CHARACTERISTICS AND CONTRIBUTORY CAUSES RELATED TO LARGE TRUCK CRASHES (PHASE-II) – ALL CRASHES

by

SIDDHARTHA KOTIKALAPUDI

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Major Professor
Dr. Sunanda Dissanayake, Ph.D., P.E.

Abstract

In order to improve safety of the overall surface transportation system, each of the critical areas needs to be addressed separately with more focused attention. Statistics clearly show that large-truck crashes contribute significantly to an increased percentage of high-severity crashes. It is therefore important for the highway safety community to identify characteristics and contributory causes related to large-truck crashes. During the first phase of this study, fatal crash data from the Fatality Analysis Reporting System (FARS) database were studied to achieve that objective. In this second phase, truck-crashes of all severity levels were analyzed with the intention of understanding characteristics and contributory causes, and identifying factors contributing to increased severity of truck-crashes, which could not be achieved by analyzing fatal crashes alone. Various statistical methodologies such as cross-classification analysis and severity models were developed using Kansas crash data. Various driver-, road-, environment- and vehicle- related characteristics were identified and contributory causes were analyzed.

From the cross-classification analysis, severity of truck-crashes was found to be related with variables such as road surface (type, character and condition), accident class, collision type, driver- and environment-related contributory causes, traffic-control type, truck-maneuver, crash location, speed limit, light and weather conditions, time of day, functional class, lane class, and Average Annual Daily Traffic (AADT). Other variables such as age of truck driver, day of the week, gender of truck-driver, pedestrian- and truck-related contributory causes were found to have no relationship with crash severity of large trucks. Furthermore, driver-related contributory causes were found to be more common than any other type of contributory cause for the

occurrence of truck-crashes. Failing to give time and attention, being too fast for existing conditions, and failing to yield right of way were the most dominant truck-driver-related contributory causes, among many others.

Through the severity modeling, factors such as truck-driver-related contributory cause, accident class, manner of collision, truck-driver under the influence of alcohol, truck maneuver, traffic control device, surface condition, truck-driver being too fast for existing conditions, truck-driver being trapped, damage to the truck, light conditions, etc. were found to be significantly related with increased severity of truck-crashes. Truck-driver being trapped had the highest odds of contributing to a more severe crash with a value of 82.81 followed by the collision resulting in damage to the truck, which had 3.05 times higher odds of increasing the severity of truck-crashes. Truck-driver under the influence of alcohol had 2.66 times higher odds of contributing to a more severe crash.

Besides traditional practices like providing adequate traffic signs, ensuring proper lane markings, provision of rumble strips and elevated medians, use of technology to develop and implement intelligent countermeasures were recommended. These include Automated Truck Rollover Warning System to mitigate truck-crashes involving rollovers, Lane Drift Warning Systems (LDWS) to prevent run-off-road collisions, Speed Limiters (SLs) to control the speed of the truck, connecting vehicle technologies like Vehicle-to-Vehicle (V2V) integration system to prevent head-on collisions etc., among many others. Proper development and implementation of these countermeasures in a cost effective manner will help mitigate the number and severity of truck-crashes, thereby improving the overall safety of the transportation system.

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Dedication

I would like to dedicate this study to my parents, K. Appa Rao and K. Lakshmi, for their tremendous support and encouragement throughout my life.

CHAPTER 1 - INTRODUCTION

1.1. Background

The transportation system is one of the most important factors responsible for economic progress of any country. In the United States, development of the road network over the past few decades has considerably increased efficiency of the movement of freight and passengers across the nation. Trucks play a major role in the transportation system in the United States, as they carry a significant portion of the nation's cargo. A large number of different types of trucks operate in the United States, depending on the duration of travel and quantity of cargo. Technologies like the Global Positioning System (GPS) and satellite communication have improved working conditions for operation of trucks by providing drivers with necessary information regarding traffic and weather conditions, along with specific route and directions to travel.

There has been a 47% increase in the number of registered large trucks and a 65% increase in truck vehicle-miles travelled (VMT) over the past 20 years from 1988 to 2008 (1). With an increase in the number of large trucks, their probability of being involved in crashes also increases. Table 1.1 shows the number of large trucks involved in crashes in the United States and their involvement rates from 2000 to 2008. In 2009, one out of every 10 traffic fatalities resulted from collisions involving large trucks (2). Nearly 84% of all fatalities in the crashes in 2009, involving large trucks, were not the occupants of the trucks (3). Also, 7% of all fatal crashes in the United States in 2009 involved a large truck (4). These numbers show that each of the critical areas regarding the large-truck-crashes must be identified and studied for improving overall safety of the transportation system (5).

Table 1.1 Large-Truck Crashes and Involvement Rates in the United States

Year	Fatal Crashes			Injury Crashes			PDO Crashes		
	Number of Crashes	Involvement Rate		Number of Crashes	Involvement Rate		Number of Crashes	Involvement Rate	
		per 100 million VMT	per 100,000 Registered Vehicles		per 100 million VMT	per 100,000 Registered Vehicles		per 100 million VMT	per 100,000 Registered Vehicles
2000	4,995	2.43	62.26	101,000	49	1,253	351,000	171	4,377
2001	4,823	2.31	61.38	90,000	43	1,143	335,000	160	4,261
2002	4,587	2.14	57.88	94,000	44	1,189	336,000	156	4,232
2003	4,721	2.17	60.86	89,000	41	1,145	363,000	167	4,681
2004	4,902	2.22	59.99	87,000	39	1,062	324,000	147	3,970
2005	4,951	2.22	58.37	82,000	37	971	354,000	159	4,178
2006	4,766	2.14	54.04	80,000	36	911	300,000	135	3,398
2007	4,633	2.04	51.32	76,000	33	839	333,000	147	3,690
2008	4,089	1.80	45.40	66,000	29	734	309,000	136	3,435

Source: *Traffic Safety Facts 2009*

In 2008, there was a crash involving a large truck in Kansas every 2.37 hours, and total financial loss associated with these crashes was around $ 0.327 billion (6). This shows that truck-crashes not only affect the safety of the transportation system, but also create an economic burden to the society. Also, large trucks comprised 14.9% of all fatal crashes in the state of Kansas in 2008, in spite of being involved in only 5.6% of the total crashes that occurred (6). Figure 1.1 shows a comparison between the total number of fatal crashes and the number of fatal large-truck crashes in the state of Kansas.

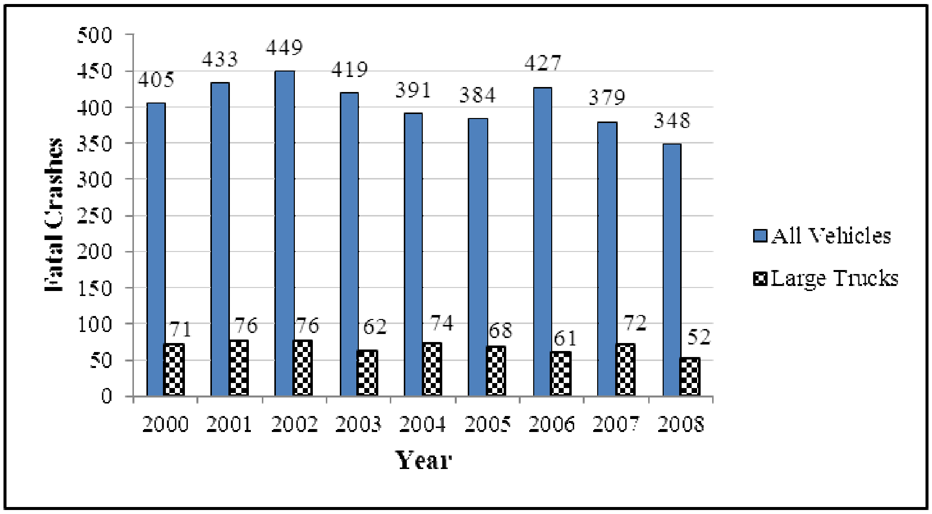

Figure 1.1 Comparisons of Total Fatal and Truck-Involved Fatal Crashes in Kansas

Size and the space needed for movement might make it difficult to maneuver and control a large truck. Large size of the truck also creates a large blind spot area, which might result in sideswipe crashes at times. Figure 1.2 shows the variation of crashes involving large trucks in Kansas, based on different severity levels.

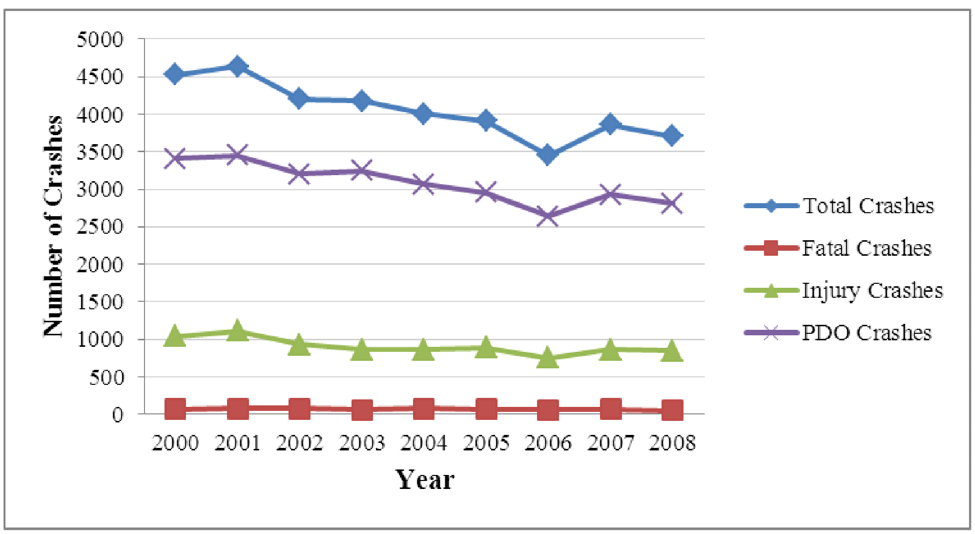

Figure 1.2 Number of Large-Truck Crashes by Severity in Kansas

Though the number of large-truck crashes in 2008 decreased when compared to the previous year and to the average of such crashes over the 10 previous years, statistics show they still comprise a uniform percentage (around 5.5%) of the total crashes in Kansas. Table 1.2 shows the number of crashes involving large trucks expressed as the percentage of total crashes by severity in Kansas. Statistics show large trucks account for a disproportionate share of fatal and injury crashes in the United States. These values were deduced from statistics obtained from the Kansas Accident Reporting System (KARS) database.

Table 1.2 Truck-Crashes as a Percentage of Total Crashes by Severity in Kansas

Year	Fatal Crashes			Injury Crashes			PDO Crashes			Total Crashes		
	Large Truck	All	%	Large Truck	All	%	Large Truck	All	%	Large Truck	All	%
2000	71	405	17.6	1045	19,454	5.4	3409	58,215	5.9	4525	78,074	5.8
2001	76	433	17.6	1110	19,346	5.7	3451	59,028	5.8	4637	78,807	5.9
2002	76	449	16.9	927	18,495	5.0	3201	59,327	5.4	4204	78,271	5.4
2003	62	419	14.8	864	17,037	5.1	3248	57,537	5.7	4174	74,993	5.6
2004	74	391	18.9	862	16,631	5.2	3067	57,080	5.2	4003	74,102	5.4
2005	68	384	17.7	885	16,185	5.5	2954	52,106	5.7	3907	68,675	5.7
2006	61	427	14.3	748	15,792	4.7	2638	49,241	5.4	3447	65,460	5.3
2007	72	379	19.0	862	16,227	5.3	2926	53,983	5.4	3860	70,589	5.5
2008	52	348	14.9	842	14,866	5.7	2808	50,644	5.5	3702	65,858	5.6

Source: *2008 Kansas Traffic Accident Facts*

1.2. Problem Statement

Large trucks, which are defined in this study as those with a gross vehicle weight rating of 10,000 pounds or more, contribute to a significant proportion of the traffic composition in the United States. Large-truck crashes are one of the major concerns regarding safety of the road transportation system. Due to the high severity of these truck-crashes, it is important to study critical factors related to truck-crashes in a more detailed manner. In 2009, nearly 296,000 large trucks were involved in road crashes in the United States, out of which 3,215 crashes resulted in at least one fatality (4). Also, large trucks accounted for nearly 7% of all vehicles involved in fatal crashes, 2% of all vehicles involved in injury crashes, and 3% of vehicles involved in PDO crashes (4). This indicates that large-truck crashes tend to be more severe. Further, statistics show truck-crashes are particularly more devastating for occupants of the other vehicles, such as passenger vehicles, involved in the crash. In 2009, 98% of all fatalities in two-vehicle, large-truck crashes involving a passenger vehicle were from the passenger vehicle (3).

Hence, there is a need to identify characteristics and contributory causes related to large-truck crashes. In the first phase of the study, the Fatality Analysis Reporting System (FARS) database was used to analyze fatal crashes in the United States (7). In this second phase of study, truck-crashes in Kansas were analyzed by considering all levels of injury severity. Findings of this study can be used to identify countermeasures and areas to be studied further, in order to improve the overall safety of the highway system.

1.3. Objectives

Mitigation of large-truck crashes can be done by identifying and analyzing characteristics and contributory causes as well as identifying factors related with increased severity of truck-crashes in Kansas. With this in mind, following are the primary objectives of this study:

1. To identify various characteristics that prevailed during occurrence of large-truck crashes.
2. To identify the vehicle-, road-, driver- and environment-related causes that contributed to the occurrence of large-truck crashes.
3. To identify and evaluate factors contributing to higher severity of large-truck crashes.

4. To identify suitable countermeasures to mitigate truck crashes and improve safety of the highway system.

1.4. Outline of the Report

This report starts with the background, problem statement, and objectives in Chapter 1. In the chapter 2, earlier studies related to this subject are summarized as part of a literature review. Chapter 3 deals with the methodology adopted in analyzing the characteristics, identifying the relationship of crash severity with some selected variables using cross-classification method and developing the model with an overview of various technical parameters associated with the model development. In Chapter 4, results of the model are summarized, along with a discussion of the results. Conclusions are presented in the final chapter, followed by references used for this study. Appendices are provided at the end of the report for further knowledge regarding this study.

CHAPTER 2-LITERATURE REVIEW

Crashes involving large trucks have been an issue for a considerable time. Many studies have focused on identifying the severity of these crashes in different states using data from corresponding databases, and identifying characteristics related to truck-crashes. This chapter summarizes some of the important studies previously done in this aspect, which has helped narrow down some of the issues involved in performing this study.

2.1. Characteristics and Contributory Causes of Truck-Crashes

Mulinazzi et al. conducted a study emphasizing high wind and adverse weather conditions as contributory causes for truck-crashes in the United States (8). Measures taken by different states to mitigate wind-induced truck-crashes were briefly discussed in the study. Data related to wind-induced truck-crashes on I-70 in Kansas for six-year time period from 2003 to 2008 were obtained from the Kansas Department of Transportation's Kansas Accident Record System (KARS) database. Data were analyzed to understand the relationship between variables such as vehicle and freight characteristics, crash occurrences and weather conditions. A multivariate linear regression model was developed using the hourly rate of truck-crashes as the dependent variable, which could predict the possibility of occurrence of wind-induced truck-crashes. Results, however, showed that high wind speed was statistically insignificant in predicting crashes. Using this study, certain corridors in Kansas were identified as potential areas for implementation of a warning system. Also, specific zones on the highways were identified where drivers of trucks do not exhibit any change in their behavior with changing speeds of the wind. Distributions of wind-induced truck-crashes were presented based on different wind speeds, and suitable recommendations were provided based on the findings.

A study was performed by Golob and Regan to determine the relationship of truck accidents with traffic-flow conditions and roadway characteristics on urban freeways (9). Crash data relating to accidents, roadways, and traffic were obtained from the Traffic Accident Surveillance and Analysis System (TASAS) database for a period of two years for six freeways in Orange County of Southern California. A multinomial logit model was developed to determine the difference in traffic and roadway conditions conducive to weaving, runoff, and rear-end types of truck accidents. The number of truck-involved crashes was found to be inversely proportional to the number of lanes and average annual daily traffic (AADT) per lane, and directly proportional to the percentage of large trucks. Further, characteristics of crashes involving trucks such as time of day, weather conditions, and days of the week were compared to non-truck crashes and were found to vary substantially.

Khattak et al. performed a study to understand how the single-vehicle truck-crashes were influenced by various driver-, vehicle-, environmental-, roadway- and crash-related events (10). In addition to independent explanatory variables, this study also considered various interaction terms like curve*rollover, grade*rollover, seatbelt*rollover, etc. A comparison was made between the rollover and non-rollover truck involved single vehicle crashes. The study was performed in North Carolina and corresponding data from 1996 to 1998 was obtained using the Highway Safety Information System (HSIS) database. Descriptive statistics, along with cross tabulations, were presented. Binary probit models, with rollover occurrence as the dependent variable, were developed to predict rollover propensity, and ordered-probit models were developed to predict injury severity. Also, multivariate statistical techniques were used to determine effects and interdependencies among explanatory variables. Rollovers were found to have occurred in 30% of all truck-crashes, and 43% of truck-crashes at curves. These rollovers were found to be more likely to increase the severity of the crash.

Dissanayake and Bezwada analyzed characteristics and contributory causes related to fatal crashes involving large trucks in the United States. Data related to five years, from 2003 to 2007, were obtained from the Fatality Analysis Reporting System (FARS) database. Various driver-, roadway-, environment- and vehicle-related factors, which contributed to the occurrence of these crashes were identified. The likelihood of these factors being present in fatal truck-crashes was compared to fatal non-truck crashes using the Bayesian Statistical Approach (7). Further, a multinomial logistic regression model was developed using the type of crash (truck or non-truck) as the dependent variable. In addition to driver-related factors such as cellular phone usage, failure to give right of way, and inattentiveness, other factors like inadequate warning signs and poor shoulder conditions were found to be predominant causes contributing to more truck-crashes than non-truck crashes. Also, the model showed that a majority of single-vehicle fatal truck-crashes occurred on rural roads.

A study was carried out by Charbotel et al. in order to assess the severity of injury sustained by drivers of the trucks involved in crashes (11). A study was performed in the Rhone region of France using data from Trauma Registry for Road Crash Victims database for the years 1995 through 1999. Different characteristics of victims (such as age, place of residence, etc.) and crash (such as place, time, antagonistic driving, and seatbelt wearing) were observed, and a multivariate analysis using logistic regression was completed. In addition, chi-square tests were performed to compare truck and car crashes. Variables were chosen based on a significance value. The study showed trucks were more dangerous for the safety of other road users. Also, it was concluded that professional driving is an occupation involving high-risk factors and the factors were identified such as age of the driver, antagonistic driving, and seatbelt usage. These factors considerable increased the severity of the truck-crashes.

Torre and Rossi performed a study with the main objective of identifying potentially dangerous locations for safety regarding heavy good vehicles (HGVs). Data was obtained for four countries (Italy, France, United Kingdom, and Finland) from a common database and crashes were grouped together based on road section, type of heavy vehicle, and type of accident (12). Analysis of the crashes was done, either by investigating the distribution of different explanatory variables from the database or by using the equation for the accident rate, which is a measure of occurrence of the crash. The findings were used to identify situations where the trucks had a higher probability of being involved in a crash. The study identified that a tractor semitrailer was the truck type most involved in severe crashes. Also, rural highways, urban highways, primary roads, and secondary roads were identified, in that order, as the most probable accident-prone situations.

Work zone locations had certain attributes such as narrow roads, traffic signs, barriers, and barricades, which relatively increased the probability of an occurrence of a crash as compared to other roadways, especially as the size of the vehicle increased. A study was done by Khattak and Darga regarding this issue in North Carolina for the year 2000. The research involved a comparison between truck and non-truck vehicles, both at work zone and non-work zone areas (13). The Highway Safety Information System (HSIS) database, along with police reports, were used to obtain statistical data such as type of work zone, presence of warning signs and cones, type of activity in the work zone, crash location, construction impact of the work zone on the roadway etc. Severity measures of various crashes were presented, either in terms of most seriously injured occupant in the crash, or as total harm, which combines crash frequency and injury severity. An ordered-probit model was developed for injury severity. The study showed that multi-vehicle crashes involving trucks were the most harmful kind of collisions among all other types of crashes.

Data related to the state of Michigan from 1987 to 1988 has been used in a study by Blower et al. Accident counts were taken from police reports and were classified based on the configuration, time of day, road type, and area type. Accident rates (measure of exposure being vehicle miles travelled) were used as the dependent variable (14). Contingency tables were prepared and accident rates of heavy truck-tractors were modeled using the log-linear method. Two models were developed, one each for fatal crashes and property-damage-only crashes, respectively. Chi-square statistics and deviance were used to obtain goodness-of-fit statistics. The study showed that for all truck types, except bobtails, the probability of being involved in an accident was more dependent on the operating environment than the configuration of the truck. Further, characteristics such as time of day, road type and area type, were more likely to cause a crash as compared to whether the vehicle was a single or double truck.

All two-vehicle crashes involving two cars or a car and a truck were analyzed, and various contributory causes were considered in a study by Mannila (15). Required crash data for a five-year period from 2000 to 2004 were obtained from the General Estimate System of the National Sampling System (NSS GES) database and Fatality Analysis Reporting System (FARS) database. Crashes were classified into different categories based on the kind of collision such as angled, rear-end, head-on, etc. Statistical analysis was done using logistic regression. Binary-logit models and multinomial logistic-regression models were used to identify factors which contributed significantly. Results obtained for car-truck crashes were compared with car-car crashes. The study showed that various environmental causes, driver-related causes, and speeding significantly increased the risk of car-truck crashes. Angled collisions were found to constitute the highest percentage of car-truck crashes. Also, speeding and alcohol involvement were found to increase the risk of crash involvement for both cars and trucks.

Duncan et al. modeled injury severities of occupants involved in rear-end collisions between trucks and passenger cars. The Federal Highway Administration's Highway Safety Information System (HSIS) was used to obtain necessary data for the state of North Carolina, which has long truck routes and high number of rear-end collisions involving trucks, according to data from HSIS 1993-1995 (16). Factors influencing injury severity in truck-involved, rear-end collisions were initially presented and then modeled using the ordered-probit model. Interactions among independent variables were also taken into consideration while modeling. Variables such as light conditions, speed, speed limits, gender of the driver, influence of alcohol and grade were found to increase injury severity of occupants of passenger cars involved in crash.

2.2. Logistic Regression

Moghaddam et al. performed a study to identify the main factors responsible for increasing crash severity on urban highways (17). Highways of Tehran, Iran, were selected for the analysis and data relating to various factors prevailing during the occurrence of crashes from

2004 to 2008 were considered for analysis. Binary-logit models were developed to determine the simultaneous influence of human factors, road, vehicle, and weather conditions, and traffic features, on the severity of the crash. Selection of significant variables was carried out using the backward-regression method. Developed models showed that severity of the crash varied under the influence of many factors acting simultaneously, instead of the action of any single factor. Factors such as age and gender of the driver, light conditions, behavior of the driver, defective vehicular components, manner of collisions, multi-vehicle crashes, etc. were found to have increased the severity of the crash.

Liu et al. illustrated patterns of injury severity, and location of injuries and their contact sources by age. The National Highway Traffic Safety Administration’s (NHTSA’s) National Automotive Sampling Systems Crashworthiness Data System (NASS-CDS) was used to obtain data for the years 1993 through 2004, and these were analyzed based on rollovers and seat belt usage (18). Frequency tables were presented and chi-square analysis was performed to determine the dependency of injury severity on age. A logistic-regression model was developed in order to predict the severity of injury based on age. Odds ratios were used as supportive information. The study showed that males sustained more severe injuries than females among young-driver crashes and females sustained more severe injury than males among older-driver crashes. A majority of the severe crashes resulted in injuries to the head or chest. Further, seal belt usage was found to reduce injury severity of the crashes significantly.

Dissanayake compared factors affecting severity of injury to the young and older drivers involved in single-vehicle crashes (19). Binary-logistic-regression models for both driver groups were developed using crash severity as the dependent variable. Variables related to roadway, environment, driver, and vehicle characteristics were used as explanatory variables. Five different models were developed, each for five different levels of severity. Data needed for this study was obtained from the Florida traffic-crash database, which was obtained from the state data program. The models were checked for goodness of fit. The driver being under the influence of drugs/alcohol was found to reduce the severity of older-driver-involved crashes. Speeding and the driver not using a restraint device were important factors causing a higher severity of crashes. Curved highways and driver ejection increased the severity of young-driver crashes and crashes with frontal-impact points increased the severity of older-driver crashes.

A study performed by Conroy et al. illustrated the differences in injury patterns, severity, and sources of drivers influenced by the kind of damage sustained by the vehicle in head-on collisions (20). Field investigations were conducted at multiple centers, and crash data for the years 1997 to 2006 were obtained from the Crash Injury Research and Engineering Network (CIREN) program. Different variables related to occupants, vehicles, and crashes were identified, and their relation to injury severity was identified using chi-square or Fisher exact-statistics-and-odds ratios. Logistic-regression models were developed and analyzed. The Hoshmer-Lemeshow goodness-of-fit statistics were used to check the fit of the logistic-regression model developed. The study showed that distribution of damage across the frontal plane, intrusion, and vehicle body type were important factors for consideration for the study of occupant injuries in crashes involving motor vehicles.

Malyshkina and Mannering studied the effects of increasing speed limits of rural interstate and multilane non-interstate routes in the state of Indiana from 2004 to 2006, since speed limits were increased there in 2005 (21). Data was obtained from the Indiana Electronic

Vehicle-Crash-Record System (EVCRS) database where data were available under three different categories, namely roadway and environmental data, vehicle data, and occupant data. The study was performed considering the occurrence of a crash as a social and economic burden, and a multinomial-logit model was developed using accident severity as the dependent variable. The study showed that speed limits did not significantly affect injury severity on interstates, unlike non-interstates where higher speeds were associated with greater injury severity.

Gabauer and Gabler studied the effects of airbags and seatbelts on the injury severity of the occupants involved in longitudinal-barrier crashes (22). Data for 1997 to 2007 were considered and extracted from the National Automotive Sampling System/Crashworthiness Data System. Binary-logistic-regression models were developed to predict the risk of occupant injury, and a comparison was made based on the type of restraint used. The study showed that concrete barriers were more associated with a high rate of airbag deployment than metal barriers. Also, in single-event, longitudinal-barrier crashes, seatbelts and airbags were found to reduce the severity of injuries sustained by occupants.

2.3. Severity Modeling

A study was performed by Eboli and Mazzulla to explore the relationship among road accident severity with number of people injured, number of vehicles involved, and some factors characterizing accidents (23). Data related to Cosenza province, Italy, for the year 2003 was considered and severity was related to different factors like road characteristics, environmental context and driver characteristics. A developed structural equation model contained latent variables which were unobserved road accident aspects that can be explained by observed variables. The parameter estimated standard error, critical ratio, level of statistical significance of each variable, and various goodness-of-fit indices were calculated, along with indirect effects of observed variables on latent variables.

Wang performed a study for the characteristics of the crashes that occurred in the work-zone areas and the factors contributing to different injury severity levels (24). Crash data for the study was obtained for the state of Florida for a period of five years from 2002 to 2006 using the Florida Crash Analysis Reporting (CAR) system database. A descriptive statistical analysis for work-zone crashes for different age groups was performed along with a comparison between the crashes occurring in work-zone and non-work-zone areas. An ordered probit model was developed to model injury severity. The study showed middle- aged drivers were involved in a higher percentage of work-zone crashes and no-injury crashes. Careless driving and failing to yield the right of way were important driver-related contributory factors in work-zone crashes. Also, heavy vehicles were found to be involved more in work-zone crashes.

Liu and Dissanayake studied the issues related to speed limits on gravel roads in Kansas. The study was performed in three facets which included field studies, questionnaire survey, and statistical analysis of crash data (25). The field study was performed in Riley County and included on-site data collection. Questionnaire survey included a collection of opinions and comments from local county engineers. Thirdly, related data from the Kansas Accident Reporting System (KARS) database was extracted for the years 2003 to 2005, and a contingency table test method was performed as part of the statistical analysis. Data obtained from the three methods were analyzed. The study showed a speed limit of 55 mph on gravel roads in Kansas is most acceptable under current existing conditions. Lower speed limits were found to characterize crashes with less severity.

Lemp et al. examined various factors affecting crash severity of occupants involved in heavy-duty truck-crashes by analyzing records in the recent Large Truck Crash Causation Study Data (LTCCS), provided by the United States Federal Motor Carrier Safety Administration (FMCSA) and National Highway Traffic Safety Administration (NHTSA). Data was also obtained through interviews with drivers, passengers, and witnesses. The Standard Ordered Probit (SOP) models and Heteroskedastic Ordered Probit (HOP) models were used to illuminate the impact of various vehicle, environmental, and occupant characteristics on injury outcomes (26). The same set of variables was used in both SOP and HOP models. HOP models offered greater model flexibility than SOP models, since they capture the effect of crash characteristics on the variance or uncertainty in crash severity. Crash severity and injury severity were used as response variables and all independent variables were broadly classified as crash-level variables, largest-truck attributes, and vehicle- and driver-related variables. SOP and HOP models developed were compared using log likelihood values, and then analyzed. Analysis showed the probability of occurrence of a fatal crash increases with the number of vehicles involved and number of truck occupants. Also, fatality likelihood was observed to increase with the number of truck trailers and decrease with length and gross vehicular weight rating of the truck.

Kockelman, in his study, developed an ordered probit model to examine the risk associated for different levels of injury severity under the categories of all crashes, single-vehicle crashes, and two-vehicle crashes, respectively (27). Data related to crash, vehicle, and persons was obtained from the National Automotive Sampling System's General Estimate System (NASS GES) for the year 1998, which was a sample of police-reported crash records. These explanatory variables were used to model injury severity of the driver, both with and without the speed variable. The study showed rollovers and head-on collisions increased the severity of the crash. Late-night driving on weekends and daylight conditions had negligibly small effects in influencing the crash and also, light-duty trucks were observed to provide relatively better safety to their occupants.

A study performed by Ma and Kockelman used data related to state highways of Washington for the year 1996, using the Highway Safety Information System (HSIS) database (28). In this study, a multivariate Poisson specification, as well as a Bayesian technique, was used to perform a joint study of crash frequency and severity. In addition, Gibb's sampler, as well as the Metropolis-Hastings (M-H) algorithm, was established to estimate parameters of interest for Bayesian statistical inference. For the purpose of comparison, a series of univariate Poisson models for injury counts were estimated. Tables were developed for all injury-severity levels showing the frequency of a condition under different injury-severity levels. Expected percentage changes in injury rates corresponding to changes in variables were calculated, and a cost analysis was done using NHTSA's estimate-of-injury costs. The study showed travel time saved by increasing the speed limit by 10mi/hr was not worth the economic loss generated due to a crash.

2.4. Countermeasure Ideas

TheI-80 corridor in Iowa was considered for a study by Burke, as it is one of the highways connecting major areas of the country (29). Also, there had been an increase there in the number of trucks, which in turn, resulted in greater congestion, greater pavement deterioration, and a spike in auto-truck accidents. Burke discussed advantages and disadvantages of providing an exclusive travel lane for trucks, and discussed the design of a truck lane by taking both passing lanes and the breakdown lane into consideration. Also, respective costs involved were predicted based on factors like cumulative mileage, right-of-way costs, terrain costs, etc. The study summarized that a dedicated truck lane helps in getting long-term benefits.

Rau performed a study regarding detection of drowsiness in the driver and effects of employing a warning system for commercial vehicle drivers (30). The National Highway Traffic Safety Administration (NHTSA) identified drowsiness as the most important factor responsible for safety concern of commercial vehicle drivers. NHTSA's five years of data from 1989 to 1993 were considered for this study. A field operational test (FOT) was later performed during 2004 to 2005 in which three main research partners had participated in order to analyze and predict the effectiveness of employing warning systems like the drowsy driver warning system (DDWS). By analyzing results from the FOT, it was concluded that further understanding was needed about highway safety benefits, fleet acceptance, operational utility, and fatigue management practices in order to reduce the problems involved in fatigue crashes.

A study performed by Council et al. included the examination of faults in non-fatal crashes, a provision of crash-based validation for unsafe driving acts (UDAs), and identification of critical combinations of crash types at specific roadway locations through an analysis of the total harm resulting from the combination of the crash and type of site (31). Analysis was performed for the state of North Carolina and findings obtained were compared with earlier standard findings. Findings obtained were observed to differ slightly from standard findings. Truck drivers were found to be more at fault during the collisions occurring due to backing, right turn, left turn, rear-end and sideswipe crashes, and when the car driver was found to be more at fault during collisions due to maneuvers such as head-on and angled collisions.

Montella and Pernetti studied a motorway in Italy, which was a 127.5 km section (32). Data for the years 2001 to 2005 were considered and obtained from a number of sources including police reports, hospital reports, and some site investigations. The main aim of this study was to point out risk factors associated with the motorway that could be considered by highway agencies and designers towards suggestions of suitable safety countermeasures which would help in reducing the run-off-the road (ROR) crash frequency and severity. The chi-square test with Yate's correction was performed to determine whether the parameter was significant or not. Number of ROR crashes for both trucks and cars were obtained and then compared. Crash severities in relation to various significant parameters were analyzed. The study showed severity of the crashes involving motor vehicles was significantly higher than those involving other vehicles. Also, severities of crashes on the roadways involving blunt-end terminals were higher than those on roadways with longitudinal barriers like guardrails.

A study performed by Wang et al. considered traffic accidents as a financial burden in addition to the loss of life (33). An attempt was made to study causes of more crashes on two-lane rural highways of Washington. Six study routes were chosen based on the length, location, and geometric characteristics for a period of six years (1999-2004), and corresponding data were obtained from the Highway Safety Information System (HSIS), Roadway Video Image Data, and Geographic Information System (GIS) retrieved from the Washington Department of Transportation. Segments of roads and intersections were considered in two different categories and T-test and analysis of variance (ANOVA) were performed to identify significant contributory causes in the occurrence of a crash. The same data was used to develop the Poisson regression model, negative binomial regression, zero- inflated Poisson, and negative binomial models. Effect of factors such as speed limit, degree of curvature, shoulder width, grade percentage, etc. on risks involved in all type of crashes and those in rear-end type of crashes were summarized. Also, cost-effective ways of mitigating risk on roadway segments, such as avoiding frequent speed-limit changes, widening surface and shoulder width etc, were also discussed.

Li and Baib developed in their study a new variable called the crash severity index (CSI), which was used and modeled as a measure of risk levels associated with work-zone crashes (34). Crash data, which included data related to fatal crashes from 1998 to 2004 and that related to injury crashes from 2003 to 2004, was obtained from a database of the Kansas Department of Transportation (KDOT). Four CSI models were developed using the logistic regression method and were analyzed using crash data. The chi-square statistic along with the Cochran – Mantel – Haenszel (CMH) statistic were used to ensure accuracy of the factors associated with the risk involved in the crashes. CSI values for most crashes at the work zones were found to be consistent with actual crash severity outcomes. Also, benefits of implementing the method of using CSI values were presented, along with countermeasures to mitigate risk involved in crashes at work zones.

Oh et al. analyzed pedestrian-vehicle crashes in Korea with an aim of mitigating fatalities and injury severity to pedestrians. Considering pedestrians as the most vulnerable elements in the highway system (35), this study focused on developing a probabilistic pedestrian-fatality model. Related data was collected for a period of one year using the accident report forms, and this data was analyzed by the National Institute of Scientific Investigation (NISI) and Center for Accident Analysis of Hanyang University. A binary logistic regression model was developed using the pedestrian fatality as the dependent variable. Out of all available data for explanatory variables, collision speed, vehicle type, and pedestrian age were the three variables selected for modeling, out of which collision speed was the most significant variable. The model was mainly developed with the aim of providing countermeasures, both in the field of transportation safety and automobile operations. The study showed the probability of a fatality decreases as age of the pedestrian increases. Also, heavy vehicles had greater probability of causing a more severe crash as compared to lighter vehicles. Findings of the study were summarized, and areas regarding future research were discussed.

Dissanayake and Lu analyzed differences between domestic and international drivers in the United States considering crashes that had occurred due to possible unfamiliarity of road rules to international tourists (36). A comparison was made between the two regarding the understanding of the traffic-control devices. The study was performed at the departing areas of two international airports in Florida, each at Tampa and Orlando. Survey forms were supplied to passengers to fill out along with a questionnaire, and these were later analyzed and checked for existing relationships between the variables using cross classification. The study showed international respondents were more satisfied with the highway system in the United States and less satisfied with traffic-control devices. Both domestic and international respondents were less satisfied with the availability and accuracy of information associated with the highway system.

Dissanayake and Ratnayake performed a study to reduce the severity of crashes on rural highways in Kansas, and to identify suitable countermeasures to enhance the safety of the rural highways (37). Related data was obtained from the Kansas Accident Reporting System (KARS) database for the years 1998 to 2002 and modeling approaches comprised of ordered choice which included ordered-probit and ordered-logit models along with log-linear models. The study showed crashes involving drivers with no safety equipment had sustained more severe injuries. Also, the severity of the injuries was high when the driver ejected out of the vehicle after the crash. Further, single-vehicle crashes and head-on collisions were found to be relatively more severe. Results were analyzed and a list of possible countermeasures to mitigate crashes in rural areas was a provided with detailed discussion of each countermeasure.

CHAPTER 3 METHODOLOGY

3.1. Data

The first phase of this study used data from the Fatality Analysis Reporting System (FARS) database to identify characteristics and contributory causes related to large-truck crashes in the United States (7). However, this database contains information relating only to fatal crashes and hence, cannot be used to study crashes of different severity levels. Data for this second phase was obtained from the Kansas Department of Transportation's (KDOT's) Kansas Accident Reporting System (KARS) database, which contains details of police-reported crashes at all severity levels that have occurred in the state of Kansas. The database consists of a complete dataset which contains information related to all the truck-crashes in Kansas, and a limited dataset which consists of data related to truck-crashes which occurred only on the state highway system comprised of Kansas highways, Interstate highways and U.S. routes. This database is an integration of various driver-, vehicle-, environment- , and road-related characteristics that prevailed at the time of the crash. The database might contain some inaccurate or missing values, either because of lack of complete information or due to human errors in entering data into the electronic format. Details such as name, address, contact number, and other such personal information related to the individuals involved in crashes are prevented from public access in order to maintain privacy. Data obtained from this database were redefined by codes to simplify the process of entering the data. These codes are explained in KDOT's Kansas Motor Vehicle Accident Report Coding Manual (39).

Injury severity of occupants involved in truck crash were determined as fatal, disabling, non-incapacitating, possible, or Property Damage Only (PDO) based on the severity level of injury sustained by the occupant. Type of severity was recorded as fatal if the death of occupant occurred within 30 days of the occurrence of the crash (39). A disabling injury is one which prevents the occupant from performing his other routine activities, like walking and driving, normally after the crash has occurred as compared to what he or she could do before the crash. A non-incapacitating injury is one, other than the disabling injury, which is observed to have occurred to the occupant at the site. All other kinds of injuries were categorized as possible injuries. A PDO type of injury involves no fatality or notable injury to the occupant of a recordable crash. Severity of a crash, which has been considered as the dependent variable for analysis in this study, is identified based on the highest level of injury severity sustained by the occupants involved in a crash.

For the purpose of this study, a truck with a gross vehicular weight rating of 10,000 pounds or more is considered as a large truck. Based on the vehicle body type, large trucks include single heavy trucks, truck and trailer(s), and tractor-trailer(s) as obtained from the Kansas Motor Vehicle Accident Report Coding Manual (39). Data related to crashes involving large trucks in Kansas for a period of five years from 2004 to 2008 were considered for this study. For crashes involving more than one truck, information relating to only one truck is considered, as the number of such crashes is negligibly small.

Different characteristics of truck-crashes were available in different files in the database and these files were initially combined using the accident key variable, which is unique for each crash. Once combined, data were further filtered using Microsoft Access and Microsoft Excel to avoid repetition of records. The resulting dataset on filtering consisted of unique records, with each record representing a single crash. A total of 18,919 unique truck crash records were obtained after filtering. This final dataset was exported to Statistical Analysis System (SAS) version 9.2 (40) for further analysis.

3.2 Cross-Classification Analysis

Cross-classification analysis, also known as contingency table analysis, can be performed to verify the dependency of various factors on the severity of truck-crashes. This test is used to identify the relationship between a pair of variables, one of them being crash severity. This analysis is associated with the hypothesis testing procedure, where the null hypothesis (H_0) and alternate hypothesis (H_A) for the study are defined as follows:

H_0: Variable considered is independent of the crash severity

H_A: Null hypothesis is not true

If the null hypothesis is true, it means there is no relationship between the variable under consideration and the severity of truck-crashes. The level of confidence was considered to be 95%. In the cross-classification procedure, variables are subdivided into suitable categories and arranged in rows and columns. The columns contain the five levels of crash severity and the rows contain the combined subcategories of the variables under consideration. For example, the variable 'Light Condition' can be categorized as Daylight, Dark with Lights, Dark without Lights, Dusk, Dawn, etc. These categories of variables are then combined to obtain reasonably large values in the cells for cross-classification analysis. This is because smaller values of sample variables create smaller values for expected frequencies, which might end up with inaccurate results at times (41).

If there are ‘n’ rows and ‘m’ columns in the matrix, then the degrees of freedom are given by the following expression (42):

$$\text{Degrees of Freedom} = (n-1)*(m-1) \tag{1}$$

Entries in the contingency table are recorded as the observed frequencies ‘O_{ij}’ where, i and j denote the corresponding row and column. Expected values for any cell in the matrix ‘E_{ij}’ are calculated by multiplying the sum of the observations in the row corresponding to the cell in the corresponding column and dividing it by the sample size of the matrix (42). In other words,

$$E_{ij} = \frac{(\text{Row Total})*(\text{Column Total})}{\text{Sample Size}} \tag{2}$$

Having found this, the chi-square (χ^2) statistic is computed as follows (42) :

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_{ij}-E_{ij})^2}{E_{ij}} \tag{3}$$

where k is the number of cells in the contingency table.

Using the value of the obtained degrees of freedom from Equation 3.1., the rejection region for a confidence interval of 95% can be determined from the standardized chi-square distribution table, which gives the tabular chi-square value. This value is compared with the calculated chi-square value obtained using the equation 3.3. If the calculated value is greater than the tabular value, then the null hypothesis is rejected, which means a relationship exists between the variable under consideration and the crash severity. On the other hand, if the calculated value is less than the tabular value, then the null hypothesis is not rejected, which means the two variables are independent of each other. Though this test is not very accurate or perfect, it gives a rough idea about the relationship between the variables. SAS version 9.2 (40) was used to perform the cross-classification analysis.

3.3. Multicollinearity

The data in the dataset developed, as mentioned in section 3.1 was imported into SAS version 9.2 (40) for further analysis. All candidate variables considered in modeling were redefined suitably to take binary values of either 0 or 1. Independent candidate variables were first checked for linear dependencies using the correlation matrix. Presence of correlated variables in the model relatively reduces the accuracy of the impact of one variable on the crash severity, while keeping the other variables constant. The PROC CORR statement available in SAS version 9.2 (40) was used to generate the matrix. Each of the values generated in the matrix are Pearson’s correlation coefficients and their magnitudes determine the extent of relationship between the corresponding variables. According to Oh et al., a Pearson’s correlation coefficient of 0.5 indicates a high multicollinearity exists between the corresponding pair of explanatory variables (35). Hence, a correlation coefficient of 0.5 was chosen as the cutoff value, and the pairs of variables having a coefficient of 0.5 or more were considered to minimize the effect of multicollinearity. The pair having the highest magnitude of the coefficient was considered first. Each of the two variables was alternately placed in the model and strength of the model was checked using model-fit statistics. The variable that resulted in a weaker model was discarded, and then the procedure was repeated for the pair of variables having the next highest magnitude of the correlation coefficient. The process was continued until no pair of variables left in the model had a correlation coefficient of 0.5 or more. This substantially mitigates the effect of multicollinearity among the explanatory variables.

3.4. Binary Logistic Regression

The odds ratio, which is defined as the ratio of the probability of the occurrence of an event to that of its non-occurrence (38), was used to understand the influence of each of the candidate variables on the severity of the crash. An event, in this study, is referred to the case where the crash-severity variable took a value of 1. Odds ratio (O) is given by the following expression:

$$O = \frac{p}{1-p} \tag{4}$$

where,

p = probability that the crash severity takes a value of 1

Probabilities are generally bounded and linear functions are unbounded. Transforming the probability to odds and taking its logarithm removes the bounded nature of the dependent variable and a logistic model is obtained by setting the logarithm of odds of the dependent variable to a linear function of the explanatory variables (38).

A logistic regression model with k explanatory variables and i = 1, 2 … n individuals has a general form as follows (38):

$$\log \left[\frac{P_i}{(1-P_i)}\right] = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \ldots\ldots\ldots\ldots\ldots \beta_k x_{ik} \tag{5}$$

where,

α = value of the intercept,

β = estimates of different independent variables in the model, and

x_{i1}, x_{i2}….x_{ik} = interval-level or indicator variables associated with crash i.

The expression for p_i can be obtained by solving the logistic equation (5) as follows:

$$p_i = \frac{1}{1+\exp(-\alpha-\beta_1 x_{i1}-\beta_2 x_{i2}-\beta_3 x_{i3}-\ldots\ldots\ldots-\beta_k x_{ik})} \quad (6)$$

Since p_i is the probability of the crash-severity variable taking the value of 1, the value of p_i ranges between 0 and 1 for all values of x's and β's. A logistic regression model predicts the probability that the dependent variable takes a given value for a particular set of explanatory variables (19). In the case of a binary logistic regression model, the dependent variable takes the values of either 0 or 1.

The binary logistic regression model is an efficient tool to model crash severity, which has been considered as a dichotomous dependent variable (38). Crash severity, denoted as 'Y' in this case, is redefined as follows:

Y = 1, if the occupants involved in the truck crash sustained injury of any severity level.

Y = 0, if the occupants involved in the truck crash did not sustain any injury.

A total of 46 independent variables related to vehicle, driver, road, and environmental conditions such as alcohol, light conditions, speed limit, etc. were considered for the model. The PROC LOGISTIC statement, available in SAS version 9.2 (40), was used to develop models using the three variable selection methods, which include forward selection, stepwise selection, and backward elimination methods. In the forward selection method, the model initially starts with no variable in it and then the variables enter one by one until all the variables in the model have significant p-value (40). A p-value of 0.05 was chosen as the level of significance and any variable having a p-value greater than 0.05 did not stay in the model (27). In the forward selection procedure, a variable once entered into the model will never leave the model (40). In the backward elimination method, model initially starts with all variables and then each variable is removed one by one until all variables left in the model have the significant p-value of 0.05 (40). Variables once left can never enter the model again. The stepwise selection procedure is a combination of forward and backward selection methods, where the variables keep entering and leaving the model until the best possible model is obtained (40). These methods are used to identify the significant variables that are to stay in the model.

The maximum likelihood method (MLM) was used for estimating the coefficients of the explanatory variables in the model. Maximum likelihood is a general approach of estimation which is widely used in many different methods of statistical modeling. According to P. D. Allison, “The basic principle of this method is to choose those parameter values as the estimates which if true, would maximize the probability of observing what we have, in fact, observed (38).”

The value of the R^2 statistic, which represents the amount of variability in the model explained by the independent variables, was used for selecting the best model with greater values of R^2 corresponding to the better model. Also, MLM generates important model fit statistics such as the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and the value of twice the negative of log likelihood (-2 log L), both for the intercept only and the fitted model. AIC and SC values are calculated as follows (38):

$$\text{AIC} = -2 * \text{log-likelihood} + 2k \tag{7}$$

$$\text{SC} = -2 * \text{log-likelihood} + k \log (n) \tag{8}$$

where

k = number of estimated parameters, and

n = sample size.

These statistics can be used for making comparisons among a set of models obtained by different variable selection methods, with smaller values representing a better model (38).

Other goodness-of-fit statistics include the percentage concordant, percentage discordant, percent tied, pairs, Somer' s D, Goodman – Kruskal Gamma, Tau-a, and C values which can evaluate the strength of the model developed. Descriptions of these parameters are as follows (7):

- Percent concordant **–** A pair of observations with different observed responses is said to be concordant if the observation with the lower ordered response value has a lower predicted mean score than the observation with the higher ordered response value.
- Percent discordant **–** If the observation with the lower ordered response value has a higher predicted mean score than the observation with the higher ordered response value, then the pair is discordant.
- Percent tied **–** If a pair of observations with different responses is neither concordant nor discordant, it is a tie.
- Pairs **–** This is a number of distinct ways of pairing up different observations. The concordant pairs, discordant pairs, and tied pairs altogether aggregate to give the total number of pairs. Each of the percent concordant, percent discordant and percent tied is calculated with respect to the total number of pairs.
- Somer's D – Somer's D is used to determine strength and direction of the relation between pairs of variables. Its values range from -1.0 (all pairs disagree) to 1.0 (all pairs

agree). It is defined as $(n_c\text{-}n_d)/t$, where n_c is the number of pairs that are concordant, n_d the number of pairs that are discordant, and t the total number of pairs with different responses (38).

- Gamma – The Goodman-Kruskal Gamma value closer to one indicates good association among the variables in the model. This method does not penalize for ties on either variable. Its values range from -1.0 (no association) to 1.0 (perfect association). It is defined as $(n_c - n_d)/ (n_c + n_d)$, where n_c is the number of pairs that are concordant and n_d is the number of pairs that are discordant (38).
- Tau-a – Kendall's Tau-a is a modification of Somers' D to take into account the difference between the number of possible paired observations and the number of paired observations with different responses. It is defined as $(n_c\text{-}n_d)/n$ where n_c is the number of pairs that are concordant, n_d the number of pairs that are discordant, and n the total number of pairs (38).
- c – Another measure of rank correlation of ordinal variables is 'c'. It ranges from 0 (no association) to 1 (perfect association). It is a variant of Somers' D index. The value of c is given as (38):

$$c = 0.5 * (1 + \text{Somer's D}) \qquad (9)$$

CHAPTER 4 RESULTS AND DISCUSSIONS

This chapter summarizes characteristics and contributory causes of the crashes involving large trucks in Kansas using combined data for five years from 2004 to 2008. Data obtained and analyzed from both the complete and limited datasets of the KARS database are presented. A total of 18,919 truck-crashes were recorded on all roads of Kansas, of which 11,762 were truck-crashes on the state highway system. Analysis of the KARS database showed that large trucks in Kansas resulted in more fatalities in the other vehicle as compared to the truck occupant. More than 81% of the fatalities that had occurred in truck-involved crashes were not the occupants of the trucks. This shows that large trucks are more devastating for occupants of other vehicles involved in truck-crashes.

4.1. Characteristics of Large-Truck Crashes on All Roads

4.1.1 Road-Related Features

The roadway where a truck crash occurs is one of the important considerations to understand the characteristics of large-truck crashes. Figures 4.1 through 4.3 show the distribution of truck-crashes in Kansas based on the type, condition, and character of the road, respectively. Blacktop surface type, dry surface conditions, and straight and level surface geometry have, respectively, recorded a majority of the crashes, among other features, under each category. One possible reason for this might be more trucks travel under such conditions, and as a result, more probability of involvement in a crash.

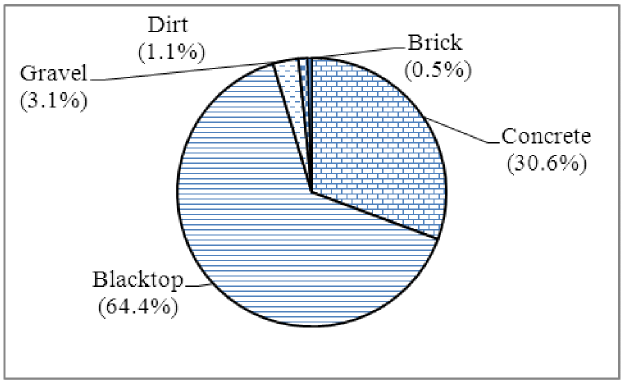

Figure 4.1 Distribution of Truck-Crashes in Kansas Based on Road Surface Type

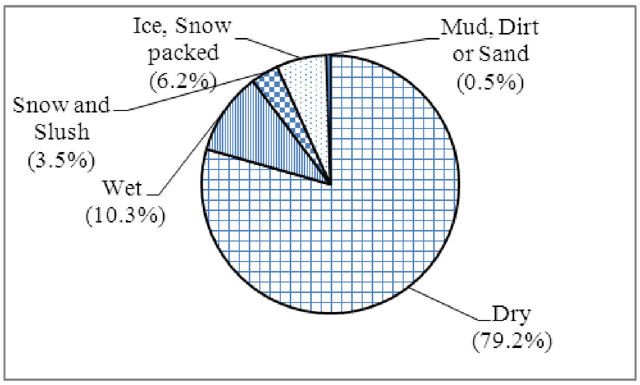

Figure 4.2 Distribution of Truck-Crashes in Kansas Based on Road Surface Condition

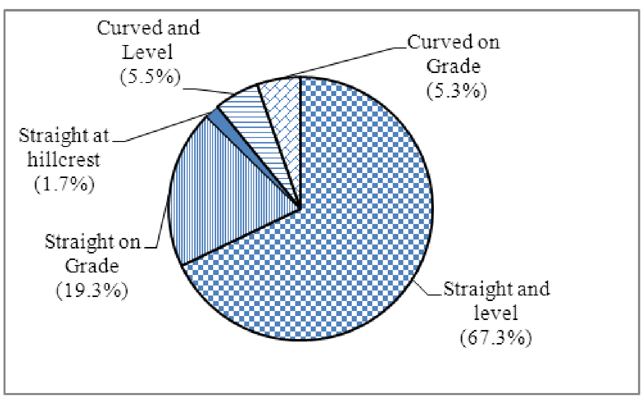

Figure 4.3 Distribution of Truck-Crashes in Kansas Based on Road Surface Geometry

4.1.2. Light Conditions

Large-truck crashes under different light conditions were categorized. Figure 4.4 shows the distribution of truck-crashes based on different light conditions. A majority of truck-crashes have occurred in daylight conditions. One possible reason for this might be because the trucks travelled more under such conditions. Percentages of crashes under other light conditions were considerably low when compared to the daylight condition.

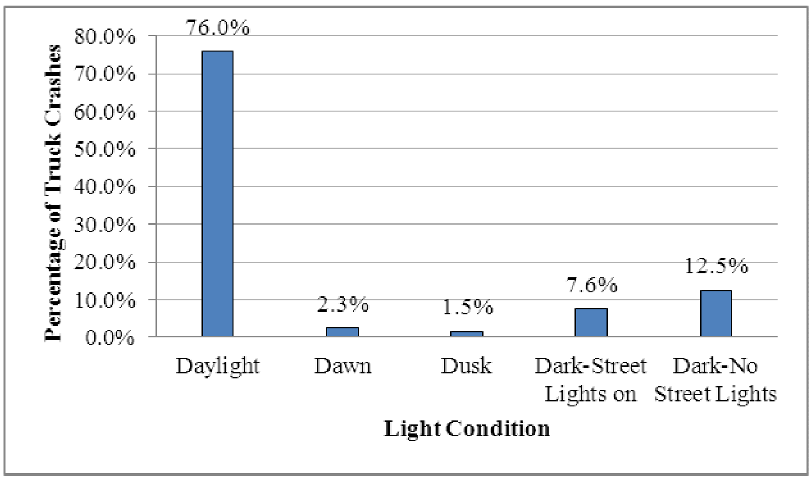

Figure 4.4 Distribution of Truck-Crashes Based on Light Conditions

4.1.3. Weather Conditions

Large-truck crashes in Kansas were categorized based on weather conditions that prevailed at the time of the occurrence of the crashes. The distribution of the crashes is presented in Figure 4.5. Analysis shows that a majority of truck-crashes occurred under no adverse weather conditions. Rain, mist, and drizzle conditions are the ones with the most number of truck-crashes among adverse weather conditions.

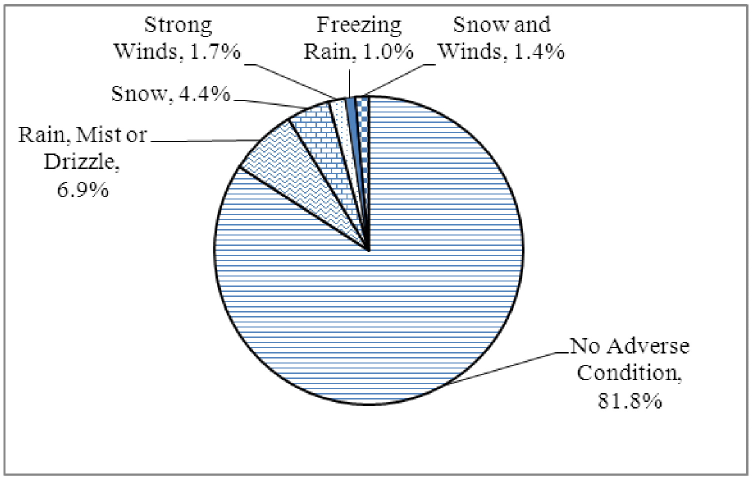

Figure 4.5 Distribution of Truck-Crashes Based on Weather Conditions

4.1.4. Time of Day

Traffic conditions vary at different times of the day due to various reasons, and hence, driving conditions differ. Figure 4.6 shows the distribution of crashes based on time of day. Analysis of the data showed a majority of truck-crashes occurred in the afternoon between 12 noon and 3:00 p.m., closely followed by number of crashes occurring from 9:00 a.m. to 12:00 noon. Overwhelming majority (77.6%) of truck-crashes occurred from 6 a.m. to 6 p.m. This might be because most of the working hours are during that time, putting more vehicles on the road. On the other hand, very few crashes occur during midnight because of relatively low traffic.

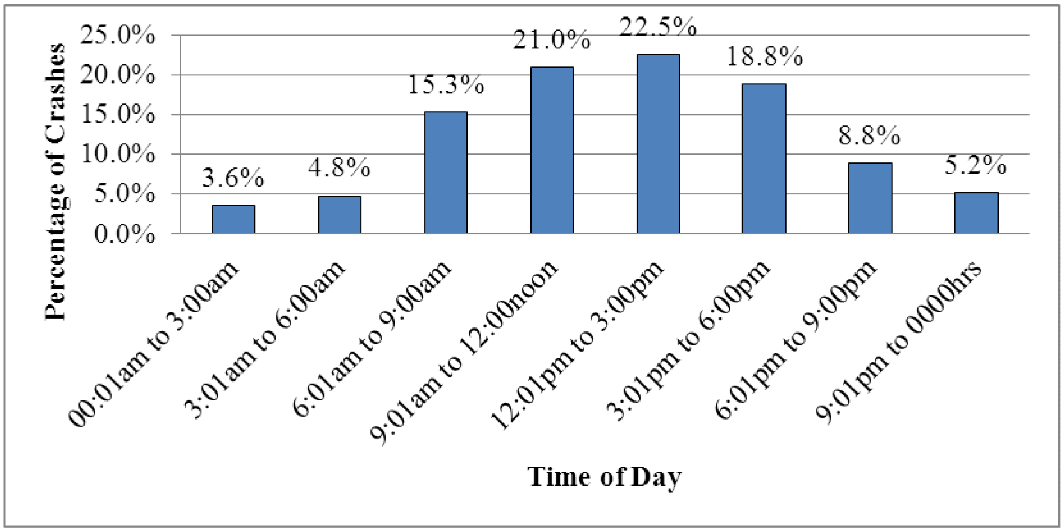

Figure 4.6 Distribution of Truck-Crashes Based on Time of Day

4.1.5. Age of Truck Driver

Age of the truck driver is one of the factors useful for understanding the characteristics of crashes involving large trucks. Figure 4.7 shows the distribution of crashes involving large trucks based on age of the truck driver. From analysis of the data, a majority of truck drivers involved in crashes were 21-40 years of age followed by those who were between 41-60 years old. While there were some young and older drivers, 80.4% of truck drivers involved in crashes were between the ages of 20 years and 60 years.

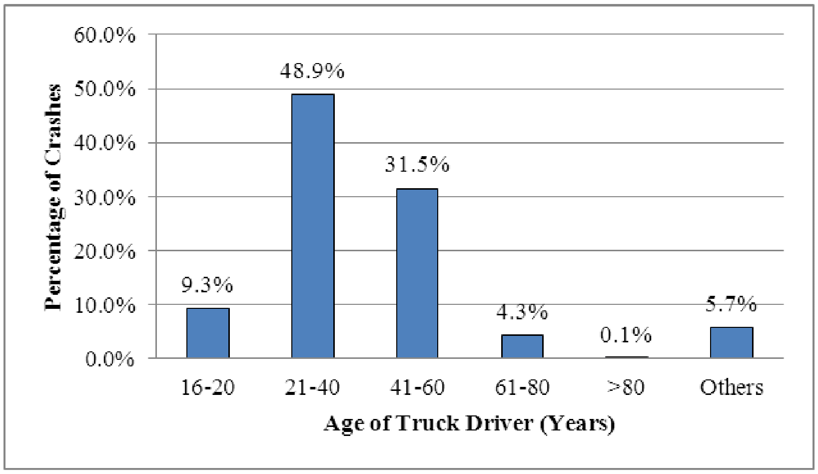

Figure 4.7 Distribution of Truck-Crashes Based on Age of Truck Driver

4.1.6. Gender of Truck Driver

Analysis of the KARS data showed that among truck drivers involved in crashes, nearly 79% were males. Figure 4.8 shows the distribution of large-truck crashes based on gender of the truck driver.

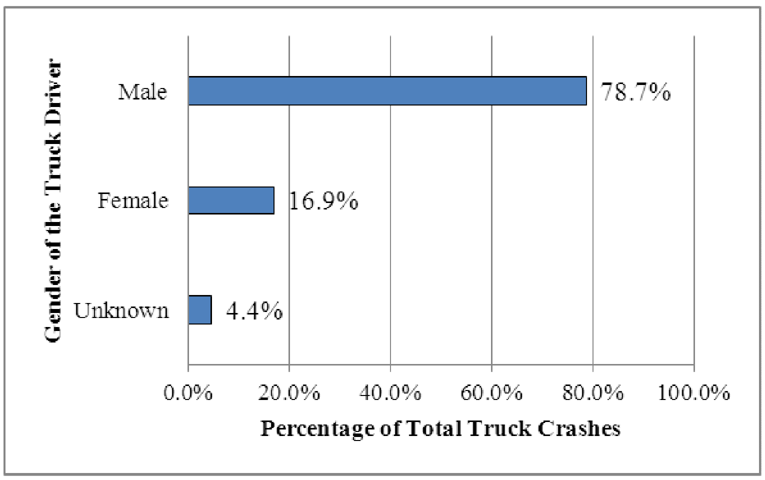

Figure 4.8 Distribution of Truck-Crashes Based on Gender of Truck Driver

4.1.7. Vehicle Maneuvers

Vehicle-related features are important to understand the characteristics of truck-crashes and develop solutions to mitigate them. Maneuverability of the truck is one such feature. Maneuverability of large trucks is relatively difficult when compared to other vehicles due to its large size. Figure 4.9 shows the distribution of large-truck crashes based on maneuvers of the truck at the time of crash occurrence. Analysis of the data showed more than half of all crashes have occurred when the truck was going straight following the road. Right turns and left turns are the other maneuvers which resulted in a significant number of crashes, followed by backing and changing lanes. Other truck maneuvers include merging, parking, backing, avoiding maneuver, stopping or slowing, and illegal parking. These maneuvers individually contribute to a small percentage of the total large-truck crashes in Kansas.

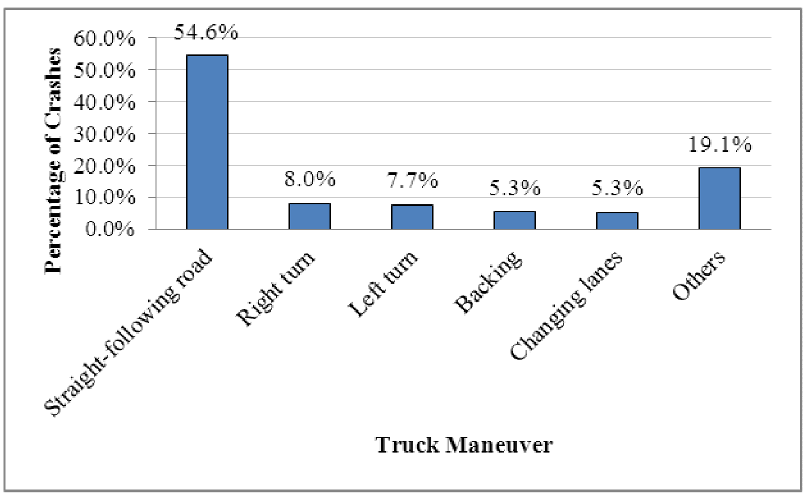

Figure 4.9 Distribution of Truck-Crashes Based on Truck Maneuvers

4.1.8. Manner of Collision

A majority of the truck-crashes involved two vehicles followed by a significant percentage of single-vehicle collisions. Figure 4.10 shows the distribution of truck-crashes based on the number of vehicles involved.

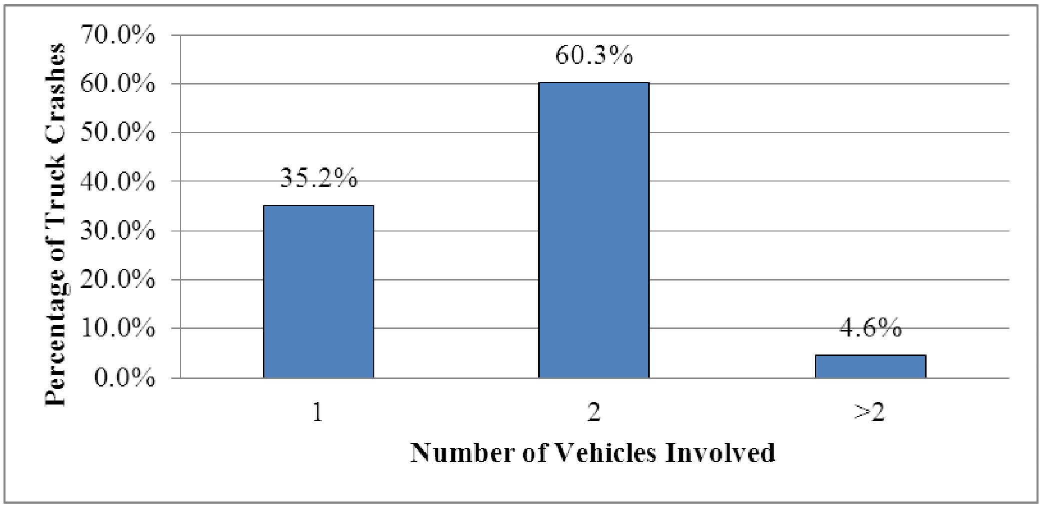

Figure 4.10 Distribution of Truck-Crashes Based on Number of Vehicles Involved

Among these, truck-crashes involving more than one vehicle were further classified on the basis of their manner of collision, as shown in Figure 4.11. Analysis of the data showed a majority (30.4%) of the multi-vehicle truck-crashes had occurred due to angled collisions. Rear-end and sideswipe collisions also characterized a significant proportion of the total multi-vehicle truck-crashes.

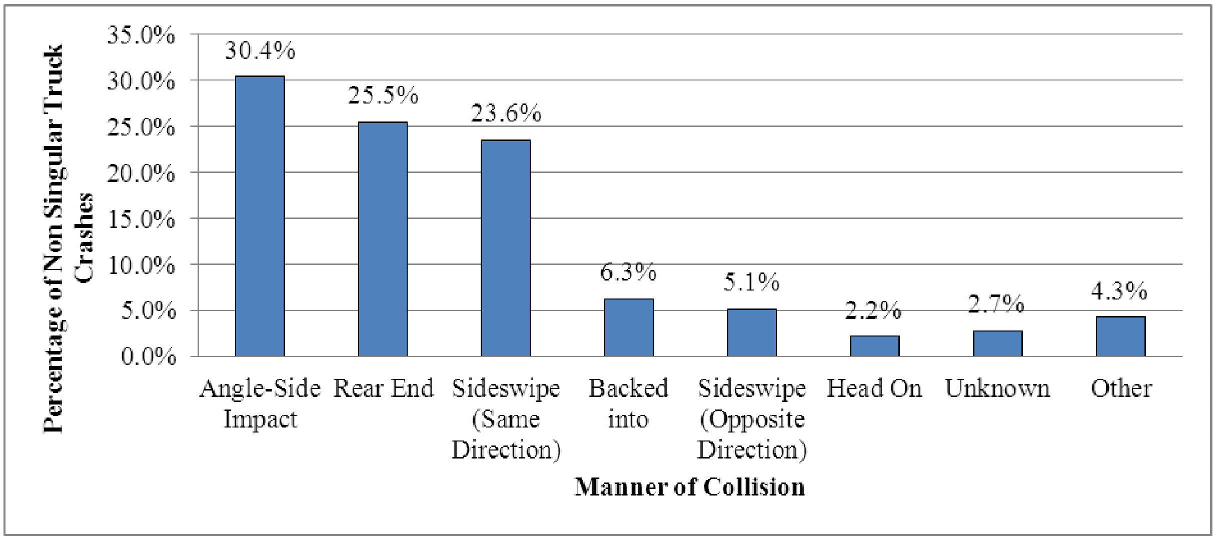

Figure 4.11 Distribution of Multi-Vehicle Truck-Crashes Based on Manner of Collision

4.1.9. Vehicle Type

Figure 4.12 shows the distribution of two-vehicle crashes involving one truck and one non-truck vehicle, based on the type of other involved vehicle. Analysis of data showed a majority of large-truck two-vehicle crashes involved an automobile, followed by pickup trucks and sports utility vehicles. The other vehicles include trains, buses, farm equipment, and camper-rv's.

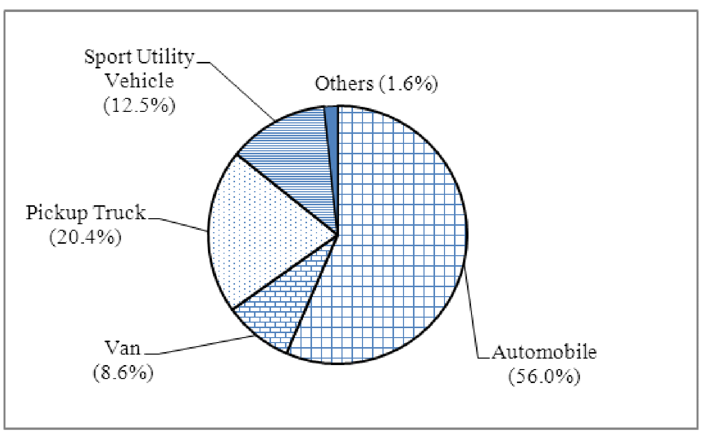

Figure 4.12 Distributions of Two-Vehicle Truck-Crashes Based on Vehicle Type

4.1.10. Day of the Week

The number of truck-crashes during weekends was relatively less than those on weekdays. Figure 4.13 shows the distribution of truck-crashes based on day of the week. Analysis of the data showed the percentage of crashes on each of the weekdays was rather uniform without much variation, with slightly more crashes being recorded on Wednesdays.

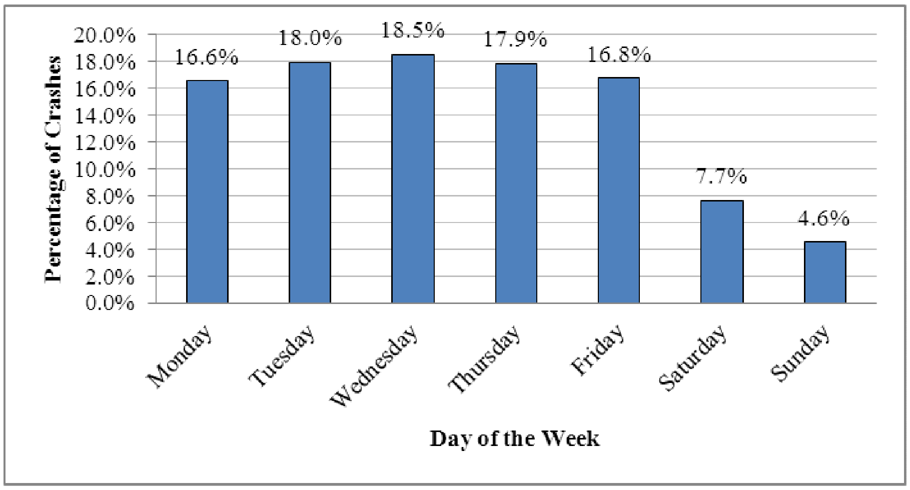

Figure 4.13 Distribution of Truck-Crashes Based on Day of the Week

4.1.11. Crash Location

Location of the crash is an important parameter for understanding the characteristics of truck-crashes. Figure 4.14 shows the distribution of truck-crashes based on location of the crash. Analysis of the data showed a majority of truck-crashes occurred on non-intersection areas.

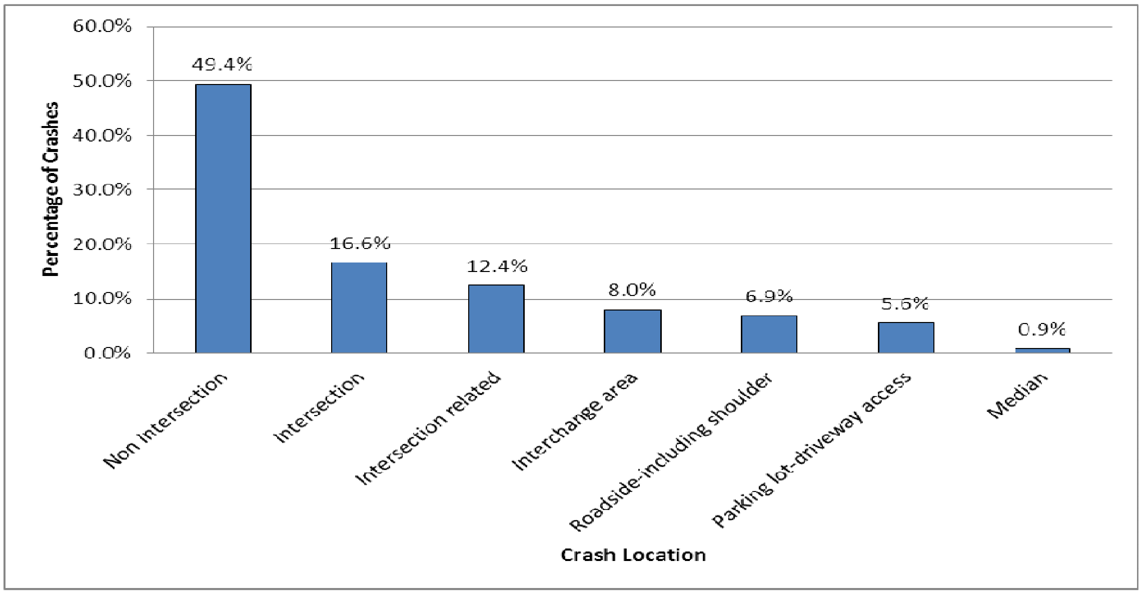

Figure 4.14 Distribution of Truck-Crashes Based on Crash Location

4.1.12. Speed Limit

Speed is an important factor that influences the severity of the crashes. Control of the vehicle becomes difficult as the vehicle attains higher speeds. Figure 4.15 shows the distribution of truck-crashes based on the speed limit at the location where the crash occurred. The speed limit of the roadway on which the truck had traversed can be considered as its approximate speed before being involved in a crash, even though this may not be an accurate assumption depending on the level of speeding.

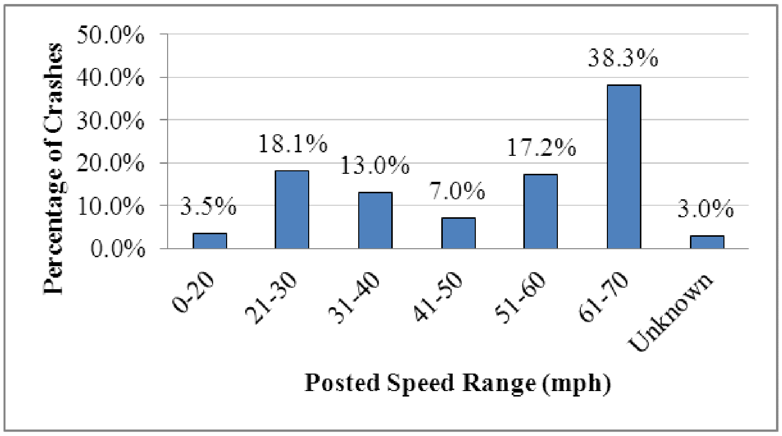

Figure 4.15 Distribution of Truck-Crashes Based on Posted Speed Limit

4.1.13. Pedestrian-Involved, Large-Truck Crashes

Pedestrian-involved truck-crashes contribute to a very small percentage of all truck-crashes in Kansas, amounting to 80 crashes in five years. Eighty five pedestrians were involved in truck-crashes. Among all truck-crashes involving pedestrians, 80% have occurred when the pedestrian was a male. Figure 4.16 and Figure 4.17 show the distribution of pedestrian-involved truck-crashes based on gender and age of the pedestrian, respectively.

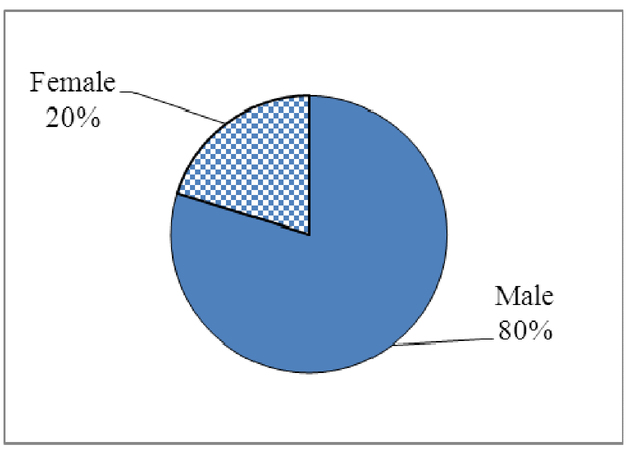

Figure 4.16 Distribution of Truck-Crashes Based on Gender of Pedestrian

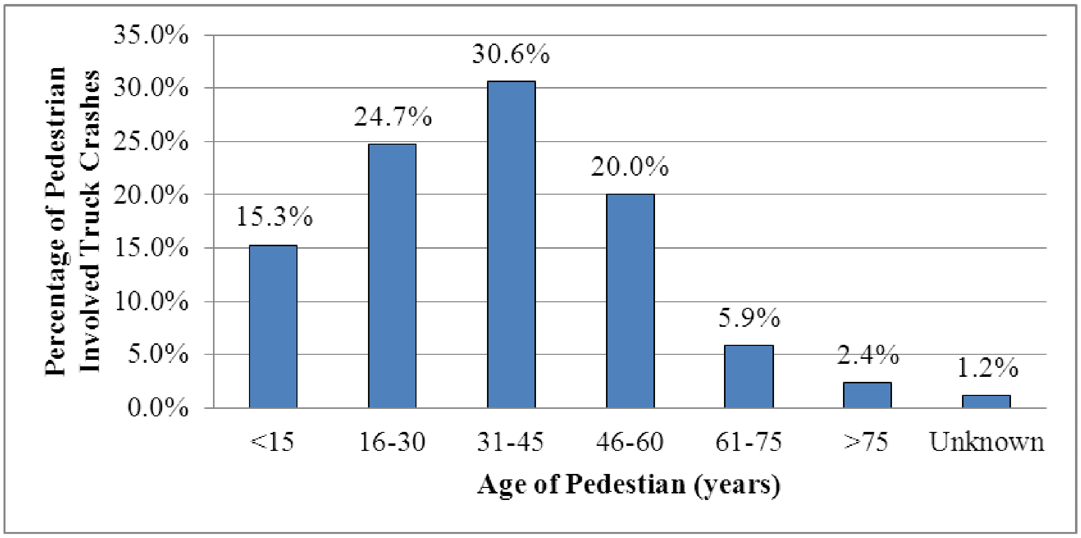

Figure 4.17 Distribution of Truck-Crashes Based on Age of Pedestrian

Also, a majority of the crashes occurred when the pedestrian was either entering or crossing the roadway. Figure 4.18 shows the distribution of pedestrian-involved large-truck crashes based on pedestrian action.

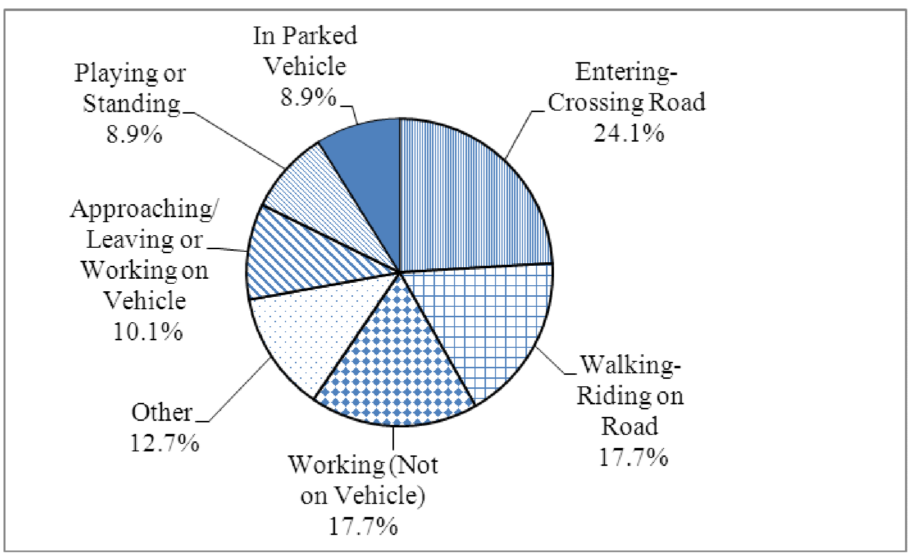

Figure 4.18 Distribution of Truck-Crashes Based on Action of Pedestrian

Another important factor which helps in understanding pedestrian-involved, large-truck-crashes is the type of pedestrian. Figure 4.19 shows the distribution of pedestrian-involved, large-truck crashes based on type of pedestrian. It is important to note that pedal-cyclists and occupants of parked vehicles were also considered as pedestrians for the purpose of reporting the data.

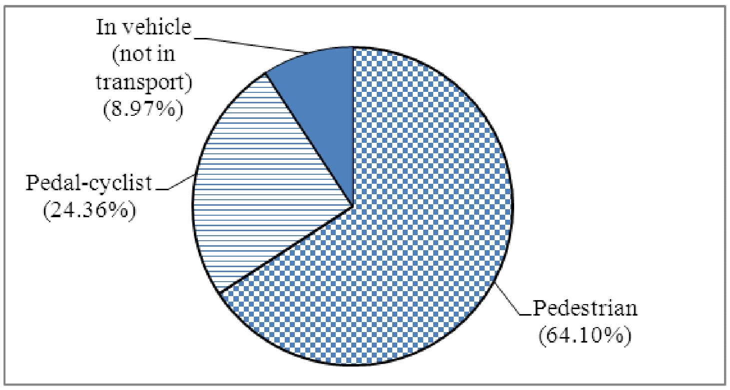

Figure 4.19 Distribution of Truck-Crashes Based on Type of Pedestrian Involved

4.2. Characteristics of Large-Truck Crashes on State Highway System

A total of 11,762 truck-crashes were recorded on the state highway system which constitutes 62.2% of all truck-crashes that occurred in Kansas, between 2004 and 2008. Following variables correspond to the truck-crashes occurred on the state highway system of Kansas which include Kansas highways, interstate highways and U.S. Routes, during the five-year time-period.

4.2.1. Accident Class

Figure 4.20 shows the distribution of large-truck crashes based on accident class. When looking at the accident class, which shows the type of collision, a majority of truck crashes involved a collision with another motor vehicle, followed by collisions with fixed objects.

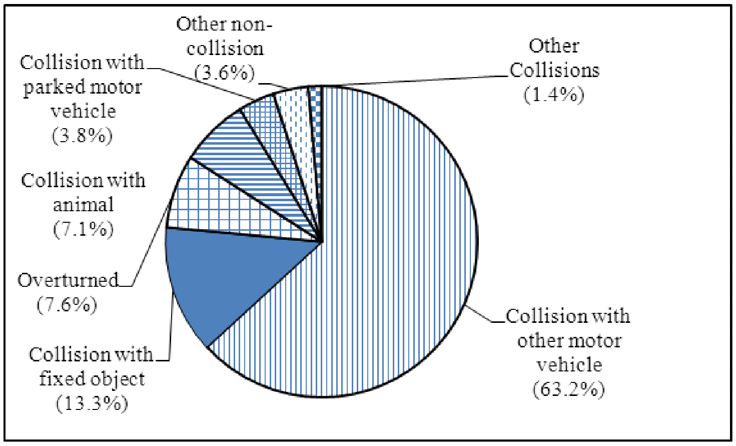

Figure 4.20 Distribution of Truck-Crashes Based on Accident Class

4.2.2. Lane Class

Analysis was performed for large-truck crashes that have occurred on the state highway system, which include Kansas highways, Interstate highways and U.S. routes, to understand their characteristics based on lane class. Figure 4.21 shows the distribution of highway truck crashes based on the lane class. The analysis showed that a majority of truck crashes occurred on two-lane, undivided roadways, closely followed by four-lane, divided roadways. Small percentages of truck crashes were recorded on two-lane, divided and eight-lane, divided highways.

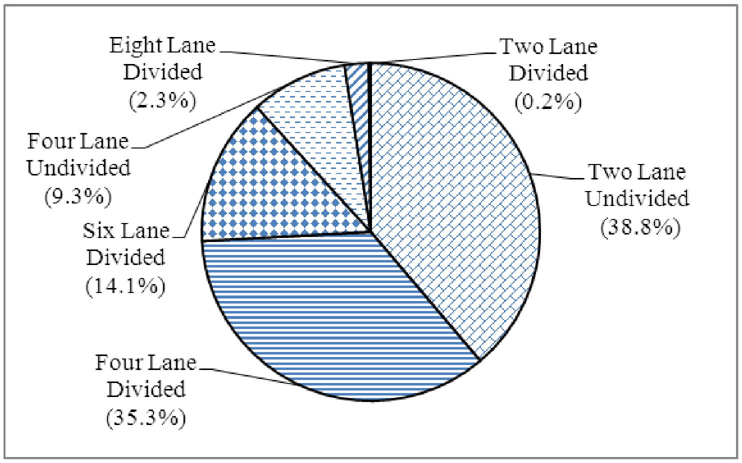

Figure 4.21 Proportion of Truck-Crashes Based on Lane Class

4.2.3. Road-Functional Class

Among truck-crashes that have occurred on the state highway system, more than a quarter have occurred on rural principle arterials. Figure 4.22 shows the distribution of the large-truck-related crashes based on road-functional class. Arterials and Interstates together comprised nearly 78% of truck-crashes.

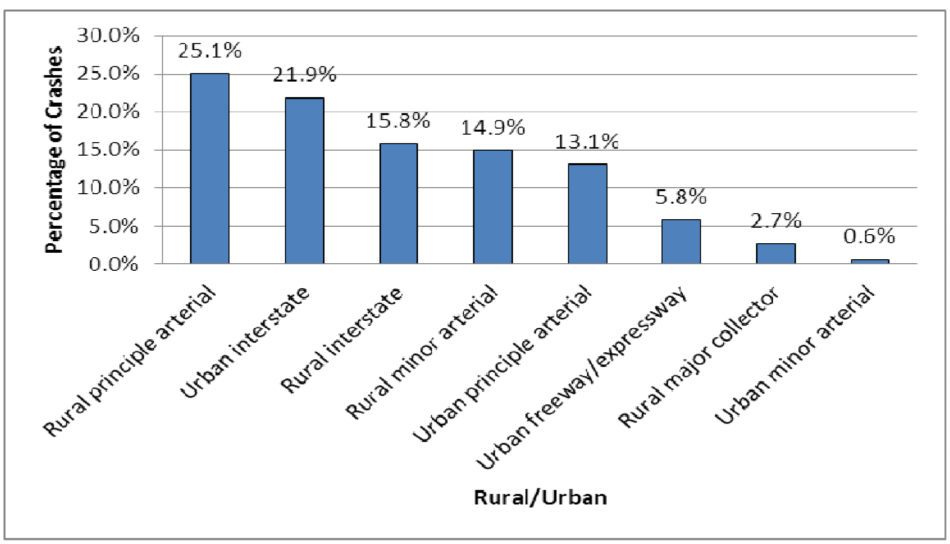

Figure 4.22 Distribution of Truck-Crashes Based on Functional Class

4.2.4. Average Annual Daily Traffic

Average Annual Daily Traffic (AADT) is defined as the average of 24-hour counts collected every day of the year (43). Figure 4.23 shows the distribution of truck-crashes, which have occurred on the state highway system, based on the AADT. Analysis of the data showed the percentage of truck-crashes generally decreased with increasing AADT, and a majority of truck-crashes were on roadways where AADT was less than 10,000 vehicles per day (vpd).

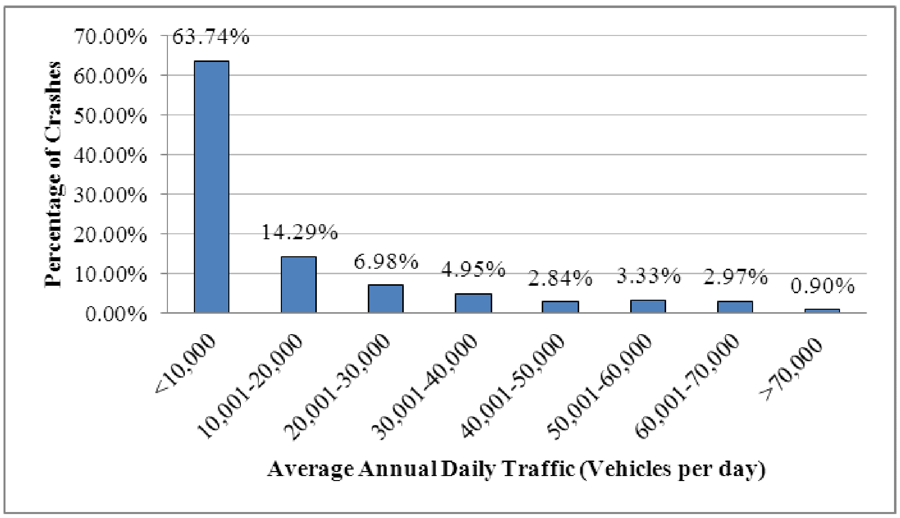

Figure 4.23 Distribution of Truck-Crashes Based on Average Annual Daily Traffic

4.3 Contributory Causes of Large-Truck Crashes

This study of the causes contributing to truck-crashes is important to improve overall safety of the highway system. Contributory causes of large-truck crashes can be broadly classified as driver-related, vehicle-related, environment-related, and road-related. Table 4.1 shows the number of crashes based on the contributory-cause category involved. Though some crashes may have more than one contributory cause involved, all crashes need not necessarily have a contributory cause identified for the crash. Analysis of KARS data showed certain crashes had occurred when influenced by two or more contributory causes.

Table 4.1. Number of Truck-Crashes Based on Type of Contributory Cause

Type of Contributory Cause	Number of Truck-Crashes	Percentage of Truck-Crashes Involving a Contributory Cause
Driver-related	13,260	73.00%
Environment-related	2,360	13.00%
Road-related	1,409	7.80%
Vehicle-related	1,112	6.10%

Based on the data presented in Table 4.1., factors related to truck drivers were the most common type of contributory causes involved. Table 4.2 shows details of truck-driver-related causes contributing to truck-crashes. Among all truck-driver-related contributory causes, a majority of the truck-crashes occurred when the truck driver failed to give time and attention. Other causes, such as the truck driver going too fast for conditions, failing to yield the right of way, changing lanes improperly, following too closely, and making improper turns also contributed significantly to truck-crashes.

Table 4.2. Number of Truck-Crashes Based on Truck-Driver-Related Contributory Causes

Truck-Driver-Related Contributory Cause	Number of Truck-Crashes	Percentage of Truck-Crashes Involving Driver-Related Causes
Failed to give time and attention	6,458	35.40%
Speeding	2,063	11.30%
Failed to yield right of way	1,644	9.00%
Improper lane change	1,196	6.60%
Followed too closely	1,178	6.50%
Made improper turn	1,016	5.60%
Disregarded traffic signs, signal	770	4.20%
Avoidance or evasive action	742	4.10%
Improper backing	726	4.00%
Improper passing	487	2.70%
Wrong side or wrong way	337	1.90%
Fell asleep	307	1.70%
Under influence of alcohol	250	1.40%
Other distraction in or on vehicle	216	1.20%
Reckless/careless driving	197	1.10%
Ill or medical condition	105	0.60%
Did not comply with license restriction	91	0.50%
Improper or no signal	77	0.40%
Impeding traffic, too slow	76	0.40%
Distraction-mobile(cell) phone	71	0.40%
Under influence of drugs	66	0.40%
Aggressive/antagonistic driving	46	0.30%
Improper parking	46	0.30%
Distraction- other electronic devices	40	0.20%
Unknown	24	0.10%
Others	18	0.10%
Total	18,247	100.00%

Truck-related factors were the next most important contributory causes related to large-truck crashes. Table 4.3 shows the number of truck-crashes in Kansas for the period of

2004 to 2008, based on truck-related contributory cause involved. Analysis of the data showed a majority of truck-crashes involving a truck-related contributory cause had occurred due to falling cargo, followed by defective tires, brakes, and wheels, respectively. These statistics were obtained as part of police reports and may not be absolutely precise, as the officers are not professional vehicle inspectors.

Table 4.3. Number of Truck-Crashes Based on Truck-Related Contributory Causes

Truck-Related Contributory Cause	Number of Truck-Crashes	Percentage of Truck-Crashes Involving Truck-Related Causes
Falling cargo	389	33.73%
Defective tires	220	19.08%
Defective brakes	175	15.18%
Defective wheel(s)	128	11.10%
Trailer-coupling related	85	7.37%
Other lights	48	4.16%
Unattended or driverless (not in motion)	41	3.56%
Unattended or driverless (in motion)	22	1.91%
Defective windows-windshield	18	1.56%
Defective exhaust system	12	1.04%
Headlights related	5	0.43%
Other	5	0.43%
Unknown	5	0.43%
Total	1,153	100.00%

After truck-driver and truck-related causes, environmental factors were the most important type of contributory cause related to the large-truck crashes. Table 4.4 shows the number of truck-crashes in Kansas for the period of 2004 to 2008 based on environment-related contributory causes involved. Animals contributed to a majority of those truck-crashes which occurred due to an environment-related contributory cause. Rain, mist or drizzle, falling snow, strong winds, etc. are other important contributory causes.

Table 4.4. Number of Truck-Crashes Based on Environment-Related Contributory Causes

Environment-Related Contributory Cause	Number of Truck-Crashes	Percentage of Truck-Crashes Involving Environment-Related Causes
Animal-related	966	37.80%
Rain, mist, or drizzle	388	15.17%
Falling snow	352	13.77%
Strong winds	336	13.14%
Sleet, hail, freezing rain	185	7.23%
Vision obstruct - glare	93	3.64%
Vision obstruct - cultural	77	3.01%
Fog, smoke, or smog	75	2.93%
Blowing sand, soil, dirt	39	1.53%
Vision obstruct - vegetation	26	1.02%
Reduced visibility due to cloud cover	17	0.67%
Unknown	2	0.08%
Total	2,556	100.00%

As the vehicle is always in contact with the road, it is very important to have good road features for safe transportation of not only trucks but all vehicles. Table 4.5 shows road-related contributory causes involved in large-truck crashes. Analysis showed that icy or slushy conditions have contributed to a majority of truck-crashes involving road-related contributory causes. Other factors like wet, snow-packed, and debris conditions also contributed to a significant number of environment-related truck-crashes.

Table 4.5. Number of Truck-Crashes Based on Road-Related Contributory Causes

Road-Related Contributory Cause	Number of Truck-Crashes	Percentage of Truck-Crashes Involving Road-Related Factor
Icy or slushy road	686	45.70%
Wet surface	281	18.70%
Snow-packed condition	239	15.90%
Debris or obstruction	113	7.50%
Road under construction/maintenance	79	5.30%
Shoulders-related	69	4.60%
Ruts, holes ,or bumps on road	20	1.30%
Inoperative traffic control device	14	0.90%
Others	1	0.10%
Total	1,502	100.00%

4.4 Cross-Classification Analysis

Cross-classification analysis was performed to check if there was a relationship between some of the selected factors and severity of truck-crashes. Twenty three variables were considered for study, and Table 4.6 shows results of the cross-classification analysis. Null hypothesis was found to have not been rejected for the variables day of week, truck-related contributory causes, pedestrian-related contributory causes, gender of truck driver, and age of truck driver, which signifies these variables do not affect the severity of truck-crashes. A sample calculation for obtaining the values of Table 4.6 has been provided in appendix A. These variables, along with some others, were further analyzed using binary logistic-regression modeling, which has been discussed in subsequent sections.

Table 4.6. Cross-Classification Analysis

Parameter	Degrees of Freedom	Chi-Square (χ^2) Value		Reject/Not Reject Null Hypothesis	Related to Crash Severity Yes/No
		Calculated Value	Tabular Value		
Accident class	8	159.2	15.5	Reject	Yes
Crash location	8	189.1	15.5	Reject	Yes
Age of the truck driver	12	9.8	21	Not Reject	No
Average annual daily traffic (AADT)	12	196.3	21	Reject	Yes
Manner of collision	12	1413.5	21	Reject	Yes
Contributory causes	12	106.6	21	Reject	Yes
Day of the week	24	29.9	36.4	Not Reject	No
Truck-driver-related contributory cause	24	598.7	36.4	Reject	Yes
Environment-related contributory cause	12	197.8	21	Reject	Yes
Functional class	12	291.9	21	Reject	Yes
Gender of truck driver	4	3.1	9.5	Not Reject	No
Lane class	8	288.6	15.5	Reject	Yes
Light conditions	8	42.4	15.5	Reject	Yes
Pedestrian-related contributory cause	6	5.7	12.6	Not Reject	No
Road Geometry	8	86.5	15.5	Reject	Yes
Road surface condition	8	23.8	15.5	Reject	Yes
Road surface type	8	29.6	15.5	Reject	Yes
Speed limit	8	653	15.5	Reject	Yes
Time of day	28	44.2	32.6	Reject	Yes
Traffic control type	20	571.7	31.4	Reject	Yes
Truck maneuver	20	568	31.4	Reject	Yes
Truck-related contributory cause	4	7.8	9.5	Not Reject	No
Weather conditions	12	22.8	21	Reject	Yes

4.5 Binary Logistic-Regression Analysis of Truck-Crashes

The binary-logistic regression technique was used to model the severity of truck-crashes in Kansas during the five-year time period from 2004 to 2008. Crash severity, which is the dependent variable in this model, is dichotomous, taking a value of 0 for a crash with no injury (Property Damage Only) and a value of 1 for an injury of any severity level.

A total of 46 variables were considered in the model development using Statistical Analysis Software (SAS) version 9.2 (40). Table 4.7 shows the description of all variables initially considered in the analysis, along with their corresponding means and variances. These variables were checked for multicollinearity using Pearson's correlation matrix to identify the significantly independent candidate variables.

Table 4.7 Description of Variables Considered in the Model

Variable	Mean	Standard Deviation	Description
ALCOHOL	0.0159	0.1249	=1 if the truck driver was under the influence of alcohol; =0 otherwise
BRAKES	0.0355	0.185	=1 if the crash occurred due to defective brakes, exhaust, headlights, windows-windshield, tires, or falling cargo; =0 otherwise
CARELESS	0.0181	0.1334	=1 if the truck driver was distracted or was too aggressive; =0 otherwise
CC_DR	0.699	0.4587	=1 if the crash occurred had a driver-related contributory cause; =0 otherwise
CC_ENV	0.1246	0.3303	=1 if the crash occurred had environment-related contributory cause; =0 otherwise
CC_RD	0.0745	0.2626	=1 if the crash occurred had road-related contributory cause; =0 otherwise
CC_VEH	0.0583	0.2343	=1 if the crash occurred had truck-related contributory cause; =0 otherwise
CLASS	0.6317	0.4824	=1 if the crash involved collision with a motor vehicle in transport; =0 otherwise

Table 4.7 Description of Variables Considered in the Model (Cont.)

Variable	Mean	Standard Deviation	Description
COLLISION	0.1793	0.3836	=1 if the crash involved a head-on collision; =0 otherwise
CONSTR_MAINT	0.0587	0.2351	=1 if crash occurred in construction, maintenance or utility zone; =0 otherwise
CONTROL	0.8108	0.3917	=1 if the crash site had a traffic control device; =0 otherwise
DAMAGE	0.8643	0.3425	=1 if the truck had damage, =0 otherwise
DAY	0.8777	0.3276	=1 if crash occurred during weekdays; =0 otherwise
DRUGS_ALCOHOL	0.0162	0.1262	=1 if the truck driver was under the influence of drugs or alcohol; =0 otherwise
EVASIVE	0.0481	0.2140	=1 if the truck driver took evasive action or was too slow; =0 otherwise
GENDR	0.7870	0.4095	=1 if the driver of the truck was a male; =0 otherwise
IMP_MAN	0.1313	0.3377	=1 if the truck driver made improper maneuver; =0 otherwise
INOPERATIVE	0.0048	0.0688	=1 if the crash occurred at construction site or had inoperative traffic control device; =0 otherwise
LIGHT	0.7596	0.4273	=1 if the light condition was daylight; =0 otherwise
LOCATION	0.2907	0.4541	=1 if the crash occurred at an intersection or intersection-related; =0 otherwise
MANEUVER	0.5456	0.4979	=1 if the truck was straight following road during crash; =0 otherwise
MIDDLE_AGED	0.6877	0.4635	=1 if the driver of the truck was between 26 and 64 years; =0 otherwise
OLD	0.022	0.1467	=1 if the driver of the truck was 65 years or more; =0 otherwise
ONAT_TC	0.8324	0.3735	=1 if the traffic-control device was on the road on which the crash had occurred; =0 otherwise
RAIN	0.0205	0.1417	=1 if the crash occurred during rain, mist, or drizzle; =0 otherwise
RUTS	0.0106	0.1025	=1 if the roadway had ruts, holes, or bumps; =0 otherwise
S_CHAR	0.6733	0.4690	=1 if surface geometry was straight and level; =0 otherwise
S_COND	0.7915	0.4062	=1 if the surface condition was dry; =0 otherwise

Table 4.7 Description of Variables Considered in the Model (Cont.)

Variable	Mean	Standard Deviation	Description
S_TYPE	0.6439	0.4789	=1 if the surface type was blacktop; =0 otherwise
SAFETY_EQUIPT	0.9456	0.2269	=1 if safety equipment was used; =0 otherwise
SMOG_SAND	0.0060	0.0774	=1 if smog, smoke, fog, dirt, or blowing sand were prevailing during the crash occurrence; =0 otherwise
SNOW	0.0418	0.2000	=1 if the crash occurred during snow, sleet, hail, freezing rain conditions; =0 otherwise
SPEED	0.1433	0.3504	=1 if the truck driver exceeded posted speed limit or was too fast for conditions; =0 otherwise
SPEED_LIMIT_1	0.3457	0.4756	=1 if speed limit was less than 40 mi/h; =0 otherwise
SPEED_LIMIT_2	0.0701	0.2550	=1 if speed limit was between 40 and 50 mi/h; =0 otherwise
SPEED_LIMIT_3	0.1718	0.3773	=1 if speed limit was between 50 and 60 mi/h; =0 otherwise
SPEED_LIMIT_4	0.3825	0.486	=1 if speed limit was between 60 and 70 mi/h; =0 otherwise
TIME_ATTN	0.4145	0.4927	=1 if the truck driver fell asleep, failed to yield right of way, or failed to give time and attention; =0 otherwise
TIME_DAY	0.8438	0.3631	=1 if crash occurred between 6 am and 8 pm; =0 otherwise
TRAPPED	0.0195	0.1383	=1 if truck driver was trapped; =0 otherwise
UNATTND	0.0033	0.0576	=1 if the crash occurred during unattended driver condition; =0 otherwise
VSN_OBSTRUCT	0.0573	0.2324	=1 if the crash occurred during a vision obstruction; =0 otherwise
WEATHER	0.1818	0.3857	=1 if the weather conditions were adverse; =0 otherwise
WET	0.0605	0.2385	=1 if the crash occurred in wet or icy conditions; =0 otherwise
WRONG	0.1327	0.3393	=1 if the truck driver made improper turn, was on wrong side or wrong way, or followed too closely; =0 otherwise
YOUNG	0.2320	0.4221	=1 if driver of the truck was between 16 and 25 years; =0 otherwise

Pearson’s correlation matrix was developed using SAS version 9.2 (40). The correlation matrix has been presented in the Appendix B. A total of 12 correlated pairs were found among the independent variables considered for a significance level of 0.5 for the p-values as the selection criterion (38), and one variable from each pair was discarded in the decreasing order of the magnitude of Pearson’s correlation coefficients based on which of the two gives the weaker model. Hence, variables related to wet or icy road conditions, obstruction to truck driver’s vision, truck driver under the influence of drugs/alcohol, younger truck drivers aged less than 25 years, defective brakes, exhaust system, headlights windows/ windshield, tires, or falling cargo, weather conditions, time of day, crash location, environment-related contributory causes, speed limit between 60 and 70 mi/hr and truck driver falling asleep, failing to give right of way or failing to give time and attention were all discarded by this method. Table 4.8 shows the variables retained after checking multicollinearity.

Table 4.8 Variables Retained Among Correlated Pairs

Correlated Variable-Pair	Pearson's Correlation Coefficient	Variable Retained
CC_RD, WET	0.895	CC_RD
DAMAGE, VSN_OBSTRUCT	0.831	DAMAGE
ALCOHOL, DRUGS_ALCOHOL	0.822	ALCOHOL
YOUNG, MIDDLE_AGED	-0.816	MIDDLE_AGED
CC_VEH, BRAKES	0.771	CC_VEH
WEATHER, S_COND	-0.750	S_COND
TIME_DAY, LIGHT	0.729	LIGHT
ONAT_TC, LOCATION	-0.689	ONAT_TC
CC_ENV, VSN_OBSTRUCT	0.653	none
SPEED_LIMIT_1, SPEED_LIMIT_4	-0.572	SPEED_LIMIT_1
CC_ENV, SNOW	0.553	SNOW
CC_DR, TIME_ATTN	0.552	CC_DR

After eliminating the correlated variables, the model development was left with a set of 35 variables. Three variable selection methods, which include Forward Selection method, Backward Elimination method and Stepwise Selection method, were performed to select the variables which were significant enough to stay in the model. A p-value of 0.05 was chosen as the significance criteria, and any variable having a p-value greater than 0.05 was considered to be insignificant to be included in the model (27). Table 4.9 shows the comparison of the model-fit statistics obtained from the three variable selection methods.

Table 4.9. Comparison of Model-Fit Statistics from the Three Variable Selection Methods

Criterion	Forward Selection Method		Stepwise Selection Method		Backward Elimination Method	
	Intercept Only	Intercept and Covariates	Intercept Only	Intercept and Covariates	Intercept Only	Intercept and Covariates
AIC	20820.1	17391.8	20820.1	17390.9	20820.1	17390.3
SC	20828	17613.7	20828.0	17610.6	20828.0	17605.7
-2logL	20818.1	17337.8	20818.1	17334.9	20818.1	17330.3
R^2	0.1680		0.1682		0.1684	

Based on these statistics, the model obtained by the Backward Elimination method was found to be the slightly better model because of relatively lower AIC, SC and -2logL values, and higher R^2 value. Table 4.10 shows some other goodness-of-fit parameters obtained by using the LOGISTIC procedure in SAS version 9.2 (40) for the three variable selection methods. From Table 4.10, relatively lower percentage discordant value and the values of Somer's D and Gamma being closer to 1 further reinforces the statement that the Backward Elimination method produced the better model among the three variable selection methods.

Table 4.10. Associations of Predicted Probabilities and Observed Responses

Statistic	Forward Selection Method	Stepwise Selection Method	Backward Elimination Method
Percent Concordant	76	76	76
Percent Discordant	23.7	23.7	23.6
Percent Tied	0.4	0.4	0.4
Pairs	65,142,718	65,142,718	65,142,718
Somers' D	0.523	0.523	0.524
Gamma	0.525	0.525	0.526
Tau-a	0.19	0.191	0.191
c	0.762	0.762	0.762

Following is the description of the variables in Table 4.9 for the Backward Elimination method (7):

- Percent concordant **–** A pair of observations with different observed responses is concordant if the observation with the lower ordered response value has a lower predicted mean score than the observation with the higher ordered response value. 76% of the pairs were found to be concordant.
- Percent discordant**:** If the observation with the lower ordered response value has a higher predicted mean score than the observation with the higher ordered response value, then the pair is discordant. 23.6% of the observations were found to be discordant.
- Percent tied: 0.4% of observations were found to be neither concordant nor discordant.
- Pairs: The concordant pairs, discordant pairs and tied pairs altogether added up to a total of 65,142,718 distinct pairs.

- Somer’s D – The value of Somer’s D was found to be 0.524, which is closer to 1, which indicates that more pairs agree than those which disagree. Somer’s D is used to determine the strength and direction of relation between pairs of variables. Its values range from -1.0 (all pairs disagree) to 1.0 (all pairs agree).
- Gamma - The Goodman-Kruskal Gamma has a value of 0.526 which indicates good association among the variables in the model. Its values range from -1.0 (no association) to 1.0 (perfect association).
- Tau-a - This value was found to be 0.191 for the model obtained. Kendall's Tau-a takes into the account the difference between the number of possible paired observations and the number of paired observations with different responses.
- c - This value was found to be 0.762 for the model obtained. It ranges from 0 (no association) to 1 (perfect association).

A total of 26 variables were found to be significant to stay in the model. Table 4.11 shows the parameter estimates and odds ratio as obtained using the Backward Elimination method. The models obtained by the other two methods have been presented in Appendix C. These parameter estimates and odds-ratio values are used to understand the relationship of the variable under consideration with the severity of the crash.

Table 4.11 Parameter Estimates and Odds Ratios of Large-Truck Crash Severity Model

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Sq	Odds Ratio	95% Wald Confidence Limits For Odds Ratio
Intercept*	-1.522	0.163	87.15	<0.0001	NA**	NA**
ALCOHOL*	0.979	0.135	52.5	<0.0001	2.66	2.04,3.47
CARELESS*	0.334	0.126	7.08	0.0078	1.40	1.09, 1.79
CC_DR*	0.6	0.054	126.08	<0.0001	1.82	1.64, 2.02
CC_RD*	-0.332	0.084	15.49	<0.0001	0.72	0.61, 0.85
CC_VEH	-0.09	0.093	0.94	0.3329	0.91	0.76, 1.10
CLASS	0.102	0.052	3.81	0.0509	1.11	1.00, 1.23
COLLISION*	0.471	0.052	82.71	<0.0001	1.60	1.45, 1.77
CONSTR_MAINT*	-0.267	0.083	10.33	0.0013	0.77	0.65, 0.90
CONTROL*	0.308	0.057	29.58	<0.0001	1.36	1.22, 1.52
DAMAGE*	1.116	0.083	181	<0.0001	3.05	2.60, 3.59
DAY	-0.003	0.058	0.00	0.9661	1.00	0.89, 1.12
EVASIVE*	0.427	0.079	29.37	<0.0001	1.53	1.31, 1.79
GENDR*	-0.129	0.049	7.06	0.0079	0.88	0.80, 0.97
IMP_MAN*	-0.453	0.068	44.48	<0.0001	0.64	0.56, 0.73
INOPERATIVE	-0.247	0.328	0.57	0.4508	0.78	0.41, 1.48
LIGHT	0.06	0.049	1.50	0.2209	1.06	0.96,1.17
MANEUVER*	0.321	0.041	61.54	<0.0001	1.38	1.27, 1.49
MIDDLE_AGED*	0.102	0.043	5.74	0.0166	1.11	1.02, 1.20
OLD	0.092	0.14	0.43	0.5141	1.10	0.83, 1.44
ONAT_TC*	-0.521	0.054	93.75	<0.0001	0.60	0.53, 0.66
RAIN*	0.33	0.132	6.25	0.0124	1.39	1.07, 1.80
RUTS	-0.148	0.224	0.44	0.5091	0.86	0.56, 1.34
S_CHAR*	-0.114	0.041	7.86	0.0051	0.89	0.82, 0.97
S_COND*	0.256	0.056	20.68	<0.0001	1.29	1.16, 1.44
S_TYPE*	0.132	0.04	10.62	0.0011	1.14	1.05, 1.24
SAFETY_EQUIPT*	-1.378	0.075	337.60	<0.0001	0.25	0.22, 0.29
SMOG_SAND	0.355	0.218	2.65	0.1037	1.43	0.93, 2.19
SNOW	0.151	0.099	2.34	0.1261	1.16	0.96, 1.41
SPEED*	0.442	0.054	66.12	<0.0001	1.56	1.40, 1.73
SPEED_LIMIT_1*	-0.801	0.051	248.48	<0.0001	0.45	0.41, 0.50
SPEED_LIMIT_2*	-0.39	0.077	25.92	<0.0001	0.68	0.58, 0.79
SPEED_LIMIT_3*	0.116	0.052	5.01	0.0252	1.12	1.01, 1.24
TRAPPED*	4.417	0.344	165.04	<0.0001	82.81	42.21, 162.44
UNATTND	0.483	0.329	2.16	0.142	1.62	0.85, 3.09
WRONG	0.014	0.058	0.06	0.8034	1.01	0.91, 1.14

*- Significant at 0.05 level
NA**- Not Applicable

The following sections explain the variables that are significant in the model at a p-value of 0.05, with regard to parameter estimates and odds ratios:

4.5.1 Roadway Characteristics

The variable S_TYPE has a positive coefficient for the estimate, indicating that blacktop-surface type has 1.14 times higher odds of causing more severe truck-crashes as compared to concrete and other surface types. Similarly, the variable S_COND has a positive coefficient estimate, and the dry-surface condition has 1.29 times higher odds of causing a more severe crash as compared to wet and other surface conditions. However, a negative coefficient for the variable S_CHAR indicates the straight- and leveled-surface geometry has 0.89 times lesser odds of causing a more severe crash as compared to other surface geometries.

The variable CC_RD has a negative coefficient of the estimate, which indicates the road-related contributory cause has 0.72 times lesser odds of causing a more severe truck crash as compared to other factors.

4.5.2 Crash Characteristics

As variables SPEED_LIMIT_1 and SPEED_LIMIT_2 have negative coefficients for the parameter estimates, vehicles speeds lower than 50 mph have lesser odds of contributing to more severe truck-crashes. On the other hand, the variable SPEED_LIMIT_3 has a positive coefficient and speed limits ranging from 60 to 70 mph have 1.12 times higher odds of ending up as a more severe crash. This shows the severity of the crash increases with an increase in the speeds of the vehicle. Further, a positive coefficient estimate for the variable COLLISION shows that head-on collisions have 1.60 times higher odds of causing a more severe crash as compared to the other collision types such as angled and sideswipe collisions.

A negative coefficient estimate for the ONAT_TC indicates that large trucks have 0.59 times lesser odds of being involved in a more severe crash when a traffic-control device is on the road along which the truck is travelling as compared to being on the road perpendicular to it. In addition, a positive coefficient estimate for the variable CONTROL shows that large trucks have 1.36 times higher odds of being involved in a more severe crash when there is a traffic-control device at the location of the crash as compared to locations where there is no traffic-control device.

A positive coefficient estimate for the MANEUVER variable shows that large trucks have 1.38 times higher odds of being involved in a more severe crash when the driver of the truck is going straight following the road as compared to when he/she makes a maneuver such as left turn, right turn, U-turn, etc. Also, the variable DAMAGE has a positive coefficient estimate which indicates any damage to the vehicle involved in the crash has 3.05 times higher odds of increasing the severity of the crash as compared to the case when minimal damage occurs to the involved truck.

A positive coefficient for the variable RAIN shows that large trucks have 1.39 times higher odds of being involved in a more severe truck crash under rain, mist, or drizzle conditions as compared to other conditions.

4.5.3 Driver Characteristics

A positive coefficient of the variable ALCOHOL shows that large trucks have 2.66 times higher odds of being involved in more severe crashes when the driver was under the influence of alcohol. Further, a positive coefficient estimate for the MIDDLE_AGED variable shows that large trucks have 1.11 times higher odds of being involved in a more severe crash when the driver is middle aged as compared to old and young drivers. Also, the negative coefficient of the GENDR variable shows that large trucks with male drivers have 0.88 times lesser odds of being involved in a more severe crash than those with female drivers. The TRAPPED variable, which has the highest magnitude of odds ratio among all the variables, has a positive coefficient estimate indicating that large-truck-involved crashes have 82.81 times higher odds of being more severe when the driver is trapped as compared to other conditions like being ejected, not ejected, etc. Similarly, a negative coefficient estimate for the SAFETY_EQUIPT variable shows that large trucks have 0.25 times lesser odds of being involved in a more severe crash when the driver puts safety equipment on as compared to when he/she did not put on safety equipment. This supports the fact that use of a safety belt reduces the severity of a truck crash.

The variable CC_DR has a positive coefficient, which indicates that large trucks have 1.82 times higher odds of having a more severe crash when there is a driver-related cause contributing to the occurrence of the crash, as compared to other conditions. A positive coefficient estimate for the variable SPEED shows that large trucks have 1.56 times higher odds of having a more severe crash when the driver is speeding, as compared to other conditions. This proves that speeding increases the severity of the truck crash. A positive coefficient estimate for the variable EVASIVE shows that large trucks have 1.53 times higher odds of ending up as a more severe crash when the driver takes an evasive action or is too slow for the existing conditions. Similarly, a positive coefficient estimate for CARELESS shows that large trucks have 1.40 times higher odds of being involved in a more severe crash when the driver is aggressive, reckless, or antagonistic while driving. However, the variable IMP_MAN has a negative coefficient which indicates that large trucks have 0.64 times lower odds of being involved in a more severe crash when the driver takes an improper action such as improper backing, improper passing, improper turning, improper or no signal, etc. as compared to other conditions.

The binary logistic-regression method provided a good measure to identify factors contributing to increased severities of the crashes involving large trucks. The model developed shows that 10 out of 26 candidate variables, which include those related to use of safety equipment, obstruction to vision, speed limit between 0 and 40 mi/hr, location of the traffic-control device, making improper maneuver, speed limit between 40 and 50 mi/hr, road-related contributory cause, construction, maintenance or utility zone, gender of the truck driver, and surface geometry have a negative coefficient for the parameter estimates in the decreasing order of the magnitude, and the rest of the variables have positive coefficients.

CHAPTER 5 IDENTIFICATION OF COUNTERMEASURES

In order to mitigate the number and severity of truck-crashes in Kansas, suitable countermeasures need to be identified and properly implemented. Education, engineering and enforcement are the three major approaches to safety program that are to be kept in mind while identifying and implementing the countermeasures. Identification of countermeasures must be done carefully, as the same countermeasure may not mitigate similar issues in two identical situations due to different external factors. In addition to the requirement and reliability of countermeasure, various monetary issues must also be considered while identifying the countermeasures. There needs to be a proper balance between all these aspects in order to come up with the most feasible and effective countermeasure. However, there should be an allowable margin of error as there is every chance that the selected countermeasure does not serve the intended purpose perfectly and such cases must be properly accounted for. Keeping all these issues in mind, it is important to properly inspect the countermeasures after implementing, at least in few test locations, in order to evaluate its effectiveness and support future studies in this regard. Besides implementing the standard practices, researchers are working on new technologies with the help of intelligent transportation system which might help in identifying new ways to mitigate truck-crashes.

Following is a summary of the countermeasures recommended for issues found in this study.

Curved and graded characters of road surface are found to be associated with less safety in terms of large-trucks. Rollovers might be one of the important types of crashes at such locations. Regular practices include ensuring adequate warning signs at harmful locations, improving sight distance at horizontal curves by providing an adequate clear zone, and frequently inspecting the pavement markings. Federal Highway Administration (FHWA), along with a private consultant Bellomo-McGee and a system integrator International Road Dynamics, developed what is called an Automated Truck Rollover Warning System (44). This system consists of numerous sensors which evaluate the speed, type, weight and rate of deceleration of the trucks, along with the curve characteristics, to identify the potential danger at curves and triggers a warning message under dangerous conditions. Bergan et al. implemented this system in 1993, as part of their study, in three test locations in Washington DC and found that the system was effective in reducing speeds and crashes in a cost effective manner (44). Implementation of this system in large-trucks, therefore, might be beneficial in improving the truck safety. Another important type of truck-crashes at horizontal curves is the Run-off-Road (ROR) collisions. Intense research is being conducted to develop two kinds of road departure warning systems, which include Lane Drift Warning Systems (LDWS) and Curve Speed Warning Systems (CSWS), to mitigate such crashes (45). LDWS is intended to mitigate the crashes due to unintentional drift of the truck out of its lane and CSWS is intended to mitigate crashes when the driver is too fast for existing conditions. Other similar technologies under study include Direct Driver Impairment Detection, Forward Obstacle Detection and Vehicle Component Failure Warning systems, development and implementation of which will effectively reduce the number and severity of truck-crashes (45).

Higher speeds were found to increase the severity of truck-crashes. Also, it was noticed that severity of the truck-crashes increases when the driver is too fast for the existing conditions.

Hence, it is important to take measures to mitigate such incidents as these factors are clearly controllable. Such conditions can be accounted by ensuring regular practices like educating the road users about the dangers involved in exceeding the speed limits, strengthening law against speeding, and ensuring adequate warning signs. An intelligent way of approaching this issue, when it comes to trucks, is through the installation of the Speed Limiters. Speed Limiters (SLs) electronically restrict the truck from exceeding a pre-programmed maximum speed, through an interaction with its engine (46). This not only minimizes the number and severity of truck-crashes that occur due to speeding, but also prolongs the life of brakes, tires and engine of the truck. Speed Limiters were made mandatory for certain heavy vehicles in other countries like Australia, Sweden, Germany and United Kingdom, as a measure to mitigate truck-crashes. According to a study performed by the European Commission, Speed Limiters are also effective in reducing the fuel consumption, maintenance costs, insurance premiums and emission of Green House Gases (GHG) (47). Hence, they make up an important component among the measures to be undertaken to improve truck safety. Other technologies include intelligent speed hump, which behaves differently based on the weights of the vehicles (48). Heavy vehicles like trucks and emergency vehicles can pass over it without any discomfort whereas lighter vehicles pass over it as a usual hump, thus, resulting in reduction of congestion which has an indirect effect on the safety of the system. Also, these speed humps results in speed reduction without any side effects like discomfort for emergency vehicles. More research is this area might help emerge with a new technology that is effective and cheaper with easy installation.

Head-on collisions were found to have increased the severity of truck-crashes indicating that there is a need to identify the causes and mitigate such crashes. Provision of rumble strips and raised medians along both the centerline and edges of the roadway is commonly practiced technique employed for alerting the driver when he/she goes out of the lane unintentionally, particularly when the driver gets drowsy. Intelligent connected-vehicle technologies like Vehicle-to-Infrastructure (VI) integration and Vehicle-to-Vehicle (V2V) integration are being developed which include communication between trucks and road side equipment (or other vehicles) in order to mitigate such crashes (49). This technology also helps to reduce crashes at the intersections where vehicles with different maneuvers go together. In addition, adequate traffic control devices at these locations must be ensured and more number of exclusive left turns might be encouraged (37).

Truck-driver under the influence of alcohol was found to be a primary factor responsible for increased severity of truck-crashes. Increased level of enforcement, especially during night times and weekends, proper training and education for truck-drivers about the harmful effects of driving under the influence of alcohol, and lowering the allowable Blood-Alcohol Concentration (BAC) are some of the traditional techniques that are implemented for mitigating such crashes. In addition, attempts are being made to develop an intelligent way of detecting the Blood-Alcohol Concentration as a combined effort by Driver Alcohol Detection and System for Safety (DADSS), Automotive Coalition from Traffic Safety (ACTS) and National Highway Traffic Safety Authority (NHTSA) (50). Electrochemical sensor devices like breathalyzer and transdermal sensors are already in to practice. New technologies like Tissue Spectrometry and Distant Spectrometry are being worked upon for development and implementation. Tissue Spectrometry is based on skin contact where skin sensors pass light through the skin to determine the BAC. On the other hand, Distant Spectrometry does not require any skin-touch and when placed in the vicinity of the driver, these sensors measure the level of BAC (50). Successful implementation of these technologies might be helpful in mitigating the truck-crashes.

Safety-equipment use is one of the most important components to be considered as part of identification of countermeasures. Use of safety-equipment significantly brings down the severity of truck-crashes. Hence, road users must be educated and encouraged to use safety belts while travelling and the benefits must be taught. Technologies like seat-belt reminders are already in practice to alert the driver to wear a seat-belt before the vehicle is started (51). Research must be done to improve this technology of alerting the truck-drivers to put the safety equipment in a user friendly manner to improve the safety associated with truck-crashes. One possible way might be to set up a central unit that can monitor the use of seat belts among a set of vehicles, such as trucks.

It was also seen in this study that driver-related contributory causes are the most important contributory causes, among other types. This indicates that there is a need to identify countermeasures to mitigate this issue. Rau introduced and studied a new technology called Drowsy Driver Detection and Warning System as part of developing countermeasure to mitigate crashes involving commercial vehicles (30). He considered drowsiness of the driver as the most important contributory cause among driver-related truck-crashes. NHTSA is supporting a research being conducted to develop the Vehicle-Based Drowsy Driver Detection System, which continuously monitors the performance and behavior of the driver and any indication of drowsiness will be detected and warned by a signal (52). Additionally, Federal Motor Carrier Safety Administration (FMCSA) has introduced new regulations to keep the fatigued drivers away from the public roadways. A 14-hour duty limit per day for truck-drivers has been imposed by the FMCSA, which include an 11-hour driving limit per day, followed by a rest of at least 10 consecutive hours before getting back to the duty. Further, a 60-70 hour duty limit per week has also been imposed which is followed by 34 consecutive hours of off duty (53). An Automatic On-Board Recording Device (AOBRD) has been developed to replace the traditional log book, to record the information related to the hours-of-service accurately. Development of this device and its implementation seems to mitigate the truck-crashes which include a driver-related contributory cause. Other traditional practices like strengthening the existing laws related to the issual of driving license and regular examination of driver's vision must be encouraged. This is because vision of the driver may depreciate with time and that might lead to the occurrence of more severe truck-crashes. Automatic License Plate Recognition (ALPR) is another technology utilized in Roadside Camera Recognition system that can be employed to identify the license-plates of the vehicles and take action against the drivers at fault (49). Proper implementation of these technologies helps mitigate truck-crashes by manifolds.

Factors like benefit-cost analysis, periodic inspection of guardrails, camber, and superelevation to check if they meet the required standards and other long term countermeasures can also be considered while identifying, developing and implementing the countermeasures. Besides, for crashes that occur in spite of implementation of the best possible countermeasures, proper emergency service must be provided so that the ambulance turns in within a short period of time. Focus must be made on developing the technologies which can enhance the emergency services and improve the communication facilities in rural areas (37).

Intelligent Transportation Systems seems to be doing a good job in coming up with new user-friendly technologies to provide prior warnings of danger. More research to expand, improve and implement these new technologies can improve the overall safety of the transportation system.

CHAPTER 6 CONCLUSIONS AND SUMMARY

6.1. Conclusions

This study identified characteristics of truck-crashes, factors contributing to their occurrences, and factors associated with increased severity of truck-crashes in relation to vehicle, driver, environment, road, and other related factors. Crash data, obtained from Kansas Department of Transportation's Kansas Accident Reporting System (KARS) database for the five-year time period from 2004 to 2008 were utilized for this study. This database is a compilation of police-reported crash-data in the state of Kansas.

A majority of truck-crashes were found to have occurred during daylight conditions and under no-adverse weather conditions. Of all truck-crashes, 35.2% were single-vehicle truck-crashes and majority of the multi-vehicle truck-crashes were characterized by angular collisions. Most of the non-truck-vehicles involved in two-vehicle truck-crashes were automobiles. More than three-quarters of all truck-crashes in the study period have occurred on weekdays. Of all truck-crashes, 54.6% occurred when the truck was moving straight following the road, which was the most common among all truck-maneuvers. Majority of truck-crashes occurred when the truck was driven by a male truck-driver aging between 20 and 60 years. Also, most of the pedestrians involved in truck-crashes were males aging between 16 and 60 years. Non-intersection locations were dominant in characterizing truck-crashes based on type of crash-location. The majority of truck-crashes occurred between 12:00 p.m. and 3:00 p.m. Blacktop-surface type, dry-surface conditions and straight- and level-surface geometries were dominant in their respective truck-crashes categories. Further, more truck-crashes were recorded in high-speed-limit locations. Among all the truck-crashes on the state highway system, 63.2% involved collision with another motor-vehicle and majority of them were recorded on arterials and interstates under low AADT conditions.

Cross-classification analysis was performed over a subset of variables to identify the relationship of truck-crash severity with various selected independent variables. Among the factors considered, variables such as type, character, and condition of the road-surface; accident class; type of collision; driver- and environment-related contributory causes; traffic-control type; vehicle maneuver; crash location; speed limit; light and weather conditions; time of day; road functional class; lane class; and Average Annual Daily Traffic (AADT) were found to be related with the severity of the truck-crashes.

Analysis of the factors contributing to the occurrences of truck-crashes showed that driver-related factors were the most dominant type of contributory causes, among others. The most important factor involved in a majority of truck-crashes, when a driver-related contributory cause was recorded, was truck-drivers failing to give time and attention. Moreover, other driver-related factors such as speeding, drivers failing to yield right of way and improper lane change also contributed to the occurrence of truck-crashes. Falling cargo comprised of 33.73% of the truck-related causes and animal-related factors comprised of 37.80% of the environment-related causes which contributed to the occurrence of truck-crashes. Among all the truck-crashes involving a road-related cause, icy and slushy road condition was the most dominant factor, which contributed to the occurrence of 45.70% of truck-crashes.

Severity modeling was performed using binary logistic-regression model in order to identify and evaluate the factors contributing to increased severity of the truck-crashes. Severity of truck-crashes was considered as a dichotomous dependent variable in order to develop the model.

Truck-driver being trapped, which had the highest odds ratio compared to any other independent variable in the model, had 82.81 times higher odds of increasing the severity of truck-crashes. Damage to the truck, with an odds ratio of 3.05, was another important factor associated with increased severity of truck-crashes. Further, truck-crashes had 2.66 times higher odds of being more severe when the truck-driver was under the influence of alcohol. Truck-driver-related causes had 1.82 times higher odds of increasing the severity of truck-crashes. Over speeding, aggressiveness and evasive driving by the truck-driver were among the truck-driver-related factors which were likely to increase the severity of truck-crashes. Head-on collisions had 1.60 times higher odds of contributing to more severe truck-crashes and traffic control devices had 1.36 times higher odds of increasing the severity of truck-crashes. Dry-surface conditions with an odds ratio of 1.29 and blacktop-surface type with an odds ratio of 1.14 were likely to cause more severe truck-crashes. Also, speed limits of 50-60 mph had 1.12 times higher odds, and middle-aged drivers had 1.11 times higher odds of contributing to higher severity of truck-crashes.

On the other hand, certain variables were found to have lower odds of increasing the severity of truck-crashes. Straight- and level-surface geometries had 0.89 times lower odds of contributing to increased severity of truck-crashes. Further, construction/maintenance zones had 0.77 times lower odds, and road-related contributory cause had 0.72 times lower odds of contributing to more severe truck-crashes. Male truck-drivers and improper truck-maneuver, with odds ratios of 0.88 and 0.64 respectively, were found to have lower odds of contributing to more severe truck-crashes.

Finally, the goodness-of-fit statistics and overall percentage concordant value of 76% have shown the extent to which the model fits the given data, thus proving that obtained model is a decent one.

These findings help researchers understand various characteristics and causes contributing to the occurrences and increased severity of truck-crashes. Various conditions have been elaborated on and by addressing these issues; suitable countermeasures were identified and recommended. Automated Truck Rollover Warning System was identified to be beneficial to prevent rollover crashes. Technologies like Lane Drift Warning Systems (LDWS) and Curve Speed Warning Systems (CSWS) could be implemented to mitigate ROR collisions. Speed of the truck-could be controlled using appropriate Speed Limiters and Vehicle-to-Infrastructure (VI) integration and Vehicle-to-Vehicle (V2V) integration could be worked up on to develop communication between trucks and road side equipment (or other vehicles). Besides technologies like breathalyzer and transdermal sensors which are already in to practice, new technologies like Tissue Spectrometry and Distant Spectrometry may be developed to simplify the process of detecting BAC. Setting up of the Automatic On-Board Recording Device (AOBRD) will be helpful to record the information related to driving hours-of-service and proper implementation of Automatic License Plate Recognition (ALPR) technology utilized in Roadside Camera Recognition system can be useful in identifying the license-plates of the vehicles and take action against the drivers-at-fault. Development of more intelligent transportation countermeasures like these and their implementation in a cost-effective manner will be helpful in mitigating the number and severity of truck-crashes, thereby, improving the overall safety of the highway system.

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APPENDICES

Appendix A- Cross-Classification Analysis

Table A.1 shows number of truck-crashes in Kansas based on the speed limit. This variable is used for cross-classification analysis, and a sample calculation is presented following Table A.1.

Table A.1. Number of Truck-crashes in Kansas Based on Speed Limit

Speed Limit (mi/h)	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Number of Crashes
		Disabled	Non Incapacitating	Possible		
50+	287	537	1,395	949	7,507	10,675
30-49	32	77	512	522	5,440	6,583
0-29	2	7	36	43	1,011	1,099
Unknown	6	16	63	42	435	562
Total	327	637	2,006	1,556	14,393	18,919

Sample Calculation

Null hypothesis (H_0): Speed limit and crash severity are independent of each other.

Alternate hypothesis (H_A): Null hypothesis is not true.

Values shown in Table A.1 are observed frequencies (O).

Expected frequencies (E) are given as:

$$E_{ij} = \frac{(\text{Row Total})*(\text{Column Total})}{\text{Sample Size}}$$

i.e., the expected frequency of fatal crashes at the speed limit of 30-49 mi/h is given as:

$$E_{21} = \frac{(6{,}583)*(327)}{18{,}919}$$

$$= 113.8$$

Similarly, the expect frequencies of all the cells are calculated. Table A.2 shows the expected frequencies of truck-crashes.

Table A.2 Expected Frequencies of Truck-crashes in Kansas Based on Speed Limit

Speed Limit	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Number of Crashes
		Disabled	Non Incapacitating	Possible		
50+	184.509	359.426	1,132	877.969	8,121	10,675
30-49	113.782	221.649	698.002	541.421	5,008	6,583
0-29	18.9953	37.0032	116.528	90.3877	836	1,099
Unknown	9.71373	18.9225	59.5894	46.2219	427.553	562
Total	327	637	2006	1556	14393	18,919

Now, the statistic chi-square (χ^2) is calculated using the formula:

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

Using the formula, the calculated chi-square value obtained is 653.03.

- Degrees of freedom= (3-1)* (5-1)

  = 8

- Chi-square value from the chi-square distribution table for 8 degrees of freedom and 95% confidence is 15.51.

Since the calculated chi-square value (653.03) > chi-square value from the table (15.51), the null hypothesis is rejected. Hence, there exists a relationship between speed limit and crash severity.

Following are some of the other tables used for analyzing the relationship of the corresponding variables with crash severity, using cross-classification analysis. In all the following tables, the unknown and others categories have been ignored as they constitute a negligible percentage of the total truck crashes.

Table A.3 Number of Truck-Crashes in Kansas Based on Crash Location

Crash Location	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Crashes
		Disabled	Non Incapacitating	Possible		
Non-Intersection-On Roadway	185	296	921	688	7,258	9,348
Intersection-On Roadway	97	159	426	308	2,154	3,144
Intersection-Related-On Roadway	15	48	179	199	1,914	2,355
Interchange Area-On Roadway	17	49	165	122	1,162	1,515
Roadside-Including Shoulder-Off Roadway	12	56	209	134	898	1,309
Pklot-Drvway Access-On Roadway	0	20	83	90	861	1,054
Median-Off Roadway	1	9	21	14	117	162
Total	327	637	2,006	1,556	14,393	18,919

Table A.4 Number of Truck-Crashes in Kansas Based on Light Conditions

Light Condition	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Number of Crashes
		Disabled	Non Incapacitating	Possible		
Daylight	229	482	1,513	1,265	10,882	14,371
Dark-No Street Lights	61	91	268	144	1798	2,362
Dark-Street Lights On	23	34	150	89	1138	1,434
Dawn	10	20	40	33	331	434
Dusk	4	9	34	23	223	293
Total	327	637	2,006	1,556	14,393	18,919

Table A.5 Number of Truck-Crashes in Kansas Based on Weather Conditions

Weather Condition	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Number of Crashes
		Disabled	Non Incapacitating	Possible		
No Adverse Conditions	272	526	1,636	1,231	11,814	15,479
Rain, Mist or Drizzle	17	34	135	136	991	1,313
Snow	4	29	79	73	647	832
Strong Winds	9	12	57	25	222	325
Snow and Winds	6	7	21	22	207	263
Freezing Rain	7	7	21	21	129	185
Fog	6	9	19	13	109	156
Sleet	1	3	5	16	109	134
Rain and Winds	1	5	17	8	92	123
Blowing Dust/Sand	3	4	8	2	19	36
Total	327	637	2,006	1,556	14,393	18,919

Table A.6 Number of Truck-Crashes in Kansas Based on Time of Day

Time of the Day	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Number of Crashes
		Disabled	Non Incapacitating	Possible		
0000 hrs-3:00 am	14	26	83	40	521	684
3:01 am-6:00 am	21	33	110	60	683	907
6:01 am-9:00 am	53	94	314	238	2202	2,901
9:01am-12:00 noon	51	139	387	365	3,022	3,964
12:01pm -3:00 pm	75	147	451	354	3,226	4,253
3:01pm-6:00 pm	55	115	379	319	2,693	3,561
6:01 pm-9:00pm	33	50	179	124	1,280	1,666
9:01 pm-11:59pm	25	33	103	56	758	975
Total	327	637	2,006	1,556	14,385	18,919

Table A.7 Number of Truck-Crashes in Kansas Based on Road Functional Class

Road Functional Class	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Number of Crashes
		Disabled	Non Incapacitating	Possible		
Rural Other Principal Arterial	153	189	370	219	2,020	2,951
Urban Interstate	9	71	268	256	1,966	2,570
Rural Interstate	22	73	236	151	1,377	1,859
Rural Minor Arterial	56	96	262	132	1,211	1,757
Urban Other Principal Arterial	19	33	131	132	1,229	1,544
Urban Freeway/Expressway	6	19	68	67	528	688
Rural Major Collector	3	21	54	34	204	316
Total	271	505	1,394	997	8,595	11,762

Table A.8 Number of Truck-Crashes in Kansas Based on AADT*

AADT*	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Number of Crashes
		Disabled	Non Incapacitating	Possible		
0-10,000	249	402	954	594	5,298	7,497
10,001-20,000	8	42	200	140	1,291	1,681
20,001-30,000	7	16	75	81	642	821
30,001-40,000	4	19	53	62	444	582
50,001-60,000	1	10	39	41	301	392
60,001-70,000	0	6	32	35	276	349
40,001-50,000	2	4	33	30	265	334
80,001 and above	0	2	3	7	43	55
70,001-80,000	0	4	5	7	35	51
Total	271	505	1394	997	8,595	11,762

*AADT is the average annual daily traffic.

Table A.9 Number of Truck-Crashes in Kansas Based on Lane Class

Lane Class	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Number of Crashes
		Disabled	Non Incapacitating	Possible		
Two Lane Undivided	200	292	614	352	3,107	4,565
Four Lane Divided	53	148	492	355	3,108	4,156
Six Lane Divided	6	48	169	184	1,250	1,657
Four Lane Undivided	10	7	90	81	901	1,089
Eight Lane Divided	1	8	28	25	211	273
Total	271	505	1,394	997	8,595	11,762

Table A.10 Number of Truck-Crashes in Kansas Based on Road-Surface Type

Road Surface Type	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Crashes
		Disabled	Non Incapacitating	Possible		
Concrete	79	175	587	541	4,399	5,781
Blacktop	229	433	1,330	948	9,242	12,182
Gravel, Dirt and Brick	18	27	80	59	695	879
Total	327	637	2,006	1,556	14,393	18,919

Table A.11 Number of Truck-Crashes in Kansas Based on Road-Surface Conditions

Surface Condition	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total
		Disabled	Non Incapacitating	Possible		
Dry	280	520	1,619	1199	11,357	14,975
Wet	27	58	213	180	1,472	1,950
Ice or Snow Packed, Snow or Slush, Mud, Dirt or Sand and Debris	20	58	168	168	1,522	1,936
Total	327	637	2,006	1,556	14,393	18,919

Table A.12 Number of Truck-Crashes in Kansas Based on the Road-Surface Geometry

Road Surface Geometry	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total
		Disabled	Non Incapacitating	Possible		
Straight and Level	215	407	1263	986	9,868	12739
Straight on Grade and Straight at Hill Crest	67	149	415	360	2,995	3986
Curved and Level, Curved on Grade and Curved at Hillcrest	45	81	322	197	1439	2084
Total	327	637	2,006	1,556	14,393	18,919

Table A.13 Number of Truck-Crashes in Kansas Based on Day of Week

Day of the Week	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Number of Crashes
		Disabled	Non Incapacitating	Possible		
Monday	59	111	359	277	2,335	3,141
Tuesday	50	112	334	295	2,609	3,400
Wednesday	58	137	357	280	2,676	3,508
Thursday	56	106	338	289	2,594	3,383
Friday	58	103	334	234	2,441	3,170
Saturday	28	41	173	110	1100	1,452
Sunday	18	27	111	71	634	861
Total	327	637	2,006	1,556	14,393	18,919

Table A.14 Number of Truck-Crashes in Kansas Based on Accident Class

Accident Class	Fatal Crashes	Injury Crashes			Property Damage Only	Total
		Disabled	Non Incapacitating	Possible		
Collision with Other Motor Vehicle	278	444	1,266	1,125	8,838	11,951
Collision with Fixed Object	7	74	255	158	2,023	2,517
All others	42	119	485	273	3,530	4,449
Total	327	637	2,006	1,556	14,393	18,919

Table A.15 Number of Truck-Crashes in Kansas Based on Contributory Cause

Contributory Cause	Fatal Crashes	Injury Crashes			Property Damage Only Crashes	Total Number of Crashes
		Disabled	Non Incapacitating	Possible		
Driver Related	289	558	1,644	1,211	9,558	13,260
Environment related	30	57	226	146	1,901	2,360
Road Condition Related	19	43	152	121	1,150	1,485
Vehicle and Pedestrian Related	20	34	122	73	893	1,142
Total	358	692	2,144	1,551	13,502	18,247

Appendix B Correlation Matrix

Table B.1 shows Pearson's correlation matrix used in the study. The Pearson's correlation coefficient greater than 0.5 for the pair of variables which are interdependent has been highlighted.

Table B.1. Correlation Matrix

Variable	ALCOHOL	LOCATION	SPEED_LIMIT_1	SPEED_LIMIT_2	SPEED_LIMIT_3	SPEED_LIMIT_4	WEATHER	S_TYPE
ALCOHOL	1.000	0.006	-0.033	0.026	-0.004	0.022	-0.012	0.002
LOCATION	0.006	1.000	0.296	0.117	-0.067	-0.287	-0.081	0.102
SPEED_LIMIT_1	-0.033	0.296	1.000	-0.200	-0.331	**-0.572**	-0.094	0.072
SPEED_LIMIT_2	0.026	0.117	-0.200	1.000	-0.125	-0.216	-0.025	0.056
SPEED_LIMIT_3	-0.004	-0.067	-0.331	-0.125	1.000	-0.359	-0.029	-0.115
SPEED_LIMIT_4	0.022	-0.287	**-0.572**	-0.216	-0.359	1.000	0.119	0.004
WEATHER	-0.012	-0.081	-0.094	-0.025	-0.029	0.119	1.000	-0.004
S_TYPE	0.002	0.102	0.072	0.056	-0.115	0.004	-0.004	1.000
S_COND	0.015	0.058	0.047	0.023	0.034	-0.072	**-0.750**	0.019
S_CHAR	0.014	0.136	0.125	0.021	-0.059	-0.074	-0.061	0.004
CONSTR_MAINT	-0.008	-0.061	-0.025	0.002	0.094	-0.047	-0.059	-0.072
LIGHT	-0.146	0.157	0.185	0.059	0.035	-0.245	-0.089	-0.039
ONAT_TC	-0.018	**-0.689**	-0.182	-0.066	0.039	0.173	0.058	-0.068
TIME_DAY	-0.169	0.138	0.161	0.048	0.039	-0.215	-0.048	-0.034
DAY	-0.077	0.038	0.071	0.024	-0.002	-0.077	-0.050	0.003
CLASS	0.050	0.281	0.119	0.098	-0.050	-0.120	-0.016	-0.085
MANEUVER	0.023	-0.177	-0.211	-0.033	0.054	0.192	0.070	0.023
DAMAGE	0.042	-0.033	-0.204	-0.007	0.071	0.148	0.062	-0.020
YOUNG	0.036	0.091	0.034	0.032	0.014	-0.056	0.001	-0.016
MIDDLE_AGED	-0.026	-0.058	-0.036	-0.022	-0.012	0.055	-0.003	0.020
OLD	-0.010	-0.041	-0.023	-0.012	0.023	0.011	-0.014	0.012
GENDR	0.019	-0.045	-0.049	-0.028	0.030	0.036	-0.021	0.045
SAFETY_EQUIPT	-0.087	-0.004	0.045	0.002	-0.075	0.013	0.041	-0.008

Table B.1. Correlation Matrix (Cont.)

Variable	ALCOHOL	LOCATION	SPEED_LIMIT_1	SPEED_LIMIT_2	SPEED_LIMIT_3	SPEED_LIMIT_4	WEATHER	S_TYPE
TRAPPED	0.074	0.002	-0.078	-0.021	0.031	0.064	0.012	0.017
CONTROL	0.009	0.122	-0.155	0.020	-0.050	0.190	0.045	0.003
COLLISION	0.040	0.059	-0.025	0.064	0.007	-0.014	0.008	-0.062
CC_RD	-0.028	-0.100	-0.105	-0.014	0.003	0.097	0.358	-0.035
CC_DR	0.071	0.153	0.169	0.053	-0.022	-0.173	-0.034	-0.042
CC_VEH	-0.026	-0.050	-0.063	-0.002	0.017	0.055	-0.054	-0.010
CC_ENV	-0.034	-0.154	-0.191	-0.055	-0.015	0.226	0.346	0.038
DRUGS_ALCOHOL	0.822	0.008	-0.030	0.022	0.000	0.019	-0.017	-0.002
SPEED	0.031	0.017	-0.075	0.000	0.014	0.047	0.226	-0.050
WRONG	0.044	0.087	0.040	0.026	-0.021	-0.037	-0.064	-0.020
IMP_MAN	-0.011	-0.015	0.074	-0.013	-0.012	-0.048	-0.069	-0.051
TIME_ATTN	0.020	0.157	0.157	0.056	-0.026	-0.155	-0.119	0.037
EVASIVE	0.007	-0.060	-0.095	-0.001	0.027	0.076	-0.004	-0.005
CARELESS	0.084	-0.007	-0.016	0.000	0.001	0.015	-0.017	0.004
SMOG_SAND	-0.004	-0.008	-0.042	-0.013	0.017	0.030	0.130	-0.002
RAIN	-0.003	-0.047	-0.058	-0.006	-0.007	0.060	0.295	-0.011
SNOW	-0.022	-0.099	-0.109	-0.037	-0.029	0.140	0.424	0.000
VSN_OBSTRUCT	-0.028	-0.126	-0.150	-0.047	-0.003	0.181	-0.039	0.060
WET	-0.027	-0.087	-0.093	-0.017	-0.022	0.103	0.403	-0.027
BRAKES	-0.017	-0.019	-0.056	-0.007	0.018	0.050	-0.047	-0.009
UNATTND	-0.007	-0.019	0.027	0.009	-0.012	-0.228	-0.006	0.001
RUTS	-0.013	-0.050	-0.051	-0.004	0.046	0.021	0.001	-0.016
INOPERATIVE	0.004	-0.019	-0.010	0.008	0.028	-0.016	-0.007	-0.010

Table B.1. Correlation Matrix (Cont.)

Variable	S_COND	S_CHAR	CONSTR_MAINT	LIGHT	ONAT_TC	TIME_DAY	DAY	CLASS	MANEUVER	DAMAGE
ALCOHOL	0.015	0.014	-0.008	-0.146	-0.018	-0.169	-0.077	0.050	0.023	0.042
LOCATION	0.058	0.136	-0.061	0.157	**-0.689**	0.138	0.038	0.281	-0.177	-0.033
SPEED_LIMIT_1	0.047	0.125	-0.025	0.185	-0.182	0.161	0.071	0.119	-0.211	-0.204
SPEED_LIMIT_2	0.023	0.021	0.002	0.059	-0.066	0.048	0.024	0.098	-0.033	-0.007
SPEED_LIMIT_3	0.034	-0.059	0.094	0.035	0.039	0.039	-0.002	-0.050	0.054	0.071
SPEED_LIMIT_4	-0.072	-0.074	-0.047	-0.245	0.173	-0.215	-0.077	-0.120	0.192	0.148
WEATHER	**-0.750**	-0.061	-0.059	-0.089	0.058	-0.048	-0.050	-0.016	0.070	0.062
S_TYPE	0.019	0.004	-0.072	-0.039	-0.068	-0.034	0.003	-0.085	0.023	-0.020
S_COND	1.000	0.065	0.053	0.085	-0.040	0.032	0.044	-0.009	-0.040	-0.051
S_CHAR	0.065	1.000	-0.019	-0.007	-0.107	-0.012	0.002	0.076	-0.040	-0.041
CONSTR_MAINT	0.053	-0.019	1.000	0.041	0.043	0.021	0.003	0.051	-0.025	-0.005
LIGHT	0.085	-0.007	0.041	1.000	-0.108	**0.729**	0.114	0.236	-0.147	-0.098
ONAT_TC	-0.040	-0.107	0.043	-0.108	1.000	-0.098	-0.022	-0.241	0.056	-0.036
TIME_DAY	0.032	-0.012	0.021	**0.729**	-0.098	1.000	0.115	0.222	-0.129	-0.085
DAY	0.044	0.002	0.003	0.114	-0.022	0.115	1.000	0.054	-0.034	-0.035
CLASS	-0.009	0.076	0.051	0.236	-0.241	0.222	0.054	1.000	-0.213	0.015
MANEUVER	-0.040	-0.040	-0.025	-0.147	0.056	-0.129	-0.034	-0.213	1.000	0.133
DAMAGE	-0.051	-0.041	-0.005	-0.098	-0.036	-0.085	-0.035	0.015	0.133	1.000
YOUNG	-0.015	0.028	-0.001	0.056	-0.077	0.055	0.006	0.232	-0.048	0.030
MIDDLE_AGED	0.014	-0.026	-0.004	-0.033	0.047	-0.042	0.006	-0.211	0.046	-0.026
OLD	0.018	-0.012	-0.004	-0.027	0.026	-0.020	-0.011	-0.139	0.030	-0.007
GENDR	0.034	-0.020	-0.022	-0.052	0.024	-0.055	0.001	-0.266	0.069	-0.005
SAFETY_EQUIPT	-0.051	0.016	0.007	-0.013	0.013	-0.007	0.010	0.048	-0.028	-0.029

Table B.1. Correlation Matrix (Cont.)

Variable	S_COND	S_CHAR	CONSTR_MAINT	LIGHT	ONAT_TC	TIME_DAY	DAY	CLASS	MANEUVER	DAMAGE
TRAPPED	0.007	-0.022	-0.012	-0.021	-0.019	-0.018	0.005	-0.010	0.040	0.055
CONTROL	0.028	-0.036	0.033	-0.001	-0.122	0.002	-0.006	0.163	0.161	0.095
COLLISION	-0.020	0.008	0.049	0.098	0.098	0.092	0.026	0.357	0.035	0.066
CC_RD	-0.430	-0.081	0.005	-0.037	0.072	-0.004	-0.038	-0.024	0.057	0.058
CC_DR	0.007	-0.014	0.052	0.181	-0.106	0.155	0.036	0.315	-0.205	0.037
CC_VEH	0.072	-0.025	-0.013	0.069	0.051	0.056	0.015	-0.055	0.085	-0.086
CC_ENV	-0.248	-0.033	-0.057	-0.249	0.105	-0.204	-0.072	-0.208	0.161	0.106
DRUGS_ALCOHOL	0.021	0.006	-0.004	-0.125	-0.019	-0.141	-0.065	0.046	0.016	0.043
SPEED	-0.259	-0.102	-0.005	0.021	-0.058	0.031	-0.021	0.029	0.068	0.111
WRONG	0.066	0.036	0.028	0.074	-0.006	0.063	0.025	0.184	-0.114	0.024
IMP_MAN	0.062	0.029	0.040	0.068	0.047	0.057	0.015	0.214	-0.285	-0.076
TIME_ATTN	0.111	0.024	0.024	0.099	-0.137	0.075	0.035	0.164	-0.035	0.012
EVASIVE	-0.001	-0.031	0.006	0.008	0.045	0.003	-0.019	-0.019	-0.056	0.046
CARELESS	0.029	0.009	0.003	-0.024	-0.006	-0.028	-0.009	0.036	0.000	0.035
SMOG_SAND	-0.029	0.006	-0.011	-0.022	0.008	-0.021	-0.015	0.017	0.009	0.013
RAIN	-0.274	-0.027	-0.017	-0.049	0.040	-0.036	-0.014	0.000	0.005	0.029
SNOW	-0.325	-0.037	-0.031	-0.041	0.066	-0.025	-0.056	-0.055	0.075	0.057
VSN_OBSTRUCT	0.059	0.004	-0.047	-0.303	0.082	-0.260	-0.051	-0.275	0.163	**0.831**
WET	-0.490	-0.078	-0.040	-0.041	0.063	0.000	-0.037	0.002	0.047	0.061
BRAKES	0.053	-0.015	-0.013	-0.049	0.028	0.038	0.004	-0.057	0.058	0.004
UNATTND	0.007	-0.016	-0.007	-0.008	0.016	-0.003	-0.001	0.010	-0.008	-0.004
RUTS	0.007	-0.025	0.007	-0.010	0.040	-0.016	-0.016	-0.077	0.043	0.003
INOPERATIVE	0.017	-0.009	0.166	0.017	0.006	0.006	0.009	0.007	-0.002	0.009

Table B.1. Correlation Matrix (Cont.)

Variable	YOUNG	MIDDLE_AGED	OLD	GENDR	SAFETY_EQUIPT	TRAPPED	CONTROL	COLLISION
ALCOHOL	0.036	-0.026	-0.010	0.019	-0.087	0.074	0.009	0.040
LOCATION	0.091	-0.058	-0.041	-0.045	-0.004	0.002	0.122	0.059
SPEED_LIMIT_1	0.034	-0.036	-0.023	-0.049	0.045	-0.078	-0.155	-0.025
SPEED_LIMIT_2	0.032	-0.022	-0.012	-0.028	0.002	-0.021	0.020	0.064
SPEED_LIMIT_3	0.014	-0.012	0.023	0.030	-0.075	0.031	-0.050	0.007
SPEED_LIMIT_4	-0.056	0.055	0.011	0.036	0.013	0.064	0.190	-0.014
WEATHER	0.001	-0.003	-0.014	-0.021	0.041	0.012	0.045	0.008
S_TYPE	-0.016	0.020	0.012	0.045	-0.008	0.017	0.003	-0.062
S_COND	-0.015	0.014	0.018	0.034	-0.051	0.007	0.028	-0.020
S_CHAR	0.028	-0.026	-0.012	-0.020	0.016	-0.022	-0.036	0.008
CONSTR_MAINT	-0.001	-0.004	-0.004	-0.022	0.007	-0.012	0.033	0.049
LIGHT	0.056	-0.033	-0.027	-0.052	-0.013	-0.021	-0.001	0.098
ONAT_TC	-0.077	0.047	0.026	0.024	0.013	-0.019	-0.122	0.098
TIME_DAY	0.055	-0.042	-0.020	-0.055	-0.007	-0.018	0.002	0.092
DAY	0.006	0.006	-0.011	0.001	0.010	0.005	-0.006	0.026
CLASS	0.232	-0.211	-0.139	-0.266	0.048	-0.010	0.163	0.357
MANEUVER	-0.048	0.046	0.030	0.069	-0.028	0.040	0.161	0.035
DAMAGE	0.030	-0.026	-0.007	-0.005	-0.029	0.055	0.095	0.066
YOUNG	1.000	**-0.816**	-0.082	-0.115	-0.051	0.020	0.021	0.112
MIDDLE_AGED	**-0.816**	1.000	-0.222	0.265	0.033	-0.006	-0.013	-0.078
OLD	-0.082	-0.222	1.000	0.064	-0.032	0.005	-0.022	-0.048
GENDR	-0.115	0.265	0.064	1.000	-0.039	-0.016	-0.055	-0.070
SAFETY_EQUIPT	-0.051	0.033	-0.032	-0.039	1.000	-0.114	0.027	-0.004

Table B.1. Correlation Matrix (Cont.)

Variable	YOUNG	MIDDLE_AGED	OLD	GENDR	SAFETY_EQUIPT	TRAPPED	CONTROL	COLLISION
TRAPPED	0.020	-0.006	0.005	-0.016	-0.114	1.000	0.038	0.020
CONTROL	0.021	-0.013	-0.022	-0.055	0.027	0.038	1.000	0.093
COLLISION	0.112	-0.078	-0.048	-0.070	-0.004	0.020	0.093	1.000
CC_RD	0.014	-0.002	-0.011	-0.010	0.031	0.001	0.048	0.012
CC_DR	0.108	-0.068	-0.046	-0.063	-0.023	0.043	0.092	0.172
CC_VEH	-0.026	0.008	0.018	0.014	-0.019	-0.007	0.037	-0.052
CC_ENV	-0.055	0.068	0.022	0.061	0.039	0.012	0.046	-0.057
DRUGS_ALCOHOL	0.031	-0.019	-0.107	0.019	-0.091	0.070	0.015	0.041
SPEED	0.045	-0.020	-0.021	0.001	-0.030	0.066	0.094	0.045
WRONG	0.064	-0.048	-0.019	-0.028	-0.005	0.014	0.067	0.283
IMP_MAN	0.045	-0.044	-0.031	-0.077	0.021	-0.032	0.012	-0.102
TIME_ATTN	0.051	-0.023	-0.019	-0.017	-0.035	0.047	0.022	0.105
EVASIVE	-0.011	0.016	0.010	0.010	-0.010	0.025	0.028	0.017
CARELESS	0.029	-0.040	-0.012	-0.022	-0.049	0.035	0.012	0.009
SMOG_SAND	-0.002	-0.001	0.016	-0.003	-0.011	0.014	-0.004	0.035
RAIN	0.011	-0.009	-0.004	-0.004	0.015	0.017	0.018	0.012
SNOW	-0.013	0.017	-0.002	0.003	0.023	0.030	0.516	0.000
VSN_OBSTRUCT	-0.078	0.092	0.031	0.089	0.034	-0.013	0.014	-0.104
WET	0.023	-0.010	-0.008	-0.016	0.037	0.001	0.060	0.024
BRAKES	-0.005	0.008	0.020	0.020	-0.030	-0.004	0.037	-0.022
UNATTND	-0.021	-0.005	-0.002	-0.021	-0.010	0.005	-0.035	0.002
RUTS	-0.017	0.016	-0.005	0.014	-0.011	0.004	-0.021	-0.035
INOPERATIVE	-0.003	0.007	-0.010	-0.005	0.010	-0.010	0.002	0.010

Table B.1. Correlation Matrix (cont.)

Variable	CC_RD	CC_DR	CC_VEH	CC_ENV	DRUGS_ALCOHOL	SPEED	WRONG	IMP_MAN	TIME_ATTN	EVASIVE	CARELESS
TRAPPED	0.001	0.043	-0.007	0.012	0.070	0.066	0.014	-0.032	0.047	0.025	0.035
CONTROL	0.048	0.092	0.037	0.046	0.015	0.094	0.067	0.012	0.022	0.028	0.012
COLLISION	0.012	0.172	-0.052	-0.057	0.041	0.045	0.283	-0.102	0.105	0.017	0.009
CC_RD	1.000	-0.036	-0.036	0.263	-0.025	0.232	-0.064	-0.078	-0.128	0.023	-0.029
CC_DR	-0.036	1.000	-0.244	0.260	0.084	0.268	0.257	0.255	**0.552**	0.148	0.089
CC_VEH	-0.036	-0.244	1.000	-0.062	-0.028	-0.054	-0.070	-0.075	-0.143	-0.025	-0.030
CC_ENV	0.263	0.260	-0.062	1.000	-0.034	0.068	-0.102	0.109	-0.213	-0.003	0.039
DRUGS_ALCOHOL	-0.025	0.084	-0.028	-0.034	1.000	0.038	0.041	-0.003	0.023	0.004	0.086
SPEED	0.232	0.268	-0.054	0.068	0.038	1.000	-0.043	0.105	-0.065	-0.016	0.052
WRONG	-0.064	0.257	-0.070	-0.102	0.041	-0.043	1.000	-0.082	-0.019	0.001	0.004
IMP_MAN	-0.078	0.255	-0.075	0.109	-0.003	0.105	-0.082	1.000	-0.072	-0.027	0.007
TIME_ATTN	-0.128	**0.552**	-0.143	-0.213	0.023	-0.065	-0.019	-0.072	1.000	-0.065	0.015
EVASIVE	0.023	0.148	-0.025	-0.003	0.004	-0.016	0.001	-0.027	-0.065	1.000	0.001
CARELESS	-0.029	0.089	-0.030	0.039	0.086	0.052	0.004	0.007	0.015	0.001	1.000
SMOG_SAND	0.017	-0.017	-0.008	0.206	0.001	0.029	0.002	-0.018	-0.023	0.008	0.005
RAIN	0.263	-0.012	-0.015	0.383	-0.016	0.089	-0.023	-0.022	-0.053	0.023	-0.011
SNOW	0.329	-0.072	-0.025	**0.553**	-0.016	0.150	-0.056	-0.067	-0.120	0.005	-0.022
VSN_OBSTRUCT	-0.051	-0.317	-0.058	**0.653**	-0.028	-0.090	-0.089	-0.087	-0.179	-0.020	-0.032
WET	**0.895**	-0.003	-0.042	0.299	-0.027	0.261	-0.056	-0.070	-0.119	0.017	-0.026
BRAKES	-0.032	-0.190	**0.771**	-0.050	-0.020	-0.041	-0.048	-0.053	-0.119	-0.019	-0.026
UNATTND	-0.002	-0.034	0.232	-0.002	-0.007	-0.018	-0.023	-0.009	-0.015	0.004	-0.008
RUTS	0.365	-0.086	0.014	-0.002	-0.009	-0.014	-0.033	-0.040	-0.054	0.015	-0.010
INOPERATIVE	0.244	-0.013	-0.011	-0.005	0.009	0.002	-0.007	-0.004	-0.010	0.017	-0.009

Table B.1. Correlation Matrix (cont.)

Variable	SMOG_SAND	RAIN	SNOW	VSN_OBSTRUCT	WET	BRAKES	UNATTND	RUTS	INOPERATIVE
TRAPPED	0.014	0.017	0.030	-0.013	0.001	-0.004	0.005	0.004	-0.010
CONTROL	-0.004	0.018	0.516	0.014	0.060	0.037	-0.035	-0.021	0.002
COLLISION	0.035	0.012	0.000	-0.104	0.024	-0.022	0.002	-0.035	0.010
CC_RD	0.017	0.263	0.329	-0.051	**0.895**	-0.032	-0.002	0.365	0.244
CC_DR	-0.017	-0.012	-0.072	-0.317	-0.003	-0.190	-0.034	-0.086	-0.013
CC_VEH	-0.008	-0.015	-0.025	-0.058	-0.042	**0.771**	0.232	0.014	-0.011
CC_ENV	0.206	0.383	**0.553**	**0.653**	0.299	-0.050	-0.002	-0.002	-0.005
DRUGS_ALCOHOL	0.001	-0.016	-0.016	-0.028	-0.027	-0.020	-0.007	-0.009	0.009
SPEED	0.029	0.089	0.150	-0.090	0.261	-0.041	-0.018	-0.014	0.002
WRONG	0.002	-0.023	-0.056	-0.089	-0.056	-0.048	-0.023	-0.033	-0.007
IMP_MAN	-0.018	-0.022	-0.067	-0.087	-0.070	-0.053	-0.009	-0.040	-0.004
TIME_ATTN	-0.023	-0.053	-0.120	-0.179	-0.119	-0.119	-0.015	-0.054	-0.010
EVASIVE	0.008	0.023	0.005	-0.020	0.017	-0.019	0.004	0.015	0.017
CARELESS	0.005	-0.011	-0.022	-0.032	-0.026	-0.026	-0.008	-0.010	-0.009
SMOG_SAND	1.000	-0.002	0.032	0.007	0.003	-0.004	-0.005	0.025	0.014
RAIN	-0.002	1.000	0.082	-0.024	0.292	-0.008	0.005	0.025	0.006
SNOW	0.032	0.082	1.000	-0.032	0.369	-0.243	-0.003	-0.004	0.005
VSN_OBSTRUCT	0.007	-0.024	-0.032	1.000	-0.045	-0.047	-0.006	-0.167	-0.014
WET	0.003	0.292	0.369	-0.045	1.000	-0.033	0.001	0.000	0.011
BRAKES	-0.004	-0.008	-0.243	-0.047	-0.033	1.000	0.014	0.000	-0.009
UNATTND	-0.005	0.005	-0.003	-0.006	0.001	0.014	1.000	-0.006	-0.004
RUTS	0.025	0.025	-0.004	-0.167	0.000	0.000	-0.006	1.000	0.045
INOPERATIVE	0.014	0.006	0.005	-0.014	0.011	-0.009	-0.004	0.045	1.000

Appendix C – Variable Selection Methods

Following are models and goodness-of-fit statistics for forward selection and stepwise selection methods of variable selection procedures, respectively:

Forward Selection Method

Table C.1 shows parameter estimates and odds-ratio values of the variables in the model obtained by the forward selection method.

C.1. Model Obtained by Forward Selection Method

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Sq	Odds Ratio	95% Wald Confidence Limits For Odds Ratio
Intercept*	-1.494	0.163	84.47	<0.0001		
ALCOHOL*	0.973	0.135	51.9	<0.0001	2.65	2.03,3.45
CARELESS*	0.331	0.125	6.98	0.0083	1.39	1.09,1.78
CC_DR*	0.589	0.053	122.43	<0.0001	1.8	1.62,2.00
CC_RD*	-0.303	0.082	13.51	0.0002	0.74	0.63,0.87
CC_VEH	-0.09	0.093	0.94	0.3329	0.91	0.76, 1.10
CLASS	0.103	0.052	3.92	0.0477	1.11	1.00,1.23
COLLISION*	0.473	0.052	83.78	<0.0001	1.61	1.45,1.78
CONSTR_MAINT*	-0.271	0.083	10.68	0.0011	0.76	0.65,0.90
CONTROL*	0.307	0.057	29.47	<0.0001	1.36	1.22,1.52
DAMAGE*	1.12	0.083	182.14	<0.0001	3.06	2.60,3.60
DAY	-0.003	0.058	0	0.9661	1	0.89, 1.12
EVASIVE*	0.43	0.079	29.83	<0.0001	1.54	1.32,1.80
GENDR*	-0.129	0.049	7.08	0.0078	0.88	0.80,0.97
IMP_MAN*	-0.455	0.068	44.85	<0.0001	0.64	0.56,0.73
INOPERATIVE	-0.247	0.328	0.57	0.4508	0.78	0.41, 1.48
LIGHT	0.06	0.049	1.5	0.2209	1.06	0.96,1.17
MANEUVER*	0.321	0.041	61.66	<0.0001	1.38	1.27,1.49
MIDDLE_AGED*	0.104	0.043	5.95	0.0147	1.11	1.021,1.21
OLD	0.092	0.14	0.43	0.5141	1.1	0.83, 1.44
ONAT_TC*	-0.517	0.054	92.35	<0.0001	0.6	0.54,0.66
RAIN*	0.312	0.132	5.64	0.0176	1.37	1.06,1.77
RUTS	-0.148	0.224	0.44	0.5091	0.86	0.56, 1.34
S_CHAR*	-0.113	0.041	7.72	<0.0001	0.89	0.83,0.97
S_COND*	0.234	0.055	18.32	<0.0001	1.26	1.14,1.41
S_TYPE*	0.133	0.04	10.87	0.001	1.14	1.06,1.24
SAFETY_EQUIPT*	-1.379	0.075	338.08	<0.0001	0.25	0.217, 0.292
SMOG_SAND	0.355	0.218	2.65	0.1037	1.43	0.93, 2.19
SNOW	0.17	0.098	3	0.0831	1.19	0.978, 1.437
SPEED*	0.449	0.054	68.62	<0.0001	1.57	1.41, 1.74
SPEED_LIMIT_1*	-0.807	0.051	253.93	<0.0001	0.45	0.40, 0.49
SPEED_LIMIT_2*	-0.396	0.076	26.95	<0.0001	0.67	0.58, 0.78
SPEED_LIMIT_3*	0.11	0.052	4.6	0.032	1.12	1.01, 1.24
TRAPPED*	4.43	0.344	166.15	<0.0001	83.95	42.80, 164.66
UNATTND	0.483	0.329	2.16	0.142	1.62	0.85, 3.09
WRONG	0.014	0.058	0.06	0.8034	1.01	0.91, 1.14

*significant at 0.05 level

Table C.2. Model Fit Statistics of the Binary Logistic-Regression Analysis

Criterion	Intercept Only	Intercept and Covariates
AIC	20820.1	17391.8
SC	20828	17613.7
-2logL	20818.1	17337.8

Table C.3 Associations of Predicted Probabilities and Observed Responses

Statistic	Value
Percent Concordant	76
Percent Discordant	23.7
Percent Tied	0.4
Pairs	65,142,718
Somers' D	0.523
Gamma	0.525
Tau-a	0.19
c	0.762

- $R^2 = 0.1680$

Stepwise Selection Method

Table C.4 shows parameter estimates and odds-ratio values of the variables in the model obtained by the stepwise selection method.

C.4. Model Obtained by Stepwise Selection Method

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Sq	Odds Ratio	95% Wald Confidence Limits For Odds Ratio
Intercept*	-1.513	0.163	86.21	<0.0001		
ALCOHOL*	0.976	0.135	52.24	<0.0001	2.65	2.04,3.46
CARELESS*	0.333	0.125	7.06	0.0079	1.4	1.09,1.79
CC_DR*	0.595	0.053	124.20	<0.0001	1.81	1.63,2.01
CC_RD*	-0.333	0.084	15.54	<0.0001	0.72	0.61,0.85
CC_VEH	-0.09	0.093	0.94	0.3329	0.91	0.76, 1.10
CLASS	0.106	0.052	4.10	0.0429	1.11	1.00,1.23
COLLISION*	0.473	0.052	83.56	<0.0001	1.6	1.45,1.78
CONSTR_MAINT*	-0.269	0.083	10.49	0.0012	0.76	0.65,0.90
CONTROL*	0.304	0.057	28.87	<0.0001	1.36	1.23,1.51
DAMAGE*	1.117	0.083	181.40	<0.0001	3.06	2.6,3.6
DAY	-0.003	0.058	0.00	0.9661	1	0.90, 1.12
EVASIVE*	0.43	0.079	29.80	<0.0001	1.54	1.32,1.80
GENDR*	-0.129	0.049	7.07	0.0078	0.88	0.80,0.97
IMP_MAN*	-0.455	0.068	44.79	<0.0001	0.64	0.56,0.73
INOPERATIVE	-0.247	0.328	0.57	0.4508	0.78	0.41, 1.48
LIGHT	0.06	0.049	1.50	0.2209	1.06	0.96,1.17
MANEUVER*	0.32	0.041	61.06	<0.0001	1.38	1.27,1.49
MIDDLE_AGED*	0.103	0.043	5.87	0.0154	1.11	1.02,1.21
OLD	0.092	0.14	0.43	0.5141	1.1	0.83, 1.44
ONAT_TC*	-0.52	0.054	93.26	<0.0001	0.6	0.54,0.66
RAIN*	0.329	0.132	6.23	0.0125	1.39	1.073,1.80
RUTS	-0.148	0.224	0.44	0.5091	0.86	0.56, 1.34
S_CHAR*	-0.114	0.041	7.88	0.005	0.89	0.82,0.97
S_COND*	0.255	0.056	20.57	<0.0001	1.29	1.16,1.44
S_TYPE*	0.132	0.04	10.69	0.0011	1.14	1.05,1.24
SAFETY_EQUIPT*	-1.38	0.075	338.74	<0.0001	0.25	0.22,0.29
SMOG_SAND	0.355	0.218	2.65	0.1037	1.43	0.93, 2.19
SNOW	0.17	0.098	3.00	0.0831	1.19	0.98,1.44
SPEED*	0.444	0.054	66.83	<0.0001	1.56	1.40,1.733
SPEED_LIMIT_1*	-0.801	0.051	249.34	<0.0001	0.45	0.41,0.50
SPEED_LIMIT_2*	-0.39	0.077	26.07	<0.0001	0.68	0.58,0.79
SPEED_LIMIT_3*	0.115	0.052	5.00	0.0254	1.12	1.01,1.24
TRAPPED*	4.419	0.344	165.23	<0.0001	83.01	42.32,162.84
UNATTND	0.483	0.329	2.16	0.142	1.62	0.85, 3.09
WRONG	0.014	0.058	0.06	0.8034	1.01	0.91, 1.14

*significant at 0.05 level

Table C.5. Model Fit Statistics of the Binary Logistic-Regression Analysis

Criterion	Intercept Only	Intercept and Covariates
AIC	20820.1	17390.9
SC	20828	17610.6
-2logL	20818.1	17334.9

Table C.6 Associations of Predicted Probabilities and Observed Responses

Statistic	Value
Percent Concordant	76
Percent Discordant	23.7
Percent Tied	0.4
Pairs	65,142,718
Somers' D	0.523
Gamma	0.525
Tau-a	0.191
c	0.762

- $R^2 = 0.1682$