	0.00596	52.21	-0.0437	0.00557	61.57	0.000578	0.00448	n.s.
Rural setting	-1.0998	0.00274	160555.8	-1.1834	0.00277	182798.0	0.0836	0.00282	876.93
Adverse weather condition	-0.0442	0.00269	269.17	-0.0756	0.00269	790.99	0.0315	0.00247	161.78
No daylight	-0.7192	0.00270	70768.87	-0.6232	0.00270	53296.36	-0.0960	0.00248	1501.10
Adverse weather and no daylight	0.1090	0.00269	1642.39	0.1449	0.00269	2906.93	-0.0359	0.00247	210.37

Note: n.s. indicates no significance found at level of 0.001.

6. ADDITIONAL FINDINGS

Our original intent was to examine differences among the four states. As we started examining the data more closely, we noticed that there were also differences in driver distractions. This variable was not included in the original model because the data differed greatly across states. However, Missouri's data were the most comprehensive and were used in a subsequent data analysis described in this section.

Distraction, or inattention, was reported in some detail in crash data of all four states. However, different states had different approaches in reporting this driver-related property. We have gathered distraction-related variables and distraction types from the four states' data in Table 11. From this table, it is apparent that the only state with a specific variable for distraction and a comprehensive distraction categorization is Missouri.

Table 11. Distraction-related variables in each state's data

States	Variable name	Distraction types	Description
Iowa	MajorCause	Inattentive/distracted by: - Passenger - Use of phone or other device - Fallen object - Fatigued/asleep	Distraction was reported as a major cause for some of the accidents.
Kansas	CC_Driver (CC_Code)	- Distraction: mobile (cell) phone - Distraction: other electronic devices Also, - Other distraction in or on vehicle - Fell asleep	Distraction was reported as a descriptor of driver's condition at the time of the accident.
Missouri	Inattention_Code	- Cell phone - Stereo/audio/video equipment - Computer/GPS/electronic games - Passenger - Tobacco use - Eating/ drinking - Reading - Grooming - Other - Inattention code is unknown	-
Nebraska	Drivers_Condition	- Fell asleep. Fatigue, etc.	Only fell asleep, fatigue, etc. is reported, as a value for Drivers_Condition variable.

Inattentive driving and driver distraction account for a substantial number of traffic crashes (Klaueret al. 2006). As such, a large number of studies have been done to explore the consequences of driver's involvement in many non-driving-related tasks.

In this study, driver distraction is distinguished from the broader category of driver inattention based on the presence of a "triggering event or activity" (Young et al.2003). According to the U.S. Department of Transportation, NHTSA, there are four major categories of driver distraction: visual, auditory, biomechanical (physical), and cognitive (Ranney et al.2000). However, most distractions are a combination of these four categories, and it is useful and practical to study certain tasks that drivers engage in rather than the more abstract categories

(Neyens & Boyle, 2007a). Defining distraction by tasks also simplifies the segmentation of distraction for those who are documenting the incidents (Pettitt, Burnett, & Stevens, 2005).

In this study, we extend the scope of previous studies (Neyens & Boyle, 2007a; Wilson et al. 2003) by considering drivers of all age groups rather than just younger drivers. With the growing use of technology and in-vehicle devices used by drivers of all ages, the goal of this research was to identify the probable relationships among distraction types and the types of crashes that all distracted drivers are most likely to be involved in. It is hypothesized that distraction types influence the odds of drivers' involvement in different crash types. This hypothesis will be tested through a multinomial logit model to predict how various distractions influence the odds that a driver will be involved in a particular type of crash.

The state of Missouri's crash databases from 2001 to 2006 were used in this study. The compiled databases contained over 1,713,000 records of vehicles involved in crashes. However, among these records, only 20,176 had specifically regarded driver's inattention as a relevant factor to the crash. Cell phone and passenger-related distractions made up more than 58% of the crashes that have a specific distraction factor, as shown in Table 12.

Based on Table 12, we focused on the three distraction types with the highest frequencies. The distraction categories will be (1) cell phone-related, (2) passenger-related, and (3) electronic device-related. This third category includes stereo, audio, and video equipment and other related distractions, plus computer, GPS, and electronic games-related distractions. Although computer, GPS, and electronic games distractions were not among the most frequent distraction types responsible for Missouri car crashes, we included them in the electronic device-related distractions category to capture the effect of using all in-car electronic devices.

Table 12. Frequency of different distraction types

Distraction type	Frequency	Percent
Cell phone	6,165	30.56
Passenger	5,578	27.65
Stereo/audio/video equipment	3,874	19.20
Eating/drinking	2,320	11.5
Tobacco use	1,152	5.71
Reading	642	3.18
Grooming	282	1.40
Computer/GPS/electronic games	163	0.81
Total	20,176	100

6.1. Crash Type Classification

Table 13 summarizes the frequencies of different crash types in the dataset and the subset records of distraction type. In this study, we will focus on three major crash types based on the data, which are rear-end crashes, angular crashes, and collisions with fixed objects (single-vehicle crashes). These crash types represent 36.9%, 30.9%, and 13.5% of all crashes, respectively. Also, they are the most frequent crash types with a specific distraction factor, representing 88% of distraction-related crashes. The reduced data used in the analysis contained 17,912 records. We did our analysis using this dataset.

Table 13. Frequency of different crash types

Distraction type	Frequency	Percent
Cell phone	6,165	30.56
Passenger	5,578	27.65
Stereo/audio/video equipment	3,874	19.20
Eating/drinking	2,320	11.5
Tobacco use	1,152	5.71
Reading	642	3.18
Grooming	282	1.40
Computer/GPS/electronic games	163	0.81
Total	20,176	100

6.2. Independent Variables

The model included factors related to distraction type, driver's age, driver's gender, presence/non-presence of passengers in the car, and environmental factors (rural versus urban, weather, and lighting conditions). These variables have all been previously identified as having an influence on crash type (Massie et al., 1995; McEvoy, Stevenson, & Woodward, 2007; Tavris, Kuhn, & Layde, 2001a; Wang et al., 2008). To make more meaningful inferences, drivers were divided into three age groups: drivers less than 25 years old, drivers between the ages of 25 and 65, and drivers over the age of 65. Presence/non-presence of passengers was categorized into two groups: no passengers, where the driver was alone in the car, or with passengers, where one or more passengers accompanied the driver. Lighting conditions were categorized into daylight and non-daylight (dawn, dusk, dark with no street lights, dark with street lights on, and dark with street lights off). Weather conditions were grouped into two categories: normal and adverse weather. Adverse weather was defined as the presence of snow, rain, fog, or sleet. The interaction between driver's gender and age and the interaction between driver's age and presence/non-presence of passengers were also included in the model.

6.3. Analysis

A multinomial logit model was used due to the discrete nature of the response variable of interest, i.e., crash type. The main objective of the multinomial logit model was to estimate a function that determines outcome probabilities (Washington et al., 2003). The analysis was done in SAS version 9.1, using the CATMOD procedure (PROC CATMOD). This procedure estimates the odds that the dependent variable will be in one of the three crash types as compared to in another crash type (e.g., angular crash compared to rear-end crash). The analysis was therefore performed to compare (1) rear-end crashes to angular crashes, (2) rear-end crashes to single-vehicle crashes, and (3) angular crashes to single-vehicle crashes.

The independent variables in this analysis are distraction type, driver's age, driver's gender, presence/non-presence of passengers, rural/urban, weather, and lighting condition (day/light). An important point to be considered in interpreting the results of this study is that the analysis are performed on crash data, and the findings are in terms of relative likelihood of involvement in a type of crash, given that a crash has occurred. Therefore, the results do not predict the odds that a driver in certain personal and environmental conditions becomes involved in a certain type of crash. Instead, they show the relative likelihood of different crash types for people in different conditions.

6.4. Results

We used 17,912 crash records in this analysis. Females were involved in about 44% of these crashes as drivers, and males in about 56%. About 30% of crashes had occurred in a rural setting, about 50% in an urban setting, and 20% of crashes had no data included regarding the urban versus rural setting variable.

We did a preliminary analysis on the data with a model including all independent variables. The results showed no significant effects for weather, driver's gender and age interaction, and driver's age and presence/non-presence of passengers interaction. These terms were eliminated from the final model. The results from the final model are displayed in Table 14. Gender, age, presence/non-presence of passengers, rural or urban setting, and light condition had significant effects on crash type.

Table 14. Comparison between odds of occurrence of different crash types

Variable	Rear-end crash vs. single-vehicle crash			Angular crash vs. single-vehicle crash			Rear-end crash vs. angular crash		
	Estimate	Std Error	χ^2	Estimate	Std Error	χ^2	Estimate	Std Error	χ^2
Intercept	-0.54	0.05	113.95	-1.30	0.06	460.69	0.76	0.06	172.06
Female drivers	-0.08	0.02	16.14	0.02	0.03	n.s.	-0.09	0.02	17.29
Driver 25 to 65 yrs	-0.01	0.04	n.s.	-0.10	0.05	n.s.	0.09	0.04	n.s.
Driver's > 65 yrs	0.09	0.08	n.s.	0.37	0.09	17.21	-0.29	0.07	15.17
Passenger(s) in the car	-0.77	0.03	514.01	-0.51	0.04	144.61	-0.25	0.04	32.43
Rural setting	-0.86	0.03	1001.62	-0.99	0.04	634.67	0.13	0.04	11.27
No daylight	-0.65	0.02	967.67	-0.48	0.03	312.84	-0.17	0.03	43.16
Distraction types									
Cell phone	-0.01	0.03	n.s.	0.30	0.04	55.74	-0.31	0.04	75.79
Passenger-related	0.38	0.04	116.65	0.53	0.04	144.80	-0.15	0.04	16.01
Electronic devices	-0.12	0.04	12.58	-0.39	0.05	58.84	0.27	0.05	31.42

Note: n.s. indicates no significance found at level of 0.001.

Based on these results, no significant difference was detected between rear-end and single-vehicle crashes for drivers distracted by cell phones. For these drivers, the odds of being involved in an angular crash were greater than for a single-vehicle or a rear-end crash. Drivers distracted by passengers were more likely to be involved in a rear-end or an angular crash than in a single-vehicle crash. The odds of their involvement in an angular crash were greater than for a rear-end crash. For drivers distracted by electronic devices, the odds of being involved in a single-vehicle crash were greater than for a rear-end or an angular crash. These drivers were more likely to be involved in a rear-end crash than an angular crash.

We can generally observe that drivers distracted by cell phones or passengers were most likely to be involved in angular crashes. For those distracted by electronic devices, the odds of involvement in single-vehicle crashes, or a collision with a fixed object, were greater than for the two other crash types examined.

7. DISCUSSION

In this study, we analyzed crash data for four Midwestern states, i.e., Iowa, Kansas, Missouri, and Nebraska, compiled from the years 2001 to 2006. Our first step towards exploring crash patterns consisted of calculating the frequencies of different crash types in each of the four states, and we found that single-vehicle crashes, rear-end crashes, and angular crashes are the major, or most frequent, crash types in each of the states, and in the four-state combined crash data, which included more than 83 percent of all four-state crashes. Therefore, we focused on these three crash types and the comparisons between their odds of occurrence for certain driver/driving conditions.

7.1. Modeling Steps and Benefits of Each

We analyzed the crash data for each of the four states separately and compared the odds of the driver's involvement in each of the three major crash types versus the two other crash types for each state. In the next step, we compared crash patterns that were observed in each of the four states to find the common crash patterns between all the four states. Then we merged the crash data of all four states into a consolidated data set to do a more effective comparison between the states' crash patterns. In the final step, we compared the Midwestern states' crash patterns to the national crash patterns to explore the probable differences. We used the same model with the same independent and dependent variables in all the analyses, with exception of the model of all Midwestern states, discussed in Section 5.6, where we entered the state variable into the model to capture the differences among states' crash patterns.

Building a separate model for each state provided the opportunity to closely observe the crash patterns and the role of different driver characteristics and driving conditions on the odds of occurrence of different crash types in each of the states. The results of these models can be insightful for various departments in each state, in terms of evaluating and modifying driving regulations. As crash patterns show variations among the four states, these state-wide models are more useful for individual state departments.

The results based on the four-state model guide us to more general conclusions about the Midwestern region as a whole. Because the four Midwestern states share some environmental and demographic properties, this region can represent shared properties, and the patterns observed in this region have the potential of being generalized to areas with similar conditions.

In reference to the specific environmental and demographic properties of the Midwestern region, the comparison between the crash patterns observed in this region and the crash patterns at national level lead us to a better understanding of those patterns that are unique to the Midwestern states. These differences may stem from different populations studied and the effects of past policy decisions.

7.2. Comparison Among the Four Midwestern States

Some of the personal and environmental factors, the independent variable in the models, were shown to influence drivers' crash patterns more consistently in all four Midwestern states, whereas others affected crash types differently. Driver's gender, driver's age, rural/urban setting, and lighting condition were the independent variables for which some similar trends were detected among all four states. Also, the interaction between driver's age and gender and the interaction between weather and lighting conditions revealed some similarities in the states' crash patterns. For some of the other variables/interaction between variables, no crash pattern was common among all four states. These variables included presence/non-presence of passengers in the car, weather condition, and the interaction between driver's age and presence/non-presence of passengers.

In the four-state analysis, Section 5.6, we modeled the combined data from all four states, controlling for the "state" in which the crash occurred. This analysis provided us with a general overview of the effect of different variables on crash patterns in the Midwestern area, with an emphasis on differences among the four states.

7.3. Comparison Between National and Midwestern Levels

The final step of our study was to compare Midwestern states to the whole nation in terms of crash patterns. We approached this goal by modeling crash types at the national level (using GES data), and at the Midwestern level for the same range of time, 2001-2006, and comparing the observed patterns discussed in Section 5.7. For this step, we treated the Midwestern states as a whole, i.e., we did not include the state variable in the model. By doing so, we obtained crash patterns for the whole Midwestern area. The comparison revealed some interesting similarities and contrasts between the Midwestern and national crash patterns.

For many of variables/interactions between variables, the results for national-level crash type analysis fully conformed to those for Midwestern level. These were driver's gender, rural/urban settings, weather conditions, lighting conditions, interaction between driver's age and gender, and interaction between weather and lighting conditions. For driver's age, the odds of a driver's involvement in rear-end versus single-vehicle crashes for drivers over 65 was the only observed difference. The other crash type comparisons were the same for both the Midwestern and national levels.

The crash patterns for the national and Midwestern levels contrasted regarding the presence/non-presence of passengers variable and the interaction between this variable and driver's age. In fact, the differences between national and Midwestern crash patterns are limited to driver's age, presence/non-presence of passengers, and the interaction between these two.

7.4. Comparing National and Midwestern Level Results to the Results of Previous Studies

Some of the patterns observed for the crash type involvement model results at the Midwestern and national levels have been previously detected in other geographical regions. Ryan et al. (1998) found that drivers under 25 years old (young drivers) are more likely to be involved in single-vehicle crashes in Western Australia. The same pattern is valid for both the national and Midwestern levels. Note that drivers younger than 25 were treated as a reference age group category, and therefore the results for this group of drivers were not explicitly shown in the tables. However, the parameter estimates for this group are easily calculated through the other two age group estimates due to the general principle that, for each variable/interaction between variables, the parameter estimates for each crash type comparison sum up to 0. As an example, for the comparison between rear-end and single-vehicle crashes, we calculate the parameter estimates for drivers aged younger than 25 by subtracting the sum of the estimate for drivers between 25 and 65 and drivers aged more than 65 from 0.

Ryan et al. (1998) also found that drivers between the ages of 30 and 59 are more likely to have same-direction (rear-end and sideswipe) crashes. We found that drivers between the ages of 25 and 65 are more likely to have rear-end crashes at both the national and Midwestern levels. These two results are fairly compatible. Ryan et al. also reported that, for drivers over 60, the odds of involvement in angular crashes are greater than for other types of crashes. In our study, we observed the same pattern for drivers over 65.

According to Khattak et al. (1998), drivers over the age of 65 are more likely to be involved in two-vehicle crashes. These were data from North Carolina. This finding agrees with what we found for this age group at national level; drivers aged more than 65 are more likely to be involved in rear-end and angular crashes than single-vehicle crashes. The relationship between angular and single-vehicle crashes is also valid at the Midwestern level. However, at this level the odds of being involved in single-vehicle crashes are greater than for rear-end crashes for drivers over the age of 65.

Khattak et el. (1998) found that, in adverse weather conditions, the odds of being involved in single-vehicle crashes are greater than for two-vehicle crashes. This result was confirmed through our study, for both the Midwestern and national levels. Khattak et al. also reported that single-vehicle crashes are more likely to occur during night time. We found that the odds of involvement in single-vehicle crashes are greater in non-daylight conditions for the national and Midwestern levels. These two findings are also compatible to one another.

Our findings about driver's gender impact on crash involvement patterns were the opposite of what Khattak et al. (1998) reported for North Carolina. In our study, we found that female drivers are more likely to be involved in rear-end and angular crashes than single-vehicle crashes, in comparison with male drivers at both the Midwestern and national levels. This implies that the odds of male drivers' involvement in single-vehicle crashes are greater than for rear-end and angular crashes. Khattak et el. found that male drivers are less likely to be involved in single-vehicle crashes relative to two-vehicle crashes. This completely disagrees with our findings.

7.5. Distraction Analysis

Different types of distraction were shown to increase the likelihood of certain types of crashes. The types of crashes that were included in the model were the three with the highest frequencies of occurrence, both in the whole data and in the distraction-related data. However, the relative frequencies of angular and single-vehicle crashes for all records are from those for the distraction-related data records only. In fact, angular and single-vehicle crashes switch places in the rankings for the two datasets. This is an interesting pattern based on the data used in this study. Rear-end crashes have the highest probability of occurrence in the presence of a reported distraction, which is about 46%, and single-vehicle crashes with 30% of occurring crashes follow them. Although the former duplicates the pattern observed in the whole data, the latter shows a completely different pattern.

The results of this study show that for cell phone and passenger-related distractions, angular crashes have the highest probabilities of occurrence, whereas for electronic device-related distractions, the most probable crash type is single-vehicle. It would have been valuable for the purpose of this analysis to have the specific task done with the cell phone such as talking, listening, dialing, text messaging, or e-mailing. As an example, text messaging requires the person to look at the cell phone's display, think about the text to write, and also engage his/her hands. Text messaging results in visual, cognitive, and biomechanical distractions all at the same time. As such, the nature of the distraction may result in a different probability for crash type involvement. For the state of Missouri, these data are not currently collected, but they may be of value to further distinguish differences in the likelihood for certain crash types.

As indicated earlier, passengers can be passively present but not be identified as a distraction or they can play an active role as a distracter. The Missouri crash database segments the passengers into either of the distraction categories. The findings show that having passengers passively present increases the likelihood of being involved in a single-vehicle crash when compared to the other two crash types, and the odds of having an angular crash are greater than having a rear-end crash. Comparing these results with those of passengers as an active distracter reveals a substantial difference because drivers are now less likely to be in a single-vehicle crash than in other crash types. This contradiction demonstrates that passengers do not necessarily act as distracters for all crash types that can occur.

Estimates from a NHTSA report showed that distractions contributed to over 22% of all crashes and near-crashes (Klauer et al., 2006). However, the Missouri crash data from 2001 to 2006 do not have similar percentages. For a vast majority of crashes, the specific distraction factor is listed as "other" for various reasons from incorrect reporting procedures to inability to discern the exact distraction at the time of the incident. Many driver distractions have no physical indicators at the crash scene, and investigations may rely on self-reporting only. Therefore, the crash data more than likely underestimates the role of distraction in car crashes. This concern was also expressed by Sundeen (2007).

The study focused on crash data for the state of Missouri from 2001 to 2006. As such, the inferences made from this study should be considered with caution. We chose crash data records from the state of Missouri due to the availability of detailed distraction data. However, we did attempt to examine other states' crash data available at the time of this study (e.g., Iowa, Kansas, and Nebraska). This reflects the need for revisions in the crash data reporting procedures. Hopefully, as more valid distraction-related data becomes available in future, further research will help explore other relationships**.** This data would ultimately lead to more precise conclusions that can help improve driving regulations.

REFERENCES

Allison, P. D. 1999. *Logistic regression using SAS system: Theory and application*. Cary, NC: SAS Institute Inc.

Borooah, V. K. 2001. Logit and probit: Ordered and multinomial models In *Sage University Papers Series on Quantitative Applications in the Social Sciences* (Vol. 07–138). Thousand Oaks, CA: Sage.

Chandraratna, S., & Stamatiadis, N. 2003. Problem driving maneuvers of elderly drivers. *Transportation Research Record*, *1843*, 89-95.

Engstrom, I., Gregerson, N. P., Granstrom, K., & Nyberg, A. 2008. Young drivers-Reduced crash risk with passengers in the vehicle. *Accident Analysis and Prevention*, *40*(1), 341-348.

Farmer, C. M., Braver, E. R., & Mitter, E. L. 1997. Two-vehicle side impact crashes: the relationship of vehicle and crash characteristics to injury severity. *Accident Analysis and Prevention*, *29*(3), 399-406.

Golob, T. F., & Recker, W. W. 2003. Relationships among urban freeway accidents, traffic flow, weather, and lighting conditions. *Journal of Transportation Engineering, 129*(4), 342-353.

Hill, J. D., & Boyle, L. N. 2006. Assessing the relative risk of severe injury in automative crashes for older female occupants. *Accident Analysis and Prevention, 38*(1), 148-154.

Hing, J. Y. C., Stamatiadis, N., & Aultman-Hall, L. 2003. Evaluating the impact of passengers on the safety of older drivers. *Journal of Safety Research, 34*(4), 343-351.

Khattak, A. J., Kantor, P., & Council, F. M. 1998. Role of adverse weather in key crash types on limited-access roadways: implications for advanced weather systems. *Transportation Research Record, 1621*, 10-19.

Kim, K., Nitz, L., Richardson, J., & Li, L. 1995. Personal and behavioral predictors of automobile crash and injury severity. *Accident Analysis and Prevention, 27*(4), 469-481.

Klauer, S. G., Dingus, T. A., Neale, V. L., Sudweeks, J. D., & Ramsey, D. J. 2006. *The impact of driver inattention on near-crash/crash risk: an analysis using the 100-car naturalistic driving study data* (No. DOT HS 810 594). Washington, DC: NHTSA.

Kockelman, K. M., & Kweon, Y.-J. 2002. Driver injury severity: an application of ordered probit models. *Accident Analysis and Prevention, 34*(3), 313-321.

Laapotti, S., & Keskinen, E. 2004. Has the difference in accident patterns between male and female drivers changed between 1984 and 2000? *Accident Analysis and Prevention, 36*(4), 577-584.

Mao, Y., Zhang, J., Robbins, G., Clarke, K., Lam, M., & Pickett, W. 1997. Factors affecting the severity of motor vehicle traffic crashes involving young drivers in Ontario. *Injury Prevention, 3*(3), 183-189.

Massie, D. L., Campbell, K. L., & Williams, A. F. 1995. Traffic accident involvement rates by driver age and gender. *Accident Analysis and Prevention, 27*(1), 73-87.

McEvoy, S. P., Stevenson, M. R., & Woodward, M. 2007. The prevalence of, and factors associated with, serious crashes involving a distracting activity. *Accident Analysis and Prevention, 39*(3), 475-482.

Neyens, D. M., & Boyle, L. N. 2007a. The effect of distraction on the crash types of

teenage drivers. *Accident Analysis and Prevention, 39*(1), 206-212.
Neyens, D. M., & Boyle, L. N. 2007b. The effect of distractions on the crash types of teenage drivers. *Accident Analysis and Prevention, 39*(1), 206-212.
NHTSA. 2005. *National Automotive Sampling System (NASS) General Estimates System (GES): Analytical user's manual 1988-2005*. Retrieved June 2008. from http://www-nrd.nhtsa.dot.gov/Pubs/AUM05.PDF.
NHTSA. 2008. General Estimates System (GES) 2001-2006. Retrieved June, 2008, from ftp://ftp.nhtsa.dot.gov/GES
Pettitt, M., Burnett, G., & Stevens, A. 2005. *Defining driver distraction.* Paper presented at the World Congress on Intelligent Transport Systems, San Francisco, CA.
Preusser, D. F., Ferguson, S. A., & Williams, A. F. 1997. The effect of teenage passengers on the fatal crash risk of teenage drivers. *Accident Analysis and Prevention, 30*(2), 217-222.
Ranney, T., Mazzae, E., Garrott, R., & Goodman, M. J. 2000. *NHTSA Driver Distraction Research: Past, Present, and Future*: NHTSA.
Richardson, J., Kim, K., Li, L., & Nitz, L. 1996. Patterns of motor vehicle crash involvement by driver age and sex in Hawaii. *Journal of Safety Research, 27*(2), 117-125.
Ryan, G. A., Legge, M., & Rosman, D. 1998. Age related changes in driver's crash risk and crash type. *Accident Analysis and Prevention, 30*(3), 379-387.
Sundeen, M. 2007. *Cell phones and highway safety: 2006 state legislative update*. Denver, CO: National Conference of State Legislatures.
Tavris, D. R., Kuhn, E. M., & Layde, P. M. 2001a. Age and gender patterns in motor vehicle crash injuries: importance of crash and occupant role. *Accident Analysis and Prevention, 33*(2), 167-172.
Tavris, D. R., Kuhn, E. M., & Layde, P. M. 2001b. Age and gender patterns in motor vehicle crash injuries: importance of type of crash and occupant role. *Accident Analysis and Prevention, 33*(2), 167-172.
Wang, Y., Hasselberg, M., Wu, Z., & Laflamme, L. 2008. Distribution and characteristics of road traffic crashes in the Chaoyang District of Beijing, China. *Accident Analysis and Prevention, 40*(1), 334-340.
Washington, S. P., Karlaftis, M. G., & Mannering, F. L. 2003. *Statistical and Econometric Methods for Transportaion Data Analysis*. Boca Raton, FL: Chapman & Hall/CRC.
Williams, A. F. 2003. Teenage drivers: patterns of risk. *Journal of Safety Research, 34*(1), 5-15.
Williams, A. F., Ferguson, S. A., & McCartt, A. T. 2007. Passenger effects on teenage driving and opportunities for reducing the risks of such travel. *Journal of Safety Research, 38*(4), 381-390.
Wilson, J., Fang, M., Wiggins, S., & Cooper, P. 2003. Collision and violation involvement of drivers who use cellular telephones. *Traffic Injury Prevention, 4*(1), 45-52.
Young, K. L., Regan, M. A., & Hammer, M. 2003. *Driver distraction: a review of the literature* (No. 206). Victoria, Australia: Monash University Accident Research Centre.