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An Application of Data Analytics to Outcomes of Missouri Motor Vehicle Crashes

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Abstract

Motor vehicle crashes are a leading cause of death in the United States, cost Americans $277 billion annually, and generate serious psychological burdens. As a result, extensive vehicle safety research focusing on the explanatory factors of crash severity is undertaken using a wide array of methodological techniques including traditional statistical models and contemporary data mining approaches. This study advances the methodological frontier of crash severity research by completing an empirical investigation that compares the performance of popular, longstanding techniques of multinomial logit and ordinal probit models with more recent methods of decision tree and artificial neural network models. To further the investigation of the benefits of data analytics, individual models are combined into model ensembles using three popular combinatory techniques.

The models are estimated using 2002 to 2012 crash data from the Missouri State Highway Patrol Traffic Division - Statewide Traffic Accident Records System database, and variables examined include various driver characteristics, temporal factors, weather conditions, road characteristics, crash type, crash location, and injury severity levels. The accuracy and discriminatory power of explaining crash severity outcomes among all methods are compared using classification tables, lift charts, ROC curves, and AUC values.

The CHAID decision tree model is found to have the greatest accuracy and discriminatory power relative to all evaluated modeling approaches. The modeling reveals that the presence of alcohol, driving at speeds that exceed the limit, failing to yield, driving on the wrong side of the road, violating a stop sign or signal, and driving

while physically impaired lead to a large number of fatalities each year. Yet, the effect of these factors on the probability of a severe outcome is dependent upon other variables, including number of occupants involved in the crash, speed limit, lighting condition, and age of the driver. The CHAID decision tree is used in conjunction with prior literature and the current Missouri rules of the road to provide better formulated driving policies. This study concludes that policy makers should consider the interaction of conditions and driver related contributing factors when crafting future legislation or proposing modifications in driving statues.

Chapter 1 – Introduction

Motor vehicle crashes are the leading cause of death for young people in the United States, and are a leading cause of death for Americans of all ages (Centers for Disease Control and Prevention, 2015). Crashes on US roadways result in a fatality every 16 minutes, and led to 32,719 deaths and 2,313,000 injuries in 2013 (National Highway Traffic Safety Administration, 2014). Traffic crashes not only result in the loss of invaluable lives, but also cost Americans $277 billion annually in lost wages, rehabilitation, medical care, etc. (Blincoe et al., 2010). Additionally, traffic crashes render serious psychological burdens, such as grief, stress, depression, guilt and travel anxiety for victims and their families (Mayou et al., 1993). As a result of these devastating effects, academicians and practitioners have undertaken extensive national and state-level traffic safety research focusing on the explanatory factors of traffic crashes and crash injury severity.

1.1 Research Techniques

To investigate crash severity data, researchers employ a wide array of methodological techniques with varying advantages and limitations that may lead to complementary, conflicting and/or inaccurate results. Savolainen et al. (2011) conducted a review of the methodological tools employed for statistical analysis of crash injury severity, and found ordered logit and probit models, binary logit and probit models, and multinomial logit models to be the most common. While not frequently used, the authors indicated that contemporary techniques including artificial neural networks (ANN) "may be better served for prediction of injury outcomes" (Savolainen et al., 2011, p. 1673) and decision tree models are an effective data mining technique. Additionally, Abdelwahab and Abdel-Aty (2001) argued that the learning capabilities and adaptive nature of ANN models could possibly be superior to traditional techniques in modeling injury severity, and called for future investigation of the use of ANN models in transportation safety applications. Furthermore, Chang and Wang (2006) called for future work in comparing decision tree model results with traditional models such as ordered probit and logistic regression models.

While researchers have made substantial progress in crash injury severity modeling, “major methodological and data challenges have yet to be fully resolved” (Savolainen et al., 2011, p. 1674). Accordingly, addressing these challenges “must be a priority in future crash-injury research” (Savolainen et al., 2011, p.1674), and “not expanding the methodological frontier, and continuing to use methodological approaches with known deficiencies, has the potential to lead to erroneous and ineffective safety policies that may result in unnecessary injuries and loss of life” (Mannering and Bhat, 2014, p. 16).

1.2 Research Questions

Driven by the physical, emotional and economic costs that follow motor vehicle crashes, it is important to examine and assess the relative merits of the different methodological approaches used for predicting crash severity outcomes. Yet few studies have compared the differing modeling approaches and no studies have been identified in which methodologies have been ensembled to attempt to gain greater accuracy and predictive power for injury severity outcomes. Even so, some researchers have theorized that combining different modeling types can create ensemble models with the ability to obtain greater accuracy relative to the individual models (Hansen and Salamon, 1990; Polikar, 2006).

1.3 Objectives

This research contributes to the body of existing literature by responding to the call for expanding the methodological frontier in crash injury severity research. An empirical investigation is performed to determine if traditional techniques, contemporary models or model ensembles offer greater accuracy and predictive power for crash injury severity outcomes.

This study uses crash data compiled by the Missouri Highway Patrol for the years 2002 to 2012 to develop, evaluate and ensemble (1) multinomial logit, (2) ordinal probit, (3) artificial neural networks and (4) decision tree models to compare the accuracy and predictive power of each approach in order to identify the best approach for influencing safety policies. This research contributes to the current body of literature by evaluating the relative accuracy and power of varying modeling types estimated on a single large dataset of vehicle crashes, and by identifying relationships among contributing variables to crash severity to produce findings that will contribute to potential Missouri legislation and education materials to enhance overall driver safety.

Specifically, the results from this study contribute to the current body of literature by addressing the following detailed research objectives:

(1) Build and estimate four different models: multinomial logit, ordinal probit, artificial neural network and decision tree models, and assess the performance of each individual model by examining the relative performance of the estimated model on a training subset and a testing subset of the data.

(2) Combine the estimated multinomial logit, ordinal probit, artificial neural network and decision tree models to build an ensemble model to test if the amalgamation of the multiple methodologies enhances the classification accuracy of crash injury severity on a training subset and a testing subset of the data.

(3) Examine and compare the predictive importance of variables as estimated by each individual model and the model ensemble to determine the contributory factors that have the greatest impact on crash injury severity outcomes.

(4) Gain greater insight into relationships in the crash data by examining how crash injury severity is affected by a wide range of possible explanatory variables.

(5) Evaluate findings relative to current Missouri driving policy and law to provide information for transportation planning, education and policy to enhance transportation safety efforts.

1.4 Organization of the Research

The research is presented in seven chapters. Chapter One includes background and justification, as well as the problem statement and objectives for this study. Chapter Two provides a review of relevant research for each methodological approach, in addition to a summary of the significant findings derived from the body of literature. Chapter Three identifies gaps in the current body of literature, recounts the call for further research in this area, and indicates the specific research questions to be answered by this study. Chapter Four presents details regarding the data and the methodological techniques employed. Chapter Five provides an analysis of the estimation and results of the individual models and the model ensembles. Chapter Six presents a discussion of findings and insights derived from the estimated models. Finally, Chapter Seven identifies research implications, limitations, and potential areas for future research.

Chapter 2 - Literature Review

Prior research has employed a wide array of methodological tools to better understand the factors that affect crash injury severity. Savolainen et al. (2011) conducted a review of the methodological tools employed for statistical analysis of crash injury severity, and identified the approaches as follows:

- Artificial neural networks
- Bayesian hierarchical binomial logit
- Bayesian ordered probit
- Binary logit and binary probit
- Bivariate binary probit
- Bivariate ordered probit
- Classification and regression tree
- Generalized ordered logit
- Heterogeneous outcome
- Heteroskedastic ordered logit/probit
- Log-linear
- Markov switching multinomial logit
- Mixed generalized ordered logit
- Mixed joint binary logit-ordered logit
- Multinomial logit
- Multivariate probit
- Nested logit
- Ordered logit and ordered probit
- Partial proportional odds
- Random parameters (mixed) logit
- Random parameters (mixed) ordered logit
- Random parameters ordered probit
- Sequential binary logit
- Sequential binary probit
- Sequential logit

Of these, the study identified the most commonly employed techniques to be ordered logit and ordered probit (approximately 30%), binary logit and binary probit (approximately 16%), and multinomial logit (approximately 13%). While not commonly used methods, the authors indicated that neural networks "may be better served for prediction of injury outcomes" (Savolainen et al., 2011, p. 1673) and that decision tree models are an effective data mining technique.

Mannering and Bhat (2014) expanded upon Savolainen et al. (2011) by identifying methodological developments and applications that have occurred since 2011. The authors identified additional publications that employed binary logit/probit models (1 publication), multinomial logit models (3 publications), nested logit models (3 publications), sequential logit/probit models (1 publication), ordered logit/probit models (8 publications), generalized ordered outcome models (5 publications), bivariate/multivariate ordered probit models (4 publications), mixed logit model (random parameters logit model) (7 publications), finite-mixture/latent-class and Markov switching models (5 publications), mixed ordered probit (random parameters probit) model (1 publication), and spatial and temporal correlations (1 publication). The authors identified no additional studies using artificial neural networks or decision tree models.

Following Savolainen et al. (2011) and Mannering and Bhat (2014) as guides, this study conducted a literature review of the most common techniques used in crash injury severity analyses (ordered logit probit, binary logit and probit, and multinomial logit - and the contemporary approaches used in crash injury severity analyses - artificial neural networks and decision trees). Table 2.1 provides a summary of the prior research identified.

Table 2.1: Summary of Prior Research

Binary Logit/Probit			
Shibata and Fukuda (1994)	Farmer et al. (1997)	Khattak et al. (1998)	Krull et al. (2000)
Zhang et al. (2000)	Al-Ghamdi (2002)	Bedard et al. (2002)	Toy and Hammitt (2003)
Ballesteros et al. (2004)	Chang and Yeh (2006)	Sze and Wong (2007)	Chimba and Sando (2009)
Pai (2009)	Rifaat and Tay (2009)	Haleem and Abdel-Aty (2010)	Peek-Asa et al. (2010)
Kononen et al. (2011)	Moudon et al. (2011)	Santolino et al. (2012)	Yu and Abdel-Aty (2014)
Multinomial Logit			
Shankar and Mannering (1996)	Carson and Mannering (2001)	Abdel-Aty and Abdelwahab (2004)	Ulfarsson and Mannering (2004)
Khorashadi et al. (2005)	Islam and Mannering (2006)	Kim et al. (2007)	Malyshkina and Mannering (2008)
Savolainen and Ghosh (2008)	Schneider et al. (2009)	Malyshkina and Mannering (2010)	Rifatt et al. (2011)
Ye and Lord (2011)	Schneider and Savolanien (2011)	Eluru (2013)	Yasmin and Eluru (2013)
Amarasingha and Dissanayake (2013)	Ye and Lord (2014)		
Ordered Logit/Probit			
Khattak et al. (1998)	Klop and Khattak (1999)	Renski et al. (1999)	Khattak (2001)
Khattak et al. (2002)	Kockelman et al. (2002)	Quddus et al. (2002)	Abdel-Aty (2003)
Austin and Faigin (2003)	Kweon et al. (2003)	Zajac and Ivan (2003)	Khattak and Rocha (2003)
Donnell and Mason (2004)	Khattak and Targa (2004)	Abdel-Aty and Keller (2005)	Lee and Abdel-Aty (2005)
Shimamura et al. (2005)	Gårder (2006)	Lu et al. (2006)	Oh (2006)
Pai and Saleh (2007)	Gray et al. (2008)	Pai and Saleh (2008)	Wang et al. (2009)
Xie et al. (2009)	Amarasingha and Dissanayake (2010)	Haleem and Abdel-Aty (2010)	Jung et al. (2010)
Quddus et al. (2010)	Ye and Lord (2011)	Zhu and Srinivasan (2011)	Abay (2013)
Jiang et al. (2013a)	Jiang et al. (2013b)	Eluru (2013)	Yasmin and Eluru (2013)
Ye and Lord (2014)	Ariannezhad et al. (2014)		
Artifical Neural Networks			
Mussone et al. (1999)	Abdelwahab and Abdel-Aty (2001)	Abdelwahab and Abdel-Aty (2002)	Abdel-Aty and Abdelwahab (2004)
Bayam et al. (2005)	Delen et al. (2006)	Chimba and Sando (2009)	
Decision Tree			
Stewart (1996)	Kuhnert et al. (2000)	Sohn and Shin (2001)	Bayam et al. (2005)
Abdel-Aty and Keller (2005)	Yan and Radwan (2006)	Chang and Wang (2006)	Abellán et al. (2013)
Eustace et al. (2014)			

This study discovered the aforementioned literature reported both complementary and contradictory findings. A summary of the significant findings related to driver characteristics, contributing circumstances, temporal factors, weather characteristics, and road conditions is presented below, followed by a detailed review of each model type.

2.1 Summary of Significant Findings in Crash Severity Research

2.1.1 Driver Characteristics

- Delen et al. (2006) and Kuhnert et al. (2000) reported age as a significant factor in influencing injury severity; whereas Khattak et al. (1998) suggested that the impact of the adult driver category on crash injury severity was not different than that of the young driver category, when controlling for other factors.

- Khattak and Rocha (2003) found that young drivers increase the risk of higher injury severity in single-vehicle crashes, and Lu et al. (2006) indicated that young drivers have a greater risk of injury severity when traffic volume on roadways is moderately high. Yet, Haleem and Abdel-Aty (2010) found that young drivers have lesser risk of severe injury at unsignalized intersections.
- Khattak et al. (2002) reported that advancing age increases the likelihood of more severe injuries, and a one year increase in drivers' age beyond 74 years old decreases the risk for minor injury and increases the risk of a moderate, severe, or fatal injury.
- Additional studies also found older drivers to have higher risks of incapacitating or fatal injury, given a crash occurs (Bédard et al., 2002; Abdel-Aty, 2003; Abdelwahab and Abdel-Aty, 2002; Schneider et al., 2009; Rifaat et al., 2011; Yasmin and Eluru, 2013).

2.1.2 Contributing Circumstances

- Chang and Wang (2006) found that contributing circumstances and driver actions are critical in determining crash injury severity.

Inattention

- Zhu and Srinivasan (2011) reported distracted drivers as having a higher risk of greater injury severity, given a truck-only crash occurs.

Passenger Presence

- Studies found passenger presence increases the risk of injury (Savolainen and Ghosh, 2008; Schneider et al., 2009; Khorashadi et al., 2005), and it was reported that crash injury severity increases as the number of vehicle passengers increase (Renski et al., 1999; Oh, 2006).

Alcohol

- Many studies reported alcohol intoxication significantly increases the risk of severe injury (Khattak et al., 1998; Renski et al., 1999; Krull et al., 2000; Bédard et al., 2002; Khattak et al., 2002; Kockelman and Kweon, 2002; Abdel-Aty, 2003; Zajac and Ivan, 2003; Donnell and Mason, 2004; Delen et al, 2006; Rifaat and Tay, 2009; Schneider et al., 2009; Wang et al., 2009; Moudon et al., 2011; Yasmin and Eluru, 2013) and fatality (Islam and Mannering, 2006; Rifaat et al., 2011).
- When the vehicle driver is intoxicated, results suggested that the risk of injury for a bicyclist (Kim et al., 2007) or motorcyclist (Schneider and Savolainen, 2011) involved in the collision increases by a large margin; and, Siddiqui et al. (2006) discovered that being struck by an intoxicated driver is one of the largest fatal injury risk factors for pedestrians.
- Model results for rear-end collisions found that alcohol was the most significant factor that effect the likelihood of a driver striking another vehicle (Yan and Radwan, 2006); and, Eustace et al. (2014) suggested that alcohol and drug use increase the probability of run-off-road injury severity levels.

Speed

- A dozen studies reported that speeding (Khattak et al., 1998; Khattak and Rocha, 2003; Schneider et al., 2009) and higher speed limits (Renski et al., 1999; Khattak et al., 2002; Oh, 2006; Gårder, 2006; Malyshkina and Mannering, 2010; Savolainen and Ghosh, 2008; Haleem and Abdel-Aty, 2010; Zhu and Srinivasan, 2011; Yasmin and Eluru, 2013) significantly increase the risk of severe injury.

- Zajac and Ivan (2003) found that, given a collision between a car and a pedestrian, speed limit did not significantly affect pedestrian injury severity as expected.
- As the ratio of the estimated speed at the time of the crash to the posted speed limit increases, results indicated that the level of injury severity increases (Abdelwahab and Abdel-Aty, 2001; Abdelwahab and Abdel-Aty, 2002).
- Research suggested that driving at speeds too fast for conditions increases the risk of crash severity (Rifaat and Tay, 2009) and crashes resulting in fatality (Shibata and Fukuda, 1994; Bédard et al., 2002).

Speed and Interaction Variables

- Results uncovered that the interaction of higher speed limits and alcohol increase the risk of crash injury severity (Yan and Radwan, 2006; Eustace et al., 2014). Eustace et al. (2014) found that females driving in a higher posted speed limit have a higher risk of injury, and males with drug involvement driving in a higher posted speed limit have a higher risk of injury.

2.1.3 Temporal Factors

Time of Day

- Research indicated that peak travel time (Khattak et al., 1998) and higher annual daily traffic (Klop and Khattak, 1999) decrease the risk of injury severity.
- Many studies reported that crashes occurring at night increase the risk of injury (Krull et al., 2000; Quddus et al., 2002; Abdel-At, 2003; Rifaat et al., 2011; Yasmin and Eluru, 2013).
- Conversely, studies also reported that crashes during day-light hours increase the risk of injury (Krull et al., 2000; Savolainen and Ghosh, 2008).

Lighting

- Findings indicated that dark, unlit conditions increase injury severity (Klop and Khattak, 1999; Rifaat and Tay, 2009; Haleem and Abdel-Aty, 2010), favorable lighting conditions decrease injury severity at freeway diverge areas (Wang et al., 2009), dusk (over dark) reduce the risk of severe injury at unsignalized intersections (Haleem and Abdel-Aty, 2010), and darkness increases the risk of greater injury severity for older drivers (Khattak et al., 2002).

2.1.4 Weather Characteristics

- Wang et al. (2009) found that favorable weather decreases injury severity; and, Abdel-Aty (2003) reported that adverse weather increases injury severity.
- Yet, Khattak et al. (1998) found adverse weather to significantly decrease the risk of severe injury for crashes; and Delen et al. (2006) indicated that weather conditions and time of crash are not influential in crash injury severity.

2.1.5 Road Conditions

- Lu et al. (2006) claimed that road condition has the greatest influence on crash severity; however, Jiang et al. (2013b) concluded that improved road quality does not essentially reduce injury severity.
- Khattak et al. (1998), Rifaat and Tay (2009), and Quddus et al. (2010) reported that wet/slippery road surface decreases the risk of severe injury; yet, Krull et al. (2000) and Zhu and Srinivasan (2011) found that dry surfaces increase the risk of severity for truck-only crashes.

2.2 Review of Methodological Approaches

2.2.1 Binary Logit and Probit

Savelonien et al. (2011) identified seventeen studies and Mannering and Bhat (2014) identified an additional study in which binary logit and probit methodologies were used to analyze motor vehicle crash-injury severity. The analyzed binary outcomes related to the crash were fatal or nonfatal personal injury (Shibata and Fukuda, 1994; Al-Ghamdi, 2001; Bédard et al., 2002; Ballesteros et al., 2002; Chang and Yeh, 2006), severe injury (fatal or incapacitating) or non-severe injury (Farmer et al., 1997; Krull et al., 2000; Toy and Hammitt, 2003; Chimba and Sando, 2009; Pai, 2009; Haleem and Abdel-Aty, 2010; Peek-Asa et al., 2010; Kononen et al., 2011) injured or not injured (Rifaat and Tay, 2009), fatal/severely injured or slightly injured (Sze and Wong, 2007) hospitalized or not hospitalized (Santolino et al., 2012), crash involvement or noninvolvement (Khattak et al. (1998), and pedestrian fatality/disability or no pedestrian fatality/disability (Moudon et al., 2011).

A review of the literature that employed binary logit and probit methodologies uncovered significant findings related to weather characteristics, road characteristics, and contributing circumstance. Excerpts from these findings are presented below, followed by a more detailed summary of each piece of research.

- Higher speed limits, greater speed of travel, and driving at speeds too fast for conditions increase the risk of crash severity (Rifaat and Tay 2009) and crashes resulting in one or more fatalities (Shibata and Fukuda, 1994; Bédard et al., 2002).

- Khattak et al. (1998) and Rifaat and Tay (2009) reported a higher probability of crash severity on wet road surfaces; yet, Krull et al. (2000) found that dry pavement increases the probability of severe injury.
- Al-Ghamdi (2001) found that the odds that a fatal crash will occur due to running a red light were 2.72 times higher than non-running-red-light crashes, and the odds ratio of being involved in a fatal crash in a wrong-way related crash were three times higher than a failure-to-yield related crash.
- Rifaat and Tay (2009) and Haleem and Abdel-Aty (2010) found a greater likelihood of crash severity during darkness; yet, Krull et al. (2000) reported greater severity during daylight hours.
- Alcohol intoxication by the driver results in a greater likelihood of crash severity (Krull et al., 2000; Bédard et al., 2002; Rifaat and Tay, 2009; Moudon et al., 2011).
- Drivers aged 80+ are associated with higher fatality odds (Bédard et al., 2002); and, young drivers experience a reduced probability of severe injury (Haleem and Abdel-Aty, 2010).

Shibata and Fukuda (1994)

Shibata and Fukuda (1994) developed two unconditional multiple logistic regression models (using dummy variables) to (1) evaluate the relationship strength for driver's license, speed, alcohol use and seatbelt/helmet use when controlling for age and (2) simultaneously control for age and other factors to determine the likelihood that a crash would result in 'death' or 'uninjured'. Results suggested that unlicensed drivers had a higher likelihood of fatality resulting from a crash, and the risk increased when the unlicensed driver was a male motorcyclist. Additionally, the authors reported that the risk for fatality increased as speed increased, and seatbelt and helmet use prevented fatalities for both genders and types of drivers (motorcyclists and non- motorcyclists). The authors concluded that education and supervision of speed, alcohol use, and seatbelt/helmet use would lead to reduction of traffic fatalities.

Farmer et al. (1997)

Farmer et al. (1997) investigated the relationship of vehicle and crash characteristics with injury severity for two-vehicle side impact crashes. The authors used chi-square statistics and logistic regressions to assess the individual and simultaneous effects of occupant, vehicle and crash characteristics on the probability of a serious injury occurring. Results indicated that light truck occupants were less likely to be seriously injured than car occupants. Additionally, right-angle crashes were more likely to cause a rollover, light trucks were 14 times more likely to roll when side struck than cars, and the likelihood of serious injury for the subject vehicle increased as the speed limit increased. The authors concluded that side-struck occupants in cars had a higher probability of being seriously injured than those in light trucks, and seat belts enhanced injury prevention for far-side occupants in side-impact crashes.

Khattak et al. (1998)

Khattak et al. (1998) explored the adverse impact of weather on crash risk using binary probit models. Results suggested that on limited-access roadways drivers did not compensate for poor visibility and slippery road surface, which resulted in a greater likelihood for crash involvements and sideswipes.

Krull et al. (2000)

Krull et al. (2000) explored the events leading to rollovers and the effect of rollovers on driver injury. The authors employed binary regression models to help identify the factors that affect crash severity, and to provide a numerical relationship between the factors and the probability that a fatal or incapacitating injury would occur. For the pooled model including Michigan and Illinois data, results indicated that rollover involvement, passenger cars, no restraint, alcohol use, day light, rural roads, higher speed limits, and dry pavement increased the probability of severe injury. The authors concluded by recommending rollover-prevention efforts to focus on improved ditch designed and curve treatments.

Zhang et al. (2000)

Zhang et al. (2000) examined the relationship between potential risk factors and crash injury severity when a motor vehicle traffic crash involved an elderly driver. Factors examined included age and sex of the driver, driver condition, driver action, seat belt use, ejection from the vehicle, month, day and hour of collision, road alignment, roadway configuration, road surface condition, speed limit, weather conditions, light conditions, crash configuration, vehicle type, vehicle maneuver, medial/physical conditions (chronic diseases or physical handicaps), and use of alcohol. The authors developed multivariate unconditional logistic regression models (using dummy variables) to estimate the magnitude of each factor in relation to crash injury severity. Results indicated that medical and physical conditions increase the risk of fatality for drivers aged 75 years and older. The authors concluded by calling for future research to examine driver actions, such as failing to yield and traffic signs violation.

Al-Ghamdi (2001)

Al-Ghamdi (2001) developed a logistic regression model to identify the most probable factors that affect crash injury severity in Saudi Arabia. Results suggested that the odds of a fatal crash occurring at a non-intersection location are 2.62 higher than at an intersection. Additionally, model outcomes indicated that the odds of a fatal crash will occur because of running a red light are 2.72 times higher than non-running-red-light crashes, and the odds ratio of being involved in a fatal crash in a wrong-way related crash are three times higher than a failure-to-yield related crash. In response to these findings, the authors concluded that logistic regression is a promising tool in providing meaningful interpretations for safety improvements.

Bédard et al. (2002)

Bédard et al. (2002) used the US Department of Transportation's Fatal Accident Reporting System database to investigate driver fatalities, given a single-vehicle crash with fixed objects occurred. Explanatory variables included in the study are driver characteristics (age, gender, blood alcohol concentration, seatbelt use), crash characteristics (impact direct, vehicle deformity, vehicle speed), vehicle characteristics (air bags, weight, wheelbase length, model year, vehicle age), and the outcome variable, injury severity, was dichotomized as fatal or non-fatal. Findings suggested that female drivers, a blood alcohol level of greater than 0.30, driver-side impacts, speeds exceeding 69 mph, and drivers aged 80+ were associated with higher fatality odds. The authors concluded that seatbelt use, speed reduction and driver-side impact reduction may prevent fatalities; and, safety measures and policy associated with older drivers and female drivers may need to be addressed separately.

Toy and Hammitt (2003)

Toy and Hammitt (2003) investigated the relative attributes of cars on the probability that a serious and fatal injury would result in a two-vehicle crash, and compared these results with LTVs. The authors obtained 6,481 observations from two-vehicle crashes that occurred during 1993 to 1999 from the Crashworthiness Data System. They developed a conceptual framework based on existing literature, which incorporated potential personal risk factors: own vehicle factors (mass, stiffness, geometry), other vehicle factors (mass, stiffness, geometry), own driver factors (age, gender, restraint use, behavior), crash factors (severity, configuration), and other driver factors (behavior). Additionally, the authors constructed a logistic regression model with the binary outcome of 'seriously injured or killed' or 'not seriously injured or killed', conditional on a crash occurring. Results indicated that vehicle characteristics have a significant impact on risk, and SUVs, vans and pickups appear more crashworthy than cars. Additionally, pickup drivers face less risk or serious injury than car drivers, and drivers who have a collision with pickups are more than twice at risk than when striking a car. Overall, findings indicated that vehicle mass, body type and crash severity increase the ability of the passenger vehicle to protect its occupants during a crash (i.e. crashworthiness of the passenger vehicle).

Ballesteros et al. (2002)

Ballesteros et al. (2002) studied 1995 to 1999 data of pedestrians who had been treated at a Maryland trauma center or died as a result of being struck by a car, sport utility vehicle (SUV), pick-up truck (PU), or van. The authors obtained vehicle type data from the Maryland Automated Accident Reporting System database, injuries data from the Maryland Trauma Registry, and fatality data from the Maryland Office of Chief Medical Examiner records, and linked the databases together in order to trace pedestrians from the crash scene to the final medical outcome. The authors categorized outcome variables as pedestrian mortality (fatal, non-fatal), pedestrian injury severity score (≤3, 4-8, 9-15, 16-24, >25), and pedestrian injuries to specific body regions. Independent variables included vehicle type (conventional automobile, SUV, PU, or van), speed limit (≤25, 30-35, >40 mph), and weight (≤2454, 2455-2906, 2907-3394, >3395 lbs.). Results indicated that compared to conventional cars, pedestrians who had been struck by an SUV or PU had a higher probability of severe injury and death; and, the increased risk could be attributed primarily to the heavier vehicle weight and faster vehicle speed. Additionally, pedestrians who were struck by an SUV, PU, or van at lower speeds were more likely to incur traumatic brain, thoracic, and abdominal injuries than those hit by a conventional car. The authors suggested that pedestrian injuries could be alleviated through vehicle design modifications.

Chang and Yeh (2006)

Chang and Yeh (2006) developed two logistic regression models to assess the risk factors that increased the likelihood of fatality for non-motorcycle drivers and motorcyclists in single-vehicle crashes, and to compare the differing risk factors between the two driver types. The results indicate that the amount of fatal injuries for motorcyclists in single-vehicle crashes was higher than non-motorcycle drivers. Both types of drivers, male gender, older in age, and time between 2200 and 0600 hours were found to increase the likelihood of a fatal crash. The authors concluded by recommending that to reduce the risk of fatal crashes for both motorcyclists and non-motorcycle drivers', seatbelt-use, running-speed management, rider's risk perceptions, and road quality should be enhanced.

Sze and Wong (2007)

Sze and Wong (2007) explored factors that lead to pedestrian injury severity resulting from traffic crashes in Hong Kong. Findings indicated that, given a collision occurs, male gender and under 15 years-old, occupying an overcrowded or obstructed footpath, and a daytime crash on a road with severe/moderate congestion have a lower risk of pedestrian mortality and severe injury. The authors called for more extensive data collection and comprehensive analysis of pedestrian flow and risk factors.

Chimba and Sando (2009)

Chimba and Sando (2009) compared artificial neural networks (ANN) and probit (OP) models for their prediction power in highway traffic crash injury severity levels coded as 0 for property damage only, possible injury, and non-incapacitating and 1 for incapacitating and fatal crashes. The authors claimed that while many studies have applied a form of the ANN technique to predict crash counts, few have applied the methodology to injury severity modeling. The authors collected data for crashes occurring in 2003 on arterial segments of the Florida state highway system from the Florida Department of Transportation, which resulted in 1,271 records. Findings indicated that the ANN resulted in an approximate prediction accuracy of 83.3%, while the OP had a prediction accuracy of 65.5%. This finding suggests that a well-structured ANN can produce higher prediction performance relative to the OP approach.

Pai (2009)

Expanding upon Pai and Saleh's (2007) exploration of motorcyclists' crash injury severity at T-junctions, Pai (2009) examined the factors impacting motorcyclist injury severity given a motorcycle-car angle crash occurred at a T-junction. The authors estimated two binary logistic models with differing explanatory variables (model 1: angle perpendicular collisions and model 2: oblique collisions) to assess killed or seriously injured motorcyclists over slight injuries, as explained by vehicle, weather, temporal, human and environmental factors. Estimation results suggested that the most dangerous crash patterns were those in which one traveling-straight motorcycle collided with a right-turn/left-turn car traveling from a minor road, primarily at stop-controlled and yield-controlled junctions. The authors presumed that this occurrence resulted from right-of-way/failure-to-yield violation, and that this finding could be used to enhance law enforcement efforts and safety educations programs.

Rifaat and Tay (2009)

Rifaat and Tay (2009) explored how differing street patterns affect crash injury severity. The authors collected 35,993 observations from Alberta Transportation crash data from 2003 to 2005 with variables including road characteristics, drivers' characteristics, crash characteristics, environmental conditions and vehicle attributes. They developed a binary regression model to determine the likelihood that, given a two-vehicle crash, an injury to any person involved would occur. Findings suggested that the loops and lollipops pattern was the only statistically significant road pattern (at a 90% confidence level) that decreased injury risk of crashes, and the gridiron pattern was the only type of street pattern to increase the risk of injury, which suggested that roads with frequent curves are marginally safer. Additionally, crash severity was higher on divided roads with no barrier, on wet surfaces, during darkness, when alcohol was used by the driver, when turning left across path and stop signs, and when driving at speeds too fast for conditions.

Haleem and Abdel-Aty (2010)

Haleem and Abdel-Aty (2010) compared ordered probit, binary probit and nested logit methodologies to aid in the selection of the best modeling technique for injury severity analysis for crashes occurring at unsignalized intersections in Florida. The authors developed two separate models to analyze the relationship between severe injuries (incapacitating injury and fatal injury), non-severe injuries (property damage only, possible injury, and non-incapacitating injury), and explanatory characteristics at three and four legged intersections. Findings indicated that lack of stop lines, one left turn lane, larger right shoulder width, and smaller intersections increase the probability of severe injury, and lower speed limits, young drivers, crashes occurring at dusk (over dark), and highly-urbanized areas reduce probability of severe injury. When comparing the binary probit and the ordinal probit frameworks, the authors concluded that the aggregated binary probit model had a lower Akaike information criterion (AIC) and a higher likelihood at convergence, which indicated that the binary probit model better fit the data.

Peek-Asa et al. (2010)

Peek-Asa et al. (2010) examined traffic crashes for 10 through 18 year-old Iowa drivers who were involved in a crash from 1995 to 2004. The authors developed a binary logit model to analyze the likelihood that a crash would result in a fatal or severe injury as the result of a rural setting (both population-based and crash location based), driver variables, crash characteristics, and environmental characteristics. Results indicated that remote rural teens were less likely to be involved in a crash than urban teens; and, suburban, rural and remote rural teens aged 10 through 15 had a higher fatal and severe crash rate when compared to urban teens. Findings indicated failure to yield to be the most common circumstance contributing to a crash for both urban and rural teen drivers. Reckless driving, speeding, and animal collisions were more commonly reported crash causes for urban drivers, and fatality rates were higher for urban drivers when following too closely. Results suggested the likelihood that a rural teen driver was involved in a fatal or severe injury crash is five times greater than a rural teen driver, and rural teen drivers are more likely to be involved in crashes that are single-vehicle, late at night, resulting from failing to yield and crossing the center divider. The authors recommended the implementation of intervention programs to address specific rural roadway risk factors for teenage drivers.

Kononen et al. (2011)

Kononen et al. (2011) developed a binomial logistic regression model to assess if delta-v (the change in vehicle velocity due to the force of the crash), direction of impact, vehicle type, belt use, number of impacts, age and gender in order to determine affect crash injury severity. Results denoted that significant predictors of serious injury resulting from a crash were delta-v, seat belt use, and crash direction.

Moudon et al. (2011)

Moudon et al. (2011) estimated the likelihood that a motor vehicle and pedestrian collision would result in a pedestrian fatality or disability. The authors developed binary logit models to analyze state routes and city routes, and included independent variables from the individual level (pedestrian socio-demographic characteristics, pedestrian behavior characteristics, driver behavior driver vehicle action), road environment (temporal characteristics of collision, road characteristics, traffic conditions), and neighborhood environment (density, land use destinations, neighborhood wealth). Results suggested that alcohol use on state routes increased the risk of injury severity; and females, older pedestrians, and more than one pedestrian involved increased the risk of severe injury on both road types.

Santolino et al. (2012)

Santolino et al. (2012) obtained 16,081 observations from the Spanish motor insurance database, and developed regression models to examine the likelihood that a motor vehicle crash results in hospital admittance and the duration of the stay. The authors reported that age, gender, vehicle type, location and nature of the injuries were significant influencers in the risk of hospital admittance and/or length of stay required for recovery. Notable findings indicated that older men with head and lower torso fractures and injuries had a higher probability of being hospitalized, and older men had a higher likelihood of a longer hospital recovery time. The authors concluded that understanding the relationship between hospital admittance and duration of stay can help form policy and educate practitioners.

2.2.2 Multinomial Logit Models

Savelonien et al. (2011) identified eighteen studies and Mannering and Bhat (2014) reported four additional studies in which multinomial logit methodologies were used to analyze crash injury severity with outcomes categorized as three, four or five levels. The three-level approach identified examined the risk of property damage only or no-injury, injury, and fatality (Shankar and Mannering, 1996; Carson and Mannering, 2001; Islam and Mannering, 2006; Malyshkina and Mannering, 2008; Malyshkina and Mannering, 2010; Rifaat and Tay, 2011), the two four-level approaches identified examined the risk of non-injury or property damage only, possible injury, evident injury or non-incapacitating, and fatal/disabling injury or fatal/incapacitating (Ulfarsson and Mannering, 2004; Khorashadi et al., 2005; Savolainen and Ghosh, 2008; Amarasingha and Dissanayake, 2013; Yasmin and Eluru, 2013) and possible or no injury, non-incapacitating, incapacitating, and fatal (Kim et al., 2007), and the five-level approach identified examined the risk of property damage only, possible injury, non-incapacitating injury, incapacitating injury, and fatal injury (Schneider et al., 2009; Schneider and Salovainen, 2011; Ye and Lord, 2014).

A review of the literature that employed multinomial logit models discovered significant findings related to weather characteristics, road characteristics, and contributing circumstances were discovered. Excerpts from these findings are presented below, followed by a more detailed summary of each piece of research.

- Given a crash occurrence, findings suggested that older drivers have higher risks of incapacitating or fatal injury (Schneider et al., 2009; Rifaat et al., 2011; Yasmin and Eluru, 2013).
- Studies suggested passenger presence increases the risk of injury (Savolainen and Ghosh, 2008; Schneider et al., 2009; Khorashadi et al., 2005) and the risk of fatality for young males and middle-aged males (Islam and Mannering, 2006).

- Research indicated that speeding and higher speed limits increase the risk of injury (Savolainen and Ghosh, 2008; Schneider et al., 2009; Malyshkina and Mannering, 2010; Yasmin and Eluru, 2013), the likelihood of fatality for middle-aged men (Islam and Mannering, 2006), and the risk of injury severity when the crash occurs at a rural location (Khorashadi et al., 2005).
- Studied reported alcohol impairment increases the risk of injury (Schneider et al., 2009; Yasmin and Eluru, 2013) and fatality (Islam and Mannering, 2006; Rifaat et al., 2011). When the vehicle driver was intoxicated, findings suggested that the risk of injury for a bicyclist (Kim et al., 2007) or motorcyclist (Schneider and Savolainen, 2011) involved in the collision increase by a large margin.
- Savolainen and Ghosh (2008) reported that crashes during day-light hours increase the risk of injury; yet, contradictory findings indicated that crashes occurring at night increase the risk of injury (Rifaatt et al., 2011; Yasmin and Eluru, 2013).
- One study found that crashes during the spring and summer seasons increase the likelihood of injury occurring in some states (Savolainen and Ghosh, 2008), while another study suggested that the winter season increase the risk of injury (Rifaatt et al., 2011).

Shankar and Mannering (1996)

Shankar and Mannering (1996) developed a multinomial logit model to determine the likelihood that a single-vehicle motorcycle crash would result in property damage only, possible injury, or fatality based on helmet use, location (interstate or arterial), high displacement, intersections, and/or alcohol intoxication. Findings suggested that a helmeted-rider and a fixed object interaction increased the risk of fatality; no-helmet and a fixed-object interaction increased the risk of evident injury; no-helmet and alcohol-impairment riding interaction increased the risk of fatality; no-helmet and low-speed interaction increased the risk of evident and disabling injury; alcohol-impaired riding increased the risk of fatality, evident and disabling injuries; motorcycle displacement increased the risk of fatality, evident or disabling injury; age-displacement interaction increased the risk of property damage, possible injury and disabling injury; motorcycle rider age increased the risk of fatality and disabling injury; ejection of rider increased the risk of any form of injury relative to property damage; speeding increased the risk of fatality, evident injury and disabling injury; rider inattention increased the risk of evident and disabling injury; interstate riding increased the risk of disabling and possible injury; and, wet pavement and not-raining interaction increased the risk of possible injury and property damage.

Carson and Mannering (2001)

Carson and Mannering (2001) evaluated the usefulness of ice-warning signs in Washington to analyze the impact of road characteristics on highway safety when ice was present. The authors developed a multinomial logit structure to determine the probability of a crash resulting in a fatal, injury, or property damage only outcome. However, the model did not identify temporal, traffic, roadway, spatial or crash placement characteristics to significantly influence crash injury severity; and, the results suggested that the presence of ice-warning signs did not significantly affect the severity of crashes when ice was involved.

Abdel-Aty and Abdelwahab (2004b)

Abdel-Aty and Abdelwahab (2004b) analyzed rear-end crashes categorized as regular passenger car striking regular passenger car; regular passenger car striking light truck; light truck striking regular passenger car; and light truck striking light truck. The authors developed a multinomial logit model as the basis for four additional nested logit models to develop an appropriate nesting structure to examine rear-end crash types, driver gender of the striker vehicle, younger driver age (between 15 and 24), older driver age (75 and older), light condition, traffic single and driver distraction data. The final model indicated the significant variables to be driver's age, traffic control device, action initiated by the lead vehicle, gender, inattention, and vision obstruction of the driver of the striker vehicle. The authors concluded that the risk of a car-truck rear-end crash increased when the driver of the striker vehicle was distracted, light truck vehicles obscure the visibility of drivers of other passenger vehicle, and that vision obstruction of the striker vehicle is the most prominent effect on rear-end crashes.

Ulfarsson and Mannering (2004)

Ulfarsson and Mannering (2004) estimated statistical models to examine the differences in crash injury severity between male and female drivers when a passenger car, pickup, sport-utility vehicle (SUV) or minivan was involved in a collision. The authors estimated separate frequency and percentage distribution models for male and female drivers for seven combinations of vehicle-crash categories using observations from 1993 to 1996 obtained from the Washington State Department of Transportation. Additionally, the authors designed separate multinomial logit models to analyze the effect of driver characteristics, driver violations, driver action proceeding crash, vehicle characteristics, road and operating characteristics, crash characteristics, environmental characteristics, and temporal characteristics on the likelihood of a crash resulting in non-injury, possible injury, evident injury, or fatal/disabling injury for male and female genders. Results indicated that female drivers of passenger cars who collide with a SUV/minivan have a higher risk of possible injury when avoidance maneuvers are exhibited; though, the same avoidance maneuvers increase the risk of evident injury for male drivers of passenger cars. Additionally, findings suggested that when sudden slowing occurs, a male driver of a passenger car has an increased risk of evident injury and a female driver of a passenger car has an increased risk of fatal/disabling injury. When striking a barrier, male drivers have a decreased risk of greater severity, while female drivers have an increased risk of greater severity. The authors claimed that the observed differences suggest that behavioral and physiological factors impact injury severity, and reported that lack of seat-belt restraint and alcohol use lead to an increased probability of higher injury-severity for both genders. Lastly, findings did not suggest driver age as statistically significant in each model; however, in the models where driver age was significant, the risk of injury severity increased for drivers who were at most 25-years-old and for drivers at least 65-years-old.

Khorashadi et al. (2005)

Khorashadi et al. (2005) developed a multinomial model to explore factors that significantly impact crash injury severity for passenger-vehicle and large-truck drivers. The authors combined records from the California Department of Transportation and the California Highway Patrol to obtain weather conditions, geometric data, road conditions, roadway terrain, pavement surface data, driver-related data, and speed limit data in order to estimate the severity of injury (categorized as no injury, complaint of pain, visible injury, and severe/fatal injury). Variables reported to have a significant increase on injury severity for urban but not rural crashes were driver age between 15 and 22, beyond left shoulder collision, broadside collision, and a vehicle model year older than 1981. The authors concluded that these differences suggest interactions between driver behavior and environmental conditions play an integral role in injury severity.

Islam and Mannering (2006)

Islam and Mannering (2006) explored the effect of driver aging on male and female single-vehicle crash injury severity to evaluate the effectiveness of safety countermeasures using 1999 data from Indiana's Accident Information System. The authors developed six models: young female drivers (aged 16 to 24), young male drivers (aged 16 to 24), middle-aged female drivers (aged 25 to 64), middle-aged male drivers (aged 25 to 64), older female drivers (aged 65 and older), and older male drivers (aged 65 and older). Likelihood ratio tests indicated that the hypothesis that the female and male injury severity models would produce equal coefficient estimates could be rejected, and significant statistical evidence suggested differences of injury severity by age for both genders. Notable results signified that rollovers increased the probability of fatality by 220% for older males, but only 116% for middle-aged males. When at least one passenger was present, probability of fatality was 114% and 70% for young males and middle-aged males respectively, but no significant effect for older males. When no seat belt was used, the risk of injury for young females increased by 119%, for middle-aged females increased by 164%, and for older females increased by 187%. Crashes in rural areas increased risk of fatality by 208% for young females, but had no significant impact on older female age categories. For middle-aged men, falling asleep at the wheel and speeding increased the risk of fatality (not found significant in female middle-aged drivers). Finally, for middle-aged females, illness and alcohol increased the likelihood of fatality; yet, neither was identified as a statistically significant factor for middle-aged men.

Kim et al. (2007)

Kim et al. (2007) developed a multinomial model to examine bicyclist injury severity resulting from a motor vehicle crash. Model results indicated that bicyclists who were at least 55 years old have a higher probability of a fatality than younger age groups, and helmet use decreases the risk of fatality and possible injury. Additionally, findings indicated bicyclist intoxication increases the risk of a fatal injury resulting from a crash with a vehicle; and, when the vehicle driver is intoxicated, the risk of fatality and incapacitating injury increase by a large margin. Results also suggested that as vehicle speed increases, the likelihood of a fatal and incapacitating injury for the bicyclist increase. Additional findings suggested collisions involving pickup trucks involve higher risk of all injury types, and head-on collisions, curved roads, and collisions in inclement weather increase the likelihood of a bicyclist fatality. The authors concluded that that behavior modification (such as helmet use), engineering, and policy can aid in the reduction of bicyclist injury severity resulting from a collision with a motor vehicle.

Malyshkina and Mannering (2008)

In response to the increased interstate speed limit in Indiana, Malyshkina and Mannering (2008) assessed the relationship between speed limit and observed crash injury severity. The authors conducted a cross-sectional data comparison of the different speed limits for specific roadways for a single year (2004 or 2006). This approach indicated that the estimates for injury severity on interstates with a 65 mph speed limit in 2004 that increased to 70 mph in 2006 did not significantly change. The authors concluded that the higher speed limits on Indiana Interstates did not significantly affect crash injury severity.

Savolainen and Ghosh (2008)

Savolainen and Ghosh (2008) examined the risk of vehicle, environmental and driver characteristics on driver injury severity resulting from deer-vehicle crashes (DVCs). The authors estimated the underreporting rate for DVC at approximately 50%, and therefore chose a multinomial logit since this methodology does not create the same biased and inconsistent model coefficient estimates that an ordered probability model could create. Results suggested that, given a deer-related crash occurs, younger drivers and female drivers have a higher risk of injury compared to older drivers and male drivers respectively. The use of a safety belt decreased the risk of moderate or severe injury, and air bag usage decreased the risk of property damage only and incapacitating/fatal injury. Additionally, findings suggested passenger presence, crashes during day light hours, run-off-the-road crashes, spring and summer season, and high speed to increase the likelihood of injury occurring.

Schneider et al. (2009)

Schneider et al. (2009) assessed driver injury severity to improve safety on rural Texas highways. The authors reported that driver injury had a higher likelihood of occurring in the medium curve radius group, and injuries were most severe when the crash vehicle ran off the road. Horizontal and vertical curvature in combination increased the risk of fatal crashes when the curvature was of medium radius by 560%. Findings suggested that as driver age increase, so does the risk of incapacitating or fatal injury; and, female drivers have a 23 to 31% higher probability of being injured than male drivers. Additionally, results indicated that driver fatigue, speeding, drug or alcohol use, and passenger presence increase the likelihood of a crash resulting in an injury. Finally, model outcomes indicated that motorcyclists have a higher risk of being seriously injury or killed, and belt use increases the probability that no injury will occur.

Malyshkina and Mannering (2010)

Malyshkina and Mannering (2010) compared thirteen design exceptions on roadway segments and 35 design exceptions at bridges with 26 roadways and 69 bridges without design exceptions in order to assess the impact of design exceptions on crash frequency and injury severity. The authors developed multinomial logit models and mixed multinomial logit models to assess the likelihood of severity, and multinomial negative binomial models to assess the likelihood of crash frequency. Estimation results indicated that vehicle age increases the risk of fatality, and snow and slush reduces the risk of fatality and injury. Findings suggested that crashes that did not occur at an intersection and those that did occur in an urban area have a lower risk of injury. Results also suggested that female drivers, higher posted speed limits, and driver-related causes increase the likelihood injury. Additionally, when assessing crash frequency, findings indicated that asphalt surface, the presence of interior shoulders, and a higher degree of curvature have a lower crash risk; and, urban roads, longer road-segments, and an increased number of ramps have an increased crash risk. The authors concluded that the current process of design expectations has sufficiently avoided adverse safety implications.

Rifaatt and Tay (2011)

Rifaatt and Tay (2011) developed a multinomial logit model to identify the effect of various street patterns - grid-iron, warped parallel, mixed and loops and lollipops - on the risk of injury severity for pedestrians and bicyclist involved in a crash. Findings implied that, when compared to other designs, the loops and lollipops pattern have a higher probability that an injury will be no-fatal, and older drivers and drivers under the influence have a higher risk fatality, given a crash occurs. Additional findings indicated that the risk of a fatality increases when the pedestrian or bicyclist is involved in a crash on a divided road with a barrier, and the risk of injury increases during the winter season and darkness hours.

Ye and Lord (2011)

Ye and Lord (2011) investigated the effect of underreporting of crash data when assessing crash severity on multinomial logit, ordered probit and mixed logit models by evaluating how each model performed for different unreported rates. The authors used a Monte-Carlo approach to verify the underreporting effects on the models, and evaluated the bias through comparison of estimation results to observed crash data from the Texas Department of Public Safety and the Texas Department of Transportation. The authors proposed using the Weighted Exogenous Sample Maximum Likelihood Estimator (WESMLE) to account for underreporting conditions. Findings suggested that the root-mean-square-error (RMSE) increased when using the maximum likelihood estimator for all three models. When ordering outcomes, the lowest severity has the largest underreported rate; and, the WESMLE performed well regardless of the size of the unreported rate for each model. The authors concluded that to minimize bias, fatal crashes should be set as the baseline severity for the mixed logit and multinomial logit models, while the ordered probit model should rank crash severity in descending order.

Schneider and Salovainen (2011)

Schneider and Salovainen (2011) developed multinomial logit models to examine motorcycle crash data to assess the effects of rider characteristics, crash characteristics, roadway geometry and environmental factors on crash injury severity. The estimation results indicated that helmet use is the most effective means of risk reduction for a fatal or severe injury, which reinforces previous findings. Additionally, the authors concluded that alcohol, female gender, motorcycle speed and age increase the risk of incapacitating or fatal injuries.

Eluru (2013)

Eluru (2013) explored the appropriate model choice for injury severity analysis through the comparison of ordered response methodologies (ordered logit model and generalized ordered logit model) with unordered response methodologies (multinomial logit models). The author developed simulation models with three independent variables and four alternate ordered dependent variables to compare the performance of the frameworks. Parameters were selected so that the models would generate consistent shares for the parameter set. To assess the model fit, the author compared the generalized ordered logit and the ordered logit models to the unordered models using the likelihood ratio test. The Bayesian Information Criterion was employed to measure the comparison for the generalized ordered logit and the multinomial logit models. Model estimation comparison results indicated that, when compared to the multinomial model, the generalized ordered logit model performed satisfactorily. The authors concluded that the results provide credibility to the generalized ordered logit model.

Yasmin and Eluru (2013)

Expanding upon Eluru (2013), Yasmin and Eluru (2013) explored methodological approaches used to assess driver injury severity in traffic crashes by comparing ordered response methodologies (order logit, generalized ordered logit, mixed generalized order logit) with unordered response methodologies (multinomial logit, nested logit, ordered generalized extreme value logit, and mixed multinomial logit). The authors selected data in which a private passenger vehicle collided with either another passenger vehicle or fixed object, and used a final dataset of approximately 30,371 records (12,170 records for estimation and 18,201 records for validation). They categorized injury outcomes as no injury (65.9%), possible injury (15.1%), non-incapacitating injury (12.1%), and incapacitating/fatal injury (6.96%). (Due to the small sample of fatal occurrences, 0.7%, fatalities were combined with incapacitating injuries.) The authors categorized explanatory variables as driver characteristics (gender, age, restraint use, alcohol and drug use); vehicle characteristics (type and age); roadway design and operational attributes (class, seed limit, interaction type and traffic control device); crash characteristics (driver ejection, roll over, air bag deployment, collision location, manner of collision); and, environmental factors (time and road surface condition). Estimation results suggested that drivers under the age of 25 have a lower risk that an injury will be severe. Model results found that the effect of driver age of at least 65 was only significant in the mixed multinomial logit model, and this population has a greater risk of incapacitating/fatal injury. Mixed generalized order logit results suggested a higher risk for injury during the morning peak and off-peak periods; yet, the mixed multinomial logit model results indicated that night-time has a higher likelihood of non-incapacitating and incapacitating/fatal injuries. Findings suggested that seatbelt use significantly decreases the risk of injury, and alcohol impairment increases the risk of injury. Additionally, findings indicated that passenger car type and older vehicles have a higher risk of injury, and as speed limits increase the risk for injury increases. The authors used a two-step approach to compare the unordered to the ordered models: step 1) the likelihood ratio established the superior model within each framework; step 2) the non-nested measure application compared the superior model from each framework. The authors concluded that the variable effect across the mixed generalized ordered logit and mixed multinomial logit were similar. When comparing the two models for underreporting and validation, results suggested that the frameworks performed extremely similarly. Results did not suggest either the unordered or ordered frameworks to outperform the other at either the aggregate or disaggregate levels. The authors concluded that the approaches offer comparable prediction for the risk of crash injury severity.

Amarasingha and Dissanayake (2013)

Amarasingha and Dissanayake (2013) developed a multinomial model to examine the impact of contributory factors on crash severity for young drivers involved in crashes in Kansas to improve safety. The authors categorized driver ages as teen (15 to 19 years old), young adult (20 to 24 years old) and experienced (25 to 64 years old) and sub-partitioned based on gender to examine fatal and severe injury, injury, possible injury and not injured. Findings suggested that teen drivers have a higher risk of injury severity when involved in crashes over other age categories, yet young males decrease the likelihood of a more severe injury. Additionally, seatbelts reduce the probability of severe injuries for young drivers, while air bags increase the risk for greater severity for young drivers.

Ye and Lord (2014)

Ye and Lord (2014) built upon Ye and Lord (2011) by comparing the sample size requirements for multinomial logit, ordered probit and mixed logit models. The research investigated the probability of crash injury severity given a single-vehicle collision occurred with a fixed object on a rural two-way highway. Using crash injury severity data from 1998 to 2001 provided by the Texas Department of Transportation and the Texas Department of Public Safety, the authors explored 25,175 outcomes with 27 explanatory variables categorized as geometric variables, driver characteristics, environmental conditions, etc. The authors reported the mixed logit model to be more "interpretive" than the multinomial logit model, since the parameter effects can vary across crashes in the mixed logit model. Additionally, they reported that the ordered probit model did not have the same interpretive power as the other methodologies, since the effects of the explanatory variables are restricted to ordered probabilities using identical coefficients. The authors combined simulation data with the four-year crash records to compare sample size effects on the three models. Findings included that the ordered probit model required the smallest samples and the mixed logit model required the largest samples as explained by the number of parameters being estimated. Overall results indicated that all three models improved in accuracy when sample size increase, the mixed logit and multinomial logit are more sensitive to smaller sample sizes, and the minimum sample size for the ordered probit, multinomial logit and mixed logit are 2,000 5,000, and 10,000 observations respectively.

2.2.3 Ordered Probit and Ordered Logit

Crash injury severity outcomes can be perceived as being inherently ordered, and as a result, ordered categorical models are very commonly used in injury severity research. Savelonien et al. (2011) identified thirty-five studies and Mannering and Bhat (2014) reported eight studies (however seven studies were reclassified), and this review discovered one additional recent study in which ordered probit or ordered logit methodologies analyzed crash injury severity. Apart from Donnell and Mason (2004), Lu et al. (2006), Jung et al. (2010), Quddus et al. (2010), Abay (2013) and Ariannezhad et al. (2014), all of the studies presented below applied the ordered probit technique.

From a review of the relevant literature, studies presented the ordered discrete outcomes categorized on three, four, five, and seven levels:

Three-levels: slight injury, serious injury, and fatal injury (Quddus et al., 2002; Pai and Saleh, 2007; Gray et al., 2008; Quddus et al., 2010); no injury, slight injury, killed/serious injury (Pai and Saleh, 2008); property damage only, injury, fatality (Donnell and Mason, 2004; Lu et al., 2006; Ariannezhad et al., 2014); and, property damage only, possible injury/non-incapacitating injury, incapacitating/fatal injury (Jung et al., 2010).

Four-levels: no injury, possible injury, non-incapacitating injury, and incapacitating/fatal injury (Yasmin and Eluru, 2013; Abdel-Aty, 2003; Wang et al., 2009); no injury/possible, evident/minor injury, incapacitating injury, fatal injury (Kockelman and Kweon, 2002;

Shimamura et al., 2005; Gårder, 2006; Oh, 2006; Zhu and Srinivasan, 2011; Jiang et al., 2013a); and, no damage, slight damage, extensive, total wreck (Quddus et al., 2002).

Five-levels: no injury/property damage only, minor/possible injury, moderate/non-incapacitating injury, severe/incapacitating injury, killed (Khattak et al., 1998; Klop and Khattak, 1999; Renski et al., 1999; Khattak, 2001; Khattak et al., 2002; Austin and Faigin, 2003; Zajac and Ivan, 2003; Khattak and Targa, 2004; Abdel-Aty and Keller, 2005; Lee and Abdel-Aty, 2005; Siddiqui et al., 2006; Xie et al., 2009; Amarasingha and Dissanayake, 2010; Ye and Lord, 2011; Ye and Lord, 2014).

Seven-levels: minor and no injury, moderate, serious, severe, critical, maximum injury (Khattak and Rocha, 2003).

The literature review uncovered significant findings related to driver characteristics, contributing circumstances, temporal factors, weather characteristics, and road characteristics. Excerpts from these findings are presented below, followed by a more detailed summary of each piece of research.

Age

- Khattak and Rocha (2003) found that young drivers have greater risk of higher injury severity in single-vehicle crashes, and Lu et al. (2006) indicated that young drivers have a greater risk of injury severity when traffic volume on roadways is moderately high. Yet, Haleem and Abdel-Aty (2010) found that young drivers have lesser risk of severe injury at unsignalized intersections.
- Khattak et al. (2002) reported that advancing age increases the likelihood of more severe injuries, and a one year increase in drivers' age beyond 74 years-old decreases the risk for minor injury and increases the risk of a moderate, severe, or fatal injury.

- For crashes occurring on roadway sections, Abdel-Aty (2003) found that drivers over the age of 68 have a higher risk for greater injury severity; and, Zhu and Srinivasan (2011) reported that truck drivers over the age of 45 have a higher likelihood that the impact of the crash will be more severe.
- Conversely, Khattak et al. (1998) found that the impact of the adult driver category on crash injury severity was not different than that of the young driver category.

Inattention

- Zhu and Srinivasan (2011) found that distracted drivers have a higher risk of greater injury severity given a truck-only crash occurs.

Passenger presence

- Renski et al. (1999) and Oh (2006) found that crash injury severity increases as the number of vehicle passengers' increase.

Speeding

- Findings suggested speeding (Khattak et al., 1998; Khattak and Rocha, 2003) and higher speed limits (Renski et al., 1999; Khattak et al., 2002; Oh, 2006; Gårder, 2006; Haleem and Abdel-Aty, 2010; Zhu and Srinivasan, 2011) to significantly increase the risk of severe injury. Khattak and Targa (2004) suggested that crashes occurring in work zones with higher posted speed limits incur greater harm and risk of injury.
- Yet, Zajac and Ivan (2003) reported that, given a collision between a car and a pedestrian, speed limit does not significantly impact pedestrian injury severity as expected.

Alcohol

- Studies reported alcohol intoxication to significantly increase the risk of severe injury (Khattak et al., 1998; Renski et al., 1999; Khattak et al., 2002; Kockelman and Kweon, 2002; Abdel-Aty, 2003; Zajac and Ivan, 2003; Donnell and Mason, 2004; Wang et al., 2009); and, Siddiqui et al. (2006) reported that one of the largest fatal injury risk factors for pedestrians is being struck by an intoxicated driver.

Temporal

- Research showed peak travel time (Khattak et al., 1998) and higher annual daily traffic (Klop and Khattak, 1999) to decrease the risk of injury severity.
- Findings suggested that more severe injuries occur from midnight to 3:59am (Quddus et al., 2002), and nighttime increases the risk for greater injury severity (Khattak, 2001; Abdel-Aty, 2003).
- Studies also reported that dark, unlit conditions increase injury severity (Klop and Khattak, 1999), favorable lighting conditions decrease injury severity at freeway diverge areas (Wang et al., 2009), crashes occurring at dusk (relative to dark) reduces the risk of severe injury at unsignalized intersections (Haleem and Abdel-Aty, 2010), and darkness increases the risk of greater injury severity for older drivers (Khattak et al., 2002).

Weather

- Studies suggested that favorable weather decreases injury severity at freeway diverge areas (Wang et al., 2009), and adverse weather increases injury severity at signalized intersections (Abdel-Aty, 2003).

- Yet, studies also reported that adverse weather significantly decreases the risk of severe injury for crashes that occur on limited-access roadways (Khattak et al., 1998).

Road

- Abdel-Aty (2003) found that horizontal curves increase the risk of higher severity for crashes occurring on roadway sections; and, Oh (2006) reported that sharper horizontal curves and higher crest vertical curves increase injury severity.
- Khattak et al. (1998) and Quddus et al. (2010) reported that wet/slippery road surface decreases the risk of severe injury; yet, Zhu and Srinivasan (2011) found that dry surfaces increase the risk of severity for truck-only crashes.
- Lu et al. (2006) claimed that road conditions have the greatest influence on crash severity; however, Jiang et al. (2013b) concluded that improved road quality does not essentially reduce injury severity.

Khattak et al. (1998)

Khattak et al. (1998) explored the impact of adverse weather on crash type and injury severity by examining limited-access roadways in North Carolina. Data from 1990 to 1995 from the Highway Safety Information System database was accessed, and results of an ordered probit model indicated that adverse weather, slippery road surfaces, and peak travel time significantly decrease the risk of severe injury; single-vehicle involvement, speeding, and alcohol/drug intoxication significantly increase the risk of severe injury; and curves and grade did not significantly impact injury. Model results revealed that the adult driver category is not different from the young driver category, and male drivers have a higher risk of being severely injured than females. The study recognized underreporting as a limitation of the study, especially relevant since crashes occurring during adverse weather are often unreported. However, the authors claimed that the driver non-reporting bias was likely to be small, since the severity considered was based on injuries only.

Klop and Khattak (1999)

Klop and Khattak (1999) explored the impact of roadway and crash variables on motor vehicle and bicycle crash injury severity on two-lane roads in North Carolina. The authors developed two ordered probit models to assess if differences in injury severity existed between rural cases and all cases, as explained by roadway and environmental variables; however, comparison between models did not reveal a significant difference. Results did signify that higher annual daily traffic decrease injury severity; and, foggy conditions, straight-grades, curved grades, and dark, unlit conditions increase injury severity. The authors recommended that additional research should examine the effects of personal characteristics and behaviors on injury severity.

Renski et al. (1999)

Renski et al. (1999) hypothesized that speed limit increases would increase driving speeds, and therefore increase the risk of crash injury severity. Using 1995 to 1997 interstate roadway data from the Highway Safety Research Center of North Carolina, the authors developed ordered probit models to estimate the risk of injury severity. Models used three study segments (speed limits increased from 55 to 60 mph, 55 to 65 mph, or 65 to 70 mph) and two control segments (unchanging speed limits at 55 or 65 mph) to compare road segments before and after the date of the speed limit change. Results revealed that segments in which speed limits were increased by 10 mph had a greater impact on crash severity than segments where speeds were increased by 5 mph.

Findings also suggested that overturned vehicle, alcohol use, trees and poles increase the level of the most severely injured, and crash severity increases as the number of vehicle passengers' increases, with a greater increase from two to three occupants.

Khattak (2001)

Khattak (2001) investigated crash injury severity of lead and following drivers, where a lead driver (Driver 1) was struck by a following driver (Driver 2) that may be struck by a third following driver (Driver 3). The authors estimated three ordered probit models to analyze crash injury severity for the lead and following drivers using a total of 487 three-vehicle crashes and 3,425 two-vehicle crashes. Findings indicated that, given a three-vehicle crash, Driver 1 and Driver 3 are less likely to be injured, and Driver 2 is more likely to be injured. Model results ascertained that nighttime increases the risk of injury severity, snow/ice increases the risk of injury severity for Driver 2, and drivers of larger vehicle types are less likely to sustain an injury than are drivers of passenger cars.

Khattak et al. (2002)

Khattak et al. (2002) investigated whether driver, environment, vehicle, roadway and crash factors increase the risk of crash injuries of older drivers, and quantified the significant factors on varying severity levels for older driver injuries. The model results signified that advancing age increases the likelihood of more severe injuries, and older male drivers incur more severe injuries than older female drivers. Results suggested alcohol intoxication, higher speed limits, farm vehicles, crashes in rural areas, darkness, overturned vehicles, vehicles colliding with parked vehicles, vehicles striking fixed objects, and vehicles hitting trains increase injury severity for older drivers, and that for a one year increase in driver's age beyond 74 years old, the likelihood of a minor injury decreases and the risk of a moderate, severe, and fatal injury increases. The authors concluded that additional studies should focus on crash causation and injury severity for older drivers.

Kockelman and Kweon (2002)

Kockelman and Kweon (2002) developed an ordered probit methodology to examine injury severity, given a two-vehicle or single-vehicle crash occurred. Model estimations suggested that gender, vehicle type, alcohol use, number of vehicles involved, and the manner of the collision effect injury severity. Model results revealed that head-on and rollover collision result in more serious injury levels, light-duty trucks have a lesser effect on injury severity, pick-ups and SUVs have a greater likelihood to rollover, and males and younger drivers in newer cars at slower speeds have a risk of lower injury severity.

Quddus et al. (2002)

Quddus et al. (2002) compared the effect of roadway, rider, and environmental factors on motorcycle injury severity to vehicle damage severity for motorcycle crashes occurring in Singapore. The authors developed an ordered probit model to explore the hypotheses that (1) roads with a higher degree of engineering standards have lower severity levels and (2) younger drivers have more severe crashes that diminish over time. A time trend variable for the month in which the crash occurred had a negative effect for both injury and damage severity, which suggested that an unobserved factor influenced crash severity. Additional findings suggested that more severe injuries occur from midnight to 3:59am, and the risk of fatality increases for crashes that result in the motorcyclists overturning or striking an off-road object. Additionally, results indicated that two way streets, crashes occurring on the outermost lane, and wet road surface increase the likelihood of severe injuries and severe damage to the motorcycle. Finally, findings inferred that non-Singaporeans have more severe injuries, drivers younger than 30 have more severe motorcycle damage, men have a 100% greater likelihood of a total wreck, and passenger presence increases the risk of injury, but decreases the risk of damage.

Abdel-Aty (2003)

Abdel-Aty (2003) developed an ordered probit model to assess driver injury severity, given a crash in a toll plaza, roadway section, or at a signalized intersection occurs. The authors obtained crash data from 1996 to 1997 from the Florida traffic crash database, and 17,647 drivers involved in 7,894 crashes were extracted. Results suggested that for crashes occurring on *roadway sections*, female drivers, older drivers (over 68 years-old), alcohol, nighttime, and horizontal curves increase the risk for higher injury severity, for crashes occurring at *signalized intersections*, inclement weather and dark-street lighting increase the risk of higher injury severity and at-fault drivers experience less severe injuries, and for crashes occurring at *toll plazas*, electronic toll collection system equipped vehicles and drivers who stopped in the electronic toll collection lane increase the risk of higher injury severity.

Austin and Faigin (2003)

Austin and Faigin (2003) explored the vehicle types and crash circumstances that increase the risk of injury severity for older drives. The authors gathered information from the 2001 National Household Travel Survey and the 1995 Nationwide Personal Transportation survey for traffic exposure, from the National Automotive Sampling

System-General Estimates System to capture crash involvement data, and from the Fatality Analysis Reporting System to derive fatality and incapacitating injury information. The study presented an ordered probit model to analyze the effect of age (grouped as 25-44, 45-64, 65-74, and 75+) on injury severity levels (categorized as fatal, incapacitating, moderate, minor and property damage only). Results suggested that the fatality rate for 25-44 year-olds, 65-74 year-olds, and 75+ fell from 1997 to 2001, which suggested that improvements in safety had a greater impact on older drivers than younger drivers. However, older driver involvement in fatal crashes was still 30% greater than the next oldest group. Results also indicated that crash involvement for older drivers is greater in passenger cars, relative to light truck and utility vehicles; and, for drivers 75+, side-impact crashes have a higher likelihood of fatality and seriously injured outcomes.

Kweon and Kockelman (2003)

Kweon and Kockelman (2003) investigated the effect passenger vehicle type (cars, minivans, pickups, motorcycles and SUVs) on the probability of motor vehicle crash injury severity for rollover and non-rollover cases. Model results indicated that SUV rollovers are more prevalent, and male drivers are more likely to sustain injury in a pickup or minivan. Middle-age and older females are more likely than males to rollover when driving a passenger car, and female drivers of all ages are more apt to rollover when driving an SUV. Results suggested that car drivers experience non-rollover crashes and non-severe injury more than other vehicle type drivers, with the exception of young females where pickups are the highest. All female drivers, young males, and older male drivers have a higher risk of fatality from a SUV rollover than a passenger car. Findings also suggested that female drivers of SUVs, pickups and minivans have a higher risk of a fatality given a crash (which could be attributed to the increased possibility of SUVs and pickups rollover), and young and middle aged male drivers of cars have a greater risk of a fatality given a crash. The authors concluded that the differences between genders are small; however, the difference across age groups is severe and additional research in this area is necessary.

Zajac and Ivan (2003)

Zajac and Ivan (2003) explored the roadway and area features that may impact driving speeds, which in turn may influence pedestrian injury severity. The authors examined crashes in which pedestrians were struck while crossing the road at locations where mainline traffic was not controlled by signals or stop signs using data from the Connecticut Department of Transportation. The study presented ordered probit models to explore the impact of area type (downtown, compact residential, village, downtown fringe, medium-density commercial, low-density commercial, and low-density residential), pedestrian age, vehicle type, alcohol involvement, light condition, road surface condition, and weather conditions on injury severity (fatal; disabling injury; not disabling injury, but visible; probability injury, but not visible; no injury). Results indicated that speed limit, on-street parking, and roadway width does not significantly impact pedestrian injury severity as expected. Additionally, findings inferred that downtown and compact residential areas have a lower risk of severe injury than low-density residential areas, and low-density and medium-density commercial areas have a lower risk of severe injury than village and downtown fringe. Finally, model results suggested that pedestrians who are at least 65-years-old, vehicle type, and driver and pedestrian alcohol involvement increase the risk of pedestrian injury severity.

Khattak and Rocha (2003)

Khattak and Rocha (2003) explored the impact of SUV rollovers on crash injury severity, and found that, when a rollover was the single indicator variable, rollovers increase injury severity. Findings indicated that SUV drivers have a lower risk of severe injury by nearly 24%, and that wearing seatbelts and the presence of airbags decrease severe injury. Additionally, results reveled that driving off the road, losing control, speeding, female drivers, young drivers, and vehicle ejection significantly increase injury severity for single-vehicle crashes.

Donnell and Mason (2004)

Donnell and Mason (2004) developed regression models to predict injury severity of median-related crashes in Pennsylvania. The authors obtained cross-median collisions (CMC) and 4,416 median barrier crash observations from the Pennsylvania Department of Transportation. The study presented an ordinal logistic regression model from a measurement model in which the latent variable was linked to an observed variable, and Fisher scoring algorithms were used to fit the model. Model results suggested that an ordinal regression model adequately fit the CMC data, and results from the CMC model suggested that drug use and a curvilinear alignment increase the probability that, given a crash occurred, the outcome would be fatal. The interstate median barrier crash model violated the proportional odds assumption (which could be a result of the small number of fatal crashes in this category); and therefore, was re-estimated using a nominal logistic regression. The model results indicated that wet surface, traffic volumes, drug or alcohol use, the presence of an interchange entrance ramp, and the interaction between the presences of an interchange entrance ramp and drug or alcohol use impact crash injury severity.

Khattak and Targa (2004)

Khattak and Targa (2004) explored the impact of work zone characteristics on injury severity and total harm for truck-involved collisions. The authors explored the total harm of the crash by assigning an economic value to each injury level and summing the costs for each injury (i.e. the total harm variable included medical emergency service costs, employer costs, traffic delay costs, victim work loss costs and property damage costs). The study presented cost estimations for crashes in North Carolina, including quality of life, as $2,925,100 for fatal injury, $144,796 for severe/incapacitating injury, $37,486 for moderate/non-incapacitating injury, $17,916 for minor/possible injury, and $3,904 for property damage only. Ordered probit and ordinary least squares (OLS) regression (three ordered probit and three OLS log-transformed models) respectively using 572 multi-vehicle truck-involved crash records estimated injury severity and total harm. Model results indicated that when a crash occurs in a work zone located on two-way undivided roadways the risk of harm and injury increases. Additionally, findings suggested that closing the roadway and detouring traffic to the opposite side of the road has a significantly higher risk of injury and total harm, and a crash occurring in this manner was suggested to have a 38.5% increased chance of injury and cost of $43,584. Finally, results indicated that crashes occurring adjacent to the work area, in work zones with higher posted speed limits, and when stop/yield/warning flashing signs are present incur greater harm and risk of injury.

Abdel-Aty and Keller (2005)

Abdel-Aty and Keller (2005) hypothesized that crash injury levels were affected by crash- and intersection-specific characteristics. Expanding upon Abel-Aty (2003), the authors developed ordered probit models to assess 33,592 crashes that occurred in 832 intersections from 2000 and 2001. Findings for the severity models for intersection characteristics suggested that division on the minor road, right turn channelization on the major road, and an increase in the number of lanes and speed limit on the minor road decrease the expected level of injury. Additionally, the authors estimated a hierarchical tree-based regression model to estimate the expected crash frequency for each crash injury severity level. Results indicated that the most significant factors for no-injury crashes, possible injury, non-incapacitating injury and incapacitating injures are traffic volume of the major road, the number of lanes on the minor road, the number of exclusive right turn lanes, and the average daily traffic on the minor road, respectively. The authors concluded that models should be developed for each level of severity as opposed to a single model for predicting the overall severity level, and the tree-based regression improves the understanding of the importance of specific factors on individual levels of severity.

Lee and Abdel-Aty (2005)

Expanding upon Abdel-Aty and Keller (2005), Lee and Abdel-Aty (2005) analyzed vehicle pedestrian crashes at intersections in Florida by examining the relationship between pedestrian, driver, traffic and environmental characteristics and frequency/injury severity of pedestrian crashes. Using data from the Florida Traffic Crash Records from 1999 to 2002, the authors developed two log-linear models to examine crashes resulting from driver fault and pedestrian fault. Results suggested that pedestrian collisions occur less frequently at rural signalized intersections, and it was proposed that drivers are more careful when approaching traffic signals than stop/yield signs in rural areas. Also, model results revealed that middle age men are more likely to be involved in a pedestrian collision as both pedestrians and as drivers, children younger than 14 have a high risk of being involved in a pedestrian-fault crash, and the risk of crash frequency at the fault of the pedestrian increases at signalized intersections. Findings also suggested that the interaction of nighttime and alcohol intoxication increases the risk of a pedestrian-caused crash more than crashes resulting from the fault of the driver. The authors then estimated ordered probit models to examine injury severity. Results suggested that older pedestrians (65+ years-old), female pedestrians, pedestrians under the influence of drugs/alcohol, higher vehicle speed, and rural areas increase the risk of sustaining higher injury levels. Overall model results indicated that pedestrians' age and alcohol/drug use, speed of the vehicle at time of crash, location of the crash, presence of traffic control, weather, lighting, and vehicle type are closely related to pedestrian injury severity. To examine the underlying behavioral factors that lead to pedestrian crashes, the authors collected walking trip data from a household travel survey. From this analysis, findings inferred that the relationship between the number of pedestrian crashes to the total duration of walking was underestimated for the older pedestrian population. The authors recommended enhanced driver education and traffic regulation with these modifications targeted towards middle-aged male drivers, that the dangers of drinking and walking be made clearer to the public, and an increased number of traffic signals and street lights be installed in rural areas.

Shimamura et al. (2005)

Shimamura et al. (2005) assessed the effect of rear-seat passengers' use of seatbelts on the injury severity of front-seat occupants. The authors examined five analyses: 1) the influence of belted and unbelted rear-seat passenger on driver injury severity, 2) the influence of belted and unbelted rear-seat passenger on front-seat passenger injury severity, 3) the effectiveness of seatbelt use by rear-seat passengers, 4) the effectiveness of seatbelt use by driver with no passengers, and 5) the effectiveness of seatbelt use by front-seat passengers with no rear-seat passengers. Results indicated that the number of vehicles with seriously injured or killed drivers is expected to decrease by 25% if unbelted rear-seat passengers initiate seatbelt use, and decrease by 28% if unbelted front-seat passengers initiate seatbelt use.

Gårder (2006)

Gårder (2006) analyzed data from the Maine Department of Transportation for head-on crashes that occurred between 2000 and 2002. The authors developed ordered probit models to assess the influence of road surface conditions, light conditions, temporal conditions, heavy-vehicle involvement, shoulder width, and speed limit on crash injury severity (fatal, incapacitating, evident, and possible). Findings indicated that head-on crashes were primarily caused by speeding or driving too fast for conditions and driver inattention/distraction. Results also suggested that increased speed limits lead to an increase in crashes that result in a fatality or incapacitating injury, and wider shoulder width and higher-speed roads lead to a greater risk of injury severity. Consequently, the authors recommended widening of two-lane roads, extra travel lanes, and speed reduction to reduce crash injury severity of head-on collisions.

Lu et al. (2006)

Lu et al. (2006) analyzed the magnitude and predictability of median crossover crashes on crash injury severity. The models included 12 explanatory variables for estimation of crash severity: crash date, geometry, light condition, liquor involvement, weather condition, road cause, road condition, weekday, driver age, total average drive time, median width, and reaction time. Model results found crash date, weather condition, road condition, road cause, and reaction time to have the greatest influence on crash severity. Results also indicated that younger drivers have a greater risk of injury severity when traffic volume on roadways is moderately high; and, seasonal factors of ice and snow increase the risk of severity of a median crossover crash.

Oh (2006)

Oh (2006) developed ordered probit regression models to assess the statistical relationship between crash injury severity and traffic maneuvers, roadway geometrics, and weather at urban four-legged signalized intersections. Findings suggested that, for models for all crash records, sharper horizontal curves, more vehicle occupants, higher speed limits, and higher crest vertical curves increase injury severity. While, wider medians, more driveways and higher annual average daily traffic on major roads, protected left turn lane, and lighted conditions decrease injury severity. Findings for models where two-vehicle crashes occurred suggested sharper horizontal curves, more vehicle occupants, and higher speed limits increase injury severity; though, higher traffic flows on major roads, manner of collision, and less commercial driveways decrease injury severity levels. When three or more-vehicle crashes occurred, model results suggested that longer sight distance, right turn lane presence, and higher annual average drive time on the minor road decrease injury severity. The authors concluded that while uncovering explanatory variables may describe some association with injury severity, it does not necessary imply the causation of injury severity; therefore, additional research in this area is necessary.

Siddiqui et al. (2006)

Siddiqui et al. (2006) examined the impact of light conditions and crossing locations on pedestrian injury severity, given a collision with a motor vehicle. Results indicated that the largest fatal injury risk factors for pedestrians are age of at least 65 years old, struck by an intoxicated driver, involved in a crash on a US road, foggy conditions, pedestrian intoxication, struck by a driver with physical disability, and struck by a large vehicle. Model results revealed that, when considering the effects of light condition and location, dark without lighting and midblock locations with any light condition has the greatest risk for pedestrian fatality.

Pai and Saleh (2007)

Pai and Saleh (2007) hypothesized that motorcyclists are more susceptible to severe injuries in approach-turn collisions (when one vehicle approaching straight collides with an approaching vehicle turning right) at T-junctions. The authors estimated three ordered probit models to examine injury severity: 1) injury severity occurring from a crash where stop or give-way signs controlled the junction; 2) injury severity occurring from a crash at an uncontrolled junction; and 3) injury severity occurring from a crash at a signalized junction. Results from model 1 implied that male or elderly riders, riding in the early morning, riding in a spring or summer month, street lights unlit, riding on a non-built-up road, riding under fine weather, greater engine size, collisions with bus or heavy good vehicle, and a collision between a motorcycle and a vehicle traveling in the same direction have the greatest association with the risk of increased injury level. Results from model 2 implied that greater engine size, elderly rider, riding in early morning, riding under fine weather, riding on the weekend, street lights unlit, collision with a bus or heavy good vehicle, riding on a non-built-up road, and a head-on collision or approach-turn collision between a motorcycle and vehicle have the greatest association with the risk of increased injury level. Finally, model 3 suggested that male riders, heavier engine size, riding during fine weather, riding on a non-built-up road, collisions with bus or heavy good vehicle, collisions between a vehicle/motorcycle approaching straight and an oncoming motorcycle/vehicle that turns right into the path of the first vehicle/motorcycle, and head-on collisions between a motorcycle a vehicle have the greatest association with the risk of increased injury level. The study concluded that the separate analysis enables insights to lessen motorcyclists' injury severity levels for collisions at three-legged junctions in the UK.

Gray et al. (2008)

Gray et al. (2008) examined characteristics that effect crash injury severity for young male drivers in order to enhance road safety measures. The authors obtained National Road Accident data from 1991 to 2003 for Great Britain, and estimated ordered probit models to assess the risk that, given a crash involving a young male driver occurs, the outcome will be fatal, serious or slight injury. Findings indicated that greater injury severity occurs early in the morning, on Thursdays, Fridays, Saturdays and Sundays, during darkness, on wet roads, if a volatile movement ensues, if an object is hit off the carriageway, and if a hazard is located in the carriageway. The authors concluded by calling for research with similar modeling for young female drivers with a comparison of results to young male drivers.

Pai and Saleh (2008)

Expanding upon Pai and Saleh (2007), Pai and Saleh (2008) explored motorcyclist crash injury severity in approach-turn collisions at T-junctions in the UK by focusing on the impact of junction control measures and driver's failure to yield. The authors estimated two ordered models to assess 1) a motorcycle approaching straight collides with a vehicle traveling from the opposite direction and turning right, and 2) a vehicle approaching straight collides with a motorcycle traveling from the opposite direction and turning right. Results indicated that junctions controlled by give-way, stop signs, or marking result in more severe injury for a motorcyclist. Additionally, findings suggested motorcyclists to be 16 times more likely to be involved in an approach-turn head-on collision with a vehicle, and more likely to result in a higher risk of greater injury severity.

Wang et al. (2009)

Wang et al. (2009) examined data from the Florida Department of Transportation to identify factors that impact crash injury severity at freeway diverge areas. The authors developed and compared the results of an ordered probit model and a partial proportional odds (PPO) model, and examined data for four ramp types: Type I, parallel from a tangent single-lane exit ramp; Type II, single-lane exit ramp without a taper; Type III, two-lane exit ramp with an optional lane; and Type IV, two-lane exit ramp without an optional lane. Results from the ordered probit model suggested that crashes occurring at a diverge area with downgrades or upgrades or curved alignment, alcohol or drug use, off-peak hours, and collision with a barrier result in more severe injuries; while, favorable weather and lighting, longer deceleration lane on diverge area, and diverge areas in business zones decrease the risk of severe injuries. The PPO model results implied that shorter ramp length, off-peak period, alcohol or drug-use increase the risk of injury severity; and, favorable weather conditions, crashes occurring in business zones, heavy-vehicle involvement, and sideswiping crashes decrease the level of injury severity. Additionally, findings inferred that the exit ramp type has no significant effect on crash injury severity when a crash occurs at a freeway diverge area. The study concluded that when comparing the two models, the PPO model was better at fitting the observations than the ordered probit model (PPO pseudo-R^2 = .0406; ordered probit pseudo-R^2 = .0273).

Xie et al. (2009)

Xie et al. (2009) estimated ordered probit models and Bayesian ordered probit (BOP) models to assess crash injury severity. To compare the two models, the authors obtained data from the 2003 NASSGES, and extracted a total of 76,994 records. Findings revealed that when the sample size was large, model fitting results for both models were closely related. However, when the sample size was reduced to 100 records, results indicated that the BOP model produced better predictions.

Amarasingha and Dissanayake (2010)

Amarasingha and Dissanayake (2010) developed ordered probit models to examine the contributing factors for injury severity of older drivers for crashes occurring in rural and urban areas in Kansas. Categories of injury severity were no injury, possible injury, non-incapacitating injury, incapacitating injury, and fatal outcome; categories of explanatory variables were driver related, crash related, environmental related, and roadway related; and, the data was sub-partitioned based on age. Findings suggested that most of the driver-related variables (i.e. age, gender, passengers, seat belt use, and alcohol) were significant in affecting injury severity for older drivers; only cars (as opposed to other vehicle types) have a significant effect on injury severity given an urban crash, speed increases injury severity, and head-on, rear-end and angle crashes increase the likelihood of more severe injuries in both rural and urban areas.

Haleem and Abdel-Aty (2010)

Haleem and Abdel-Aty (2010) compared ordered probit, binary, and nested logit methodologies to aid in the selection of the best modeling technique for injury severity analysis for crashes occurring at unsignalized intersections. The authors used geometric, traffic and driver-related data from six counties in Florida to explore the effect of traffic and roadway covariates on crash injury-severity. The Florida Department of Transportation provided data for 10,722 crashes occurring over four years at unsignalized intersections. The study used two separate models to analyze the relationship between severe injuries and non-severe injuries, and explanatory characteristics at three and four legged intersections. Findings indicated that lack of stop lines, one left turn lane, larger right shoulder width, and smaller intersections increase the probability of severe injury; and, lower speed limits, young drivers, crashes occurring at dusk (relative to dark), and highly-urbanized areas reduce probability of severe injury. When comparing the binary probit and the ordinal probit frameworks, results suggested that the aggregated binary probit model had a lower AIC and higher likelihood of convergence, indicating that the binary probit model better fit the data. The authors claimed that this finding indicates that the aggregate model performs better when analyzing injury severity, given a crash at an unsignalized intersection.

Jung et al. (2010)

Jung et al. (2010) applied rain-related crash data and real-time information to assess weather conditions and aid in the prediction of crash severity outcomes. The authors compiled four databases to obtain 33 explanatory variables categorized as driver demographics, roadway geometrics, collision types, pavement conditions, vehicle types, and temporal and weather conditions, and ordinal logistic and sequential logistic regression models were developed. Results revealed that a backward implementation of the sequential logistic regression model outperformed others in the prediction of crash injury severity. Statistically significant factors that affect crash injury severity in rainy weather were identified as rainfall intensity, roadway terrain, wind speed, drivers' gender, and safety belt use.

Quddus et al. (2010)

Quddus et al. (2010) investigated the relationship between the level of traffic congestion and individual crash injury severity by employing an ordered logit model, a heterogeneous choice model (HCM), and a partially constrained generalized ordered logit (PC-GOLOGIT) model. Diagnostic tests suggested that the ordered logit model was not appropriate for the data, both the HCM and the PC-GOLOGIT model fit the data equally well, and the results between the HCM and the PC-GOLOGIT were consistent. Estimation results indicated that the level of traffic congestion did not affect crash injury severity; increases in traffic flow, darkness, wet road surface, and decreases in road curvature resulted in decrease severity; and, three-lane stretches, weekdays, and single-vehicle crashes increase severity.

Ye and Lord (2011)

Ye and Lord (2011) investigated the effect of underreporting of crash data on injury severity estimations using multinomial logit, ordered probit and mixed logit models, and evaluated how each model performed for different unreported rates. The authors proposed using the Weighted Exogenous Sample Maximum Likelihood Estimator (WESMLE) to account for underreporting conditions. Results determined that the root-mean-square-error (RMSE) increased when using the maximum likelihood estimator for all three models; the lowest ordered severity level had the largest underreported rate; and, the WESMLE performed well regardless of the magnitude of the unreported rate for each model. The authors concluded that to minimize bias, fatal crashes should be set as the baseline severity for the mixed logit and multinomial logit models, while the ordered probit model should rank crash severity in descending order (from fatal to property-damage-only).

Zhu and Srinivasan (2011)

Zhu and Srinivasan (2011) assessed injury severity for large-truck crashes using data from the 2001 to 2003 Large Truck Crash Causation Study, which contained approximately 1,000 crashes from 24 sites in 17 states. The authors developed ordered probit models to assess injury severity as explained by crash type, fire, crash location roadway design characteristics, road-surface conditions, and temporal characteristics. Results suggested that for truck-only crashes, collisions with fixed objects, on non-interstate highways, on multi-lane highways, at a higher speed, on the weekend, on dry surface, with heavy cargo (>20,000kg) and during dark but lighted conditions had a greater risk of severe injury. In addition, older truck drivers (>45 years old), African-American drivers, taller drivers, drivers with less experience, and distracted drivers were involved in more severe crashes. For collisions between trucks and cars, findings suggested emotional factors (such as depression) and fatigue to result in more severe crashes. Interestingly, results indicated that seatbelt use was insignificant in both the truck-only crashes and truck-car crashes.

Abay (2013)

Abay (2013) explored pedestrian injury severity relative to road user characteristics using alternative disaggregated models. The study presented four models: standard fixed-parameter ordered logit (OL), random parameters ordered logit (RPOL), standard fixed-parameter multinomial logit (MNL), and mixed logit (MXL). Findings suggested that substantial differences in the marginal effect of the variables in the OL with the RPOL and MXL exist, and the underestimation can lead to misinformed safety planners. For example, the OL model underestimated the effect of an older-aged pedestrian and the effect of being struck by a driver proceeding straight-ahead, which could misguide guide policy intended to help vulnerable road users. Consequently, the researchers called for more "encompassing, flexible and alternative model specification when analyzing injury severity data" (p. 132).

Jiang et al. (2013a)

Jiang et al. (2013a) examined the effect of curbs on single-vehicle crash injury severity by use of a zero inflated ordered probit (ZIOP) model to compensate for the potential bias imposed by the traditional ordered probit model in situations of highly unbalanced occurrences of a specific category of the dependent variable. The ZIOP model assumes that injury severity is the result of injury propensity and injury severity. Using 2003 to 2007 data from the Illinois Highway Safety Information Database, the authors discovered that single-vehicle crashes that occur on curbed roadways are more likely to be injury prone, and the existence of a curb decreases the risk of severe injury when the crash is in the injury prone category. Moreover, findings suggested that the presence of curbs have a higher risk of non-injury and minor injury and a lower risk of incapacitating injury and fatality.

Jiang et al. (2013b)

Jiang et al. (2013b) linked together data from the Tennessee Roadway Information Management System and the Tennessee Department of Transportation's Pavement Management System to obtain crash information and pavement management status for the state route highways from 2004 to 2008. The authors examined injury severity for three types of two-vehicle crashes: rear-end collisions, sideswipe collisions, and angle collisions. The study presented and compared an ordered probit and a Bayesian ordered probit model based on the parameter estimates. As expected due to the large sample size, results from both models for each type of crash were very close. Results from the Bayesian ordered probit model suggested that annual average daily traffic, speed limit, peaking hour, rural/urban location, and light condition were consistently significant across a crash types; and, pavement distress index, rut depth and rut depth difference were not statistically significant. Results suggested that two-vehicle sideswipe, rear-end and angle crashes that occur on rougher roads are less likely to incur a severe injury. The authors concluded that improved road quality does not essentially reduce injury severity, given a two-vehicle crash occurs.

Eluru (2013)

Eluru (2013) explored the appropriate model choice for injury severity analysis through the comparison of ordered response methodologies (an ordered logit model and a generalized ordered logit model) with unordered response methodologies (a multinomial logit model). The authors created simulations with three independent variables and four alternatives ordered dependent variables to compare the performance of the frameworks. The authors selected parameters so that the models would generate consistent sample shares for the parameter set. To assess model fit, the study compared generalized ordered logit and the ordered logit models using the likelihood ratio test, and used the Bayesian Information Criterion to compare the generalized ordered logit and the multinomial logit models. Model estimation results indicated that, when compared to the multinomial model, the generalized ordered logit model performed satisfactory. The authors concluded that the results provide credibility to the generalized ordered logit model.

Yasmin and Eluru (2013)

Expanding upon Eluru (2013), Yasmin and Eluru (2013) explored methodological approaches used to assess driver injury severity in traffic crashes by comparing ordered response methodologies (order logit, generalized ordered logit, and mixed generalized order logit) with unordered response methodologies (multinomial logit, nested logit, ordered generalized extreme value logit, and mixed multinomial logit). The authors selected data in which a private passenger vehicle collided with either another passenger vehicle or a fixed object from the 2010 General Estimates System, and a final dataset of

30,371 records were used. To measure the comparison of the overall fit of the models, the study employed the likelihood ratio test to compare the ordered models to one another, and to compare the unordered models to one another. The study presented a two-step approach to compare the unordered to the ordered models: 1) use the likelihood ratio test to establish the superior model within each framework and 2) compare the superior model from each framework using a non-nested measure application. Estimation results suggested that drivers under the age of 25 and occupants wearing seatbelts have a lower risk of severe injury. Additionally, findings indicated that drivers who are under the influence of alcohol and those driving older vehicles have a higher risk of injury, and as speed limit increases the risk for injury increases. The authors determined that neither the unordered or ordered frameworks outperform the other at either the aggregate or disaggregate level, and concluded that the findings signify that the different approaches offer comparable prediction for the risk of crash injury severity.

Ye and Lord (2014)

Ye and Lord (2014) built upon Ye and Lord (2011) by comparing the sample size requirements for estimating multinomial logit, ordered probit and mixed logit models. The research investigated the probability of crash injury severity given a single-vehicle collision occurred with a fixed object on a rural two-way highway. Using crash injury severity data from 1998 to 2001 provided by the Texas Department of Transportation and the Texas Department of Public Safety, the authors explored 25,175 outcomes with 27 explanatory variables categorized as geometric variables, driver characteristics, environmental conditions, etc. The study reported that the ordered probit model does not have the same interpretive power as the other methodologies, since the effects of the explanatory variables are restricted to ordered probabilities using identical coefficients. Additionally, the ordered probit model has threshold values that are fixed across observations, which can lead to inconsistent model estimation. The authors combined simulation data with the four-year crash records to compare scale size effects on the three models. Findings included that confidently estimating an ordered probit model required the smallest samples and fitting the mixed logit model required the largest sample. Overall results indicated that all three models improved in accuracy when sample size increased, the mixed logit and multinomial logit were more sensitive to smaller sample sizes, and an approximate reasonable minimum sample size for the ordered probit, multinomial logit and mixed logit models are 2,000 5,000, and 10,000 respectively.

Ariannezhad et al. (2014)

Ariannezhad et al. (2014) examined the impact of conditional, environmental, rider, crash and roadway characteristics on motorcycle crash severity in the suburban areas of Iran. The authors developed an ordered logit model to analyze crash injury severity, and results suggested that greater injury severity occurs on weekends, during the fall and winter months, during night hours, during foggy weather, when road imperfections are present, and on curved and level roads. Additionally, findings suggested that drivers aged younger than 25 and older than 60, not having driving experience/permit, not wearing a helmet, speeding, losing control of the motorcycle, overtaking, colliding with large vehicles, disobeying driving rules, and who are inattentive, fatigued and hasty are associated with crashes with greater injury severity.

2.2.4 Decision Tree Models

Savolainen et al. (2011) categorized one study as 'classification and regression tree.' This literature review discovered eight additional studies in which decision tree models were estimated to analyze crash injury severity. Even though this review found that relatively little research has employed such an approach, Savolainen et al. (2011) remarked that decision tree models are an effective data mining technique, Abdel-Aty and Keller (2005) claimed that tree-based regression improves the understanding of the importance of specific factors on individual levels of severity, Oh (2006) concluded that variables associated with injury severity levels may not be the cause of injury severity and additional research in this area is necessary, and Abay (2013) called for a more encompassing and alternative model specification for injury severity data analysis.

A review of the literature wherein tree model techniques were used to uncover complex crash patterns is presented below. Below, specific findings related to driver characteristics, contributing circumstances, temporal factors, and road characteristics are identified, followed by a more detailed review of each piece of research.

- Kuhnert et al. (2000) concluded that the most important factor for predicting crash injury severity is age; and, Yan and Radwan (2006) found that drivers under the age of 21 and over 75 have the greatest risk of rear-end collisions.
- Findings suggested that the interaction of higher speed limits and alcohol increases the risk of crash injury severity (Yan and Radwan, 2006; Eustace et al., 2014).
- Eustace et al. (2014) found that females in circumstances of higher posted speed limits have higher risk of injury, and males with drug involvement in higher posted speed limit circumstances have a higher risk of injury.

- Model results for rear-end collisions indicated that alcohol is the most significant factor impacting a drivers' striking another vehicle (Yan and Radwan, 2006); and, Eustace et al. (2014) found that alcohol and drug use increase the probability of run-off-road injury severity levels.
- Yan and Radwan (2006) found that the risk for a rear-end collision is higher for daytime condition than nighttime condition.
- Wet or slippery road surfaces were found to increase the risk of incapacitating injury for rear-end collisions (Yan and Radwan, 2006); and, male drivers in crashes on wet road surfaces were found to have a higher risk of injury severity (Eustace et al., 2014).
- Chang and Wang (2006) reported that contributing circumstances and driver actions are critical in determining crash injury severity.

Stewart (1996)

Stewart (1996) presented a classification tree model and regression tree model in roadway safety studies. The model included injury severity, locality, number of lanes, speed limit, highway class, roadway feature, vehicle type, and model year group as the analysis variables. The study illustrated three example models: 1) the classification tree model using binary variables to estimate the likelihood of a severe or fatal injury; 2) the regression tree model using continuous variables to estimated average injury severity costs; and 3) classification and regression tree (CART) to identify interactions to be included in a Poisson crash model. From the comparison of the performance of the example models, the author concluded that CART models are a useful tool in each of these roles.

Kuhnert et al. (2000)

Kuhnert et al. (2000) combined multivariate adaptive regression spline (MARS) and classification and regression tree (CART) models with logistic regression to illustrate the improved information provided for crash injury severity. The authors collected data via case interviews of hospitalized patients following motor vehicle crashes in Brisbane, Australia from 1997 to 1998. Information gathered included driving experience, driver aggression, general safety precautions, and demographic variables; and, a follow-up questionnaire was used to obtain additional information of driver attitude, behavior and experience. Using the data obtained, the authors estimated CART, MARS, and logistic regression models. The CART model produced an overall accuracy of 79.4%, and yielded results that suggested older drivers who do not wear a seatbelt and older female drivers who do not wear seatbelts are high risk groups. Findings inferred that the most important factor was age. The MARS model had an overall accuracy of 83.2% and results suggested that respondents with little experience, respondents between the age of 30 and 45 with many years of experience, and respondents between the ages of 40 and 80 with little experience were the three major areas of risk. The logistic regression model produced an overall accuracy of 75.9%, and suggested seatbelt use as the only significant variable. As deemed important from the MARS model results, the authors incorporated age and experience results into the logistic regression model, and found the interaction between age and experience statistically significant. The authors encouraged the use of MARS and CART as exploratory tools for a more detailed analysis when using conventional and well-known methods.

Sohn and Shin (2001)

Sohn and Shin (2001) developed decision tree, neural network, and logistic regression models to assess the factors that affect traffic crash injury severity in Korea. The classification tree identified the six factors used in the neural network and logistic regression models (accident mode, road width, car shape, speed before accident, violent driving, and protective device). Model results revealed protective device (i.e. safety belt use or helmet improperly worn) as the most influential variable for classification of crash severity. The model identified decision tree rules as: if no protective device is used and car to pedestrian collision occurs, then fatality or injury is likely to occur; if no protective device is used and a car-to-car frontal collision or car-to-car when turning collision and violent driving occurs, then fatality or injury is likely to occur; and if no protective device is used and a car collision against a wall or barricade with the car shape bonnet occurs, then property damage is likely to occur. The study then trained a neural network for crash severity using the same dataset, and did not find the classification accuracy to be significantly different from the decision tree. Finally, the authors fit a logistic regression using the same six aforementioned variables. The estimation suggested accident type and speed before the crash to be the only statistically significant factors; and, if car to car frontal collision, car to car collision when passing, car to car collision when parking and car to car collision when turning occur, injury and death has a higher likelihood of occurring. Overall, the authors concluded that variable reduction was effective, and the three models were not significantly different in performance.

Bayam et al. (2005)

Bayam et al. (2005) provided a meta-analysis of prior literature on older drivers and illustrated the use of data mining techniques for injury severity analysis. The study reported that for older drivers the risk of fatality increases, left-turn crashes are more common, the tendency to strike fixed objects increases, the risk of fatality substantially increases at speeds exceeding 69 mph, driving distance decreases, more time is taken to turn, visual abilities decline, slower speeds are driven, and crashes occurring at intersections have a higher risk of fatality. Upon completion of the literature review, the authors reported that little data mining had been used for examination of older drivers and crashes to identify hidden patterns and relationships. Using survey results, the study presented a CART models to predict the occurrence of a crash or non-crash, given driver, roadway, vehicle, and other variables. The tree depth was five layers, and the age variable represented the root node split. The model accuracy for the trained model and the test model was 81.1% and 68.78% respectively. The authors suggested the small sample size to be the cause of the poor predictive power in the test data; and, as a result, findings were not robust enough to be generalizable. However, the authors claimed that a larger data set "could be quite useful for this type of application" (p. 623). Additionally, the authors identified over-fitting as a limitation of the decision tree approach, and an approach that either stops the tree from growing or prunes the tree after it has been fit may be used to correct the issue. The authors concluded that data mining should be used to discover unknown relationships for crashes for senior and teenage drivers.

Abdel-Aty and Keller (2005)

Abdel-Aty and Keller (2005) hypothesized that crash injury levels were affected by crash and intersection specific characteristics. Expanding upon Abel-Aty (2003), the authors developed ordered probit models to assess 33,592 crashes that occurred in 832 intersections from 2000 and 2001. The study presented three ordered probit models (1) independent variables equaled crash types, 2) independent variables equaled intersection characteristics, and 3) independent variables equaled a combination of crash types and intersection characteristics) to determine the factors that impact crash severity, and to determine if a difference existed when the models were based on completeness of the data. Findings suggested that division on the minor road, right turn channelization on the major road, and an increase in the number of lanes and speed limit on the minor road decrease the expected level of injury. For the third severity model using both crash types and intersection characteristics as independent variables, collisions involving bicyclists or pedestrians had the highest likelihood of severe injury; angle, head-on and left-turn collisions had the highest likelihood of a higher injury severity level; and, median presence and higher speed limit on the minor road lowered the likelihood of a severe injury. The study also presented a hierarchical tree-based regression model to estimate the expected crash frequency for each crash injury severity level. Results indicated that the most significant factors for no-injury crashes, possible injury, non-incapacitating injury and incapacitating injures are traffic volume of the major road, the number of lanes on the minor road, the number of exclusive right turn lanes, and the average daily traffic on the minor road, respectively. The authors concluded that the models should be developed for each level of severity as opposed to predicting the overall severity level, and the tree-based regression improves the understanding of the importance of specific factors on individual levels of severity.

Yan and Radwan (2006)

Yan and Radwan (2006) used the classification tree approach to investigate factors of rear-end crashes that occur at signalized intersections. The Florida crash data used was restricted to two-vehicle, rear-end collisions, and the striking driver was considered to be the at-fault party. The authors developed a classification tree based on the entropy algorithm, $i_t = -p_t \log (p_t) - (1 - p_t) \log (1 - p_t)$, to split the data until each subset reached the appropriate level: Model 1, two-vehicle crashes at a signaled intersection categorized as rear-end crashes and non-rear-end crashes; Model 2, only rear-end crashes categorized as striking and struck. Model 1 results suggested the most important variables to split the data are speed limit, alcohol use, and crash injury severity, a higher probability for rear-end crash to occur at an intersection if the speed limit was 45-55 mph, and an increased likelihood of no injury or possible injury for crashes occurring at these higher speeds. Findings also inferred that alcohol combined with either lower or higher speed limits increase the likelihood of a rear-end crash occurring, the risk for a rear-end collision is higher for daytime conditions than nighttime conditions, and wet or slippery road surfaces increase the risk of rear-end collisions and incapacitating injury. Model 2 results indicated that alcohol was the most significant factor impacting a drivers' striking another vehicle. Model results suggested that drivers under the age of 21 and over 75 have the greatest risk of rear-end collisions. As a result, the authors recommended speed limit reduction to 40 mph at signalized intersections, enforcement for reducing alcohol intoxicated drivers, and additional education for drivers under the age of 21 years-old for reducing rear-end crashes at signalized intersections, and concluded that the classification trees are an appropriate approach in investigating crash propensity.

Chang and Wang (2006)

Chang and Wang (2006) developed a CART model to examine the impact of gender, age, sobriety condition, crash location, vehicle type, contributing circumstance and collision type on crash injury severity. Model results illustrated an initial split based on vehicle type; and, suggested that bicyclist, motorcyclists and pedestrians have the highest risk, and contributing circumstance, collision type, and driver action are important in determining crash injury severity. The authors concluded by calling for future work in comparing CART model results with traditional models such as ordered probit and logistic regression models.

Abellán et al. (2013)

Abellán et al. (2013) developed decision trees to analyze traffic crash severity for motorcyclists in Granda, Spain. The authors extracted single-vehicle crash observations that occurred on two-lane rural highways from 2003 to 2009 for a total of 1,801 observations, and identified the following rules as having a high risk of a severe injury outcome for motorcyclists: when only one occupant was involved in a single vehicle crash; when at-fault motorcyclists were involved in a run-off-road crash in favorable weather conditions; when male motorcyclists were involved in a run-off-road crash as the result of driver characteristics; and when male motorcyclists were involved in a run-off-road crash in favorable weather. Findings inferred additional rules to be a high risk of killed/seriously injured crashes on two-lane rural highways when no safety barriers are in place: motorcyclists with no-restrained site distance; crashes in the evening in good weather conditions with no lighting; and crashes with pedestrians during favorable weather when the driver is male. The authors concluded that the method allowed for a high number of rules to be identified, and the method could be extrapolated for studies on other datasets.

Eustace et al. (2014)

Eustace et al. (2014) employed classification tree models in conjunction with generalized ordered logit models to examine factors that contribute to injury severity for run-off-road crashes in Ohio. Results indicated that the most important predictor variables as run-off-road crash types, road condition, vehicle type, posted speed limit, gender, road contour, alcohol- and drug-related factors. The study then presented an ordered logit regression using maximum likelihood and results confirmed the significant factors that increase the probability of run-off-road injury severity levels to be curves and grades, alcohol and drug use, female victims, wet-roadway surfaces, overturn/rollover crashes, and speed limits of at least 40 mph. Important interactions identified by the decision tree model included: females on higher posted speed limits have higher risk of injury; males with drug involvement and a higher posted speed limit have a higher risk of injury; alcohol use on a road with speed limits over 40 mph have higher risk of injury; and, male drivers in crashes on wet road surfaces have higher risk of injury. The authors concluded that not only does the decision tree model analysis identify significant factors of injury severity, it also allows for the detection of multi-level interactions.

2.2.5 Artificial Neural Networks

Abdelwahab and Abdel-Aty (2001) argued that the learning capabilities and adaptive nature of ANN models make this methodology possibly superior to traditional techniques, and called for future investigation of the use of ANN models in transportation safety applications. Additionally, Savolainen et al. (2011) stated that ANN models "provide a robust function for prediction and classification problems" (p. 1673). Yet, Chimba and Sando (2009) claimed that while many studies have applied a form of the ANNs technique to predict crash counts, few have applied the methodology to injury severity modeling. Savolainen et al. (2011) categorized only two studies as 'artificial neural networks', Mannering and Bhat (2014) identified a single study, and three additional studies were discovered in which ANN models were developed to analyze crash injury severity.

A review of literature of neural network techniques that examined crash injury severity is presented below. Below, specific findings related to driver characteristics, contributing circumstances, temporal factors, and road characteristics are identified, followed by a more detailed review of each piece of research.

- Prior results suggested age as a significant factor in influencing injury severity, and older drivers have a greater risk of injury (Abdelwahab and Abdel-Aty, 2001; Abdelwahab and Abdel-Aty, 2002).
- Delen et al. (2006) found that alcohol/drug intoxication is a significant factor in influencing injury severity.
- As the ratio of the estimated speed at the time of the crash to the posted speed limit (referred to as the speed ratio) increase, findings suggested that the level of injury

severity increases (Abdelwahab and Abdel-Aty, 2001; Abdelwahab and Abdel-Aty, 2002).

- Abdelwahab and Abdel-Aty (2002) discovered that rural areas are more dangerous than urban areas, given a crash occurs.
- Delen et al. (2006) reported that weather conditions and time of crash are not influential in crash injury severity.
- Mussone et al. (1999) found no significant correlation between accident index (the ratio of the number of crashes for a given intersection and the number of crashes at the most dangerous intersection) and meteorological conditions or road surface conditions.

Mussone et al. (1999)

Mussone et al. (1999) developed ANN models to assess the accident index (the ratio of the number of crashes for a given intersection and the number of crashes at the most dangerous intersection) for crashes occurring at intersections. A feed-forward neural network used back-propagation learning, and the optimal network structure consisted of ten neurons for eight variables - day/night, flow, virtual conflicts, real conflicts, intersection, accident type, road surface, and weather – four hidden nodes, and one output node – accident index. The authors reported the following significant findings: night-time collision for any crash type at a signalized intersection has the highest degree of danger; any crashes with a pedestrian at non-signalized intersection at night time has the highest degree of danger; no significant correlation between accident index and meteorological conditions or road surface conditions exists; accident index is greater at a unsignalized intersection with average complexity over an unsignalized intersection with the same complexity; accident index is greater for small signalized intersection over small unsignalized intersection; virtual conflict is less important than real conflict points (not dependent on traffic light); and, the accident index at an intersection does not depend on crash type.

Abdelwahab and Abdel-Aty (2001)

Abdelwahab and Abdel-Aty (2001) developed ANN models to predict injury severity for crashes occurring at signalized intersections. The authors used crash data from 1997 from Central Florida, and obtained 2,336 cases (split into a training set (2,000) and a testing set (336)). The study presented multilayer perception (MLP) neural networks, fuzzy adaptive resonance theory (ART) neural networks, and ordered logit for comparison, and suggested that the MLP had better generalizable performance. The authors conducated a simulation experiment with all combinations of input variables to develop the MLP neural network, so as to assign an output severity level for each input pattern to allow for an understanding of the specific factors that lead to severe injuries. Results suggested that the level of injury severity increases as the speed ratio (the ratio of the estimated speed at the time of the crash to the posted speed limit) increases, and older drivers and female drivers have a greater risk of injury. Findings also indicated that at-fault drivers are less likely to be injured than not-at-fault drivers, and seatbelt use decreases the risk of severe injury. The authors claimed that the learning capabilities and adaptive nature of ANN models are important features that make this model superior to traditional techniques; and, that “MLP in particular, and ANNs in general, have promising potential in modeling injury severity” (p.12-13). The authors end by calling for future investigation of the use of ANN models in transportation safety application.

Abdelwahab and Abdel-Aty (2002)

Expanding upon Abdelwahab and Abdel-Aty (2001), Abdelwahab and Abdel-Aty (2002) developed statistical models and ANNs to assess traffic safety at toll plazas. The authors obtained crash reports for 1999 and 2000 from the Central Florida expressway system consisting of ten main-line toll plazas and 42 on/off ramp toll plazas with an annual average daily traffic (AADT) of 420,000 vehicles. They developed a logit model and Radial Basis Function (RBF) model, a type of ANN, to assess frequency and injury severity, given a crash occurs before a toll plaza, at a toll plaza, or after a toll plaza. Findings suggested a two-level nested logit model to be the best model to describe the probabilities of crash location. Model results indicated that he significant variables effecting the likelihood of a crash occurring are E-pass use, plaza type, vehicle type, and peak period. The RBF model was identified as the best model for assessing crash injury severity; and, results suggested that older drivers, female drivers, and E-pass users have a greater risk for injury, and seatbelt use was found to decrease the risk of severe injury. The authors concluded by recommending improvements in lane markings to be undertaken, lane width should be wide enough to accommodate large trucks, and signage should be appropriately represented before and at the plaza location.

Abdel-Aty and Abdelwahab (2004a)

Abdel-Aty and Abdelwahab (2004a) expanded upon Abdelwahab and Abdel-Aty (2001 and 2002) by comparing the viability and benefits of MLP and ART neural networks in predicting traffic crash injury severity. The authors developed and compared MLP, fuzzy ARTMAP (a type of ART) neural networks and ordered probit, and found the MLP model to perform better than the other two models. Results indicated that as the ratio of the estimated speed at the time of the crash to the posted speed limit (i.e. speed ratio) increases, injury severity also increases; older drivers have a greater risk of injury; female drivers have a greater risk of severe injury; and rural areas are more dangerous than urban areas.

Bayam et al. (2005)

Bayam et al. (2005) provided a meta-analysis of prior literature on older drivers involved in crash incidents and illustrated the use of data mining techniques for injury severity analysis. The meta-analysis of the literature suggested that for older drivers: the risk of fatality increases, left-turn crashes are more common, the tendency to strike fixed objects increases, the risk of fatality substantially increases at speeds exceeding 69 mph, driving distance decreases, more time is taken to turn, visual abilities decline, slower speeds are driven, and crashes occurring at intersections have a higher risk of fatality. Upon completion of the literature review, findings inferred that little data mining had been used for examination of older drivers and crashes to identify hidden patterns and relationships. The authors conducted a survey to explore key characteristics (e.g. temporal information, passenger presence, number of crashes, etc.) of older drivers residing in Montgomery County, Maryland. Using survey data, the final neural network included 22 input layer nodes, two first hidden layer nodes and three second hidden layer nodes, and reached an accuracy of 87.5%. Results suggested strong relationships between the comfort level in certain driving situations and crash injury severity. From this, the authors concluded that if elderly drivers feel comfortable to change direction, the risk of crash involvement decreases.

Delen et al. (2006)

Delen et al. (2006) developed a series of ANNs to model non-linear relationships between crash injury severity and crash-related factors, given a multi-vehicle collision crash, single vehicle fixed-object crash, or single vehicle rollover crash occur. The authors accessed data from the National Automotive Sampling System General Estimates System and obtained 30,358 records from 1995 to 2000. The study presented eight binary MLP neural network models with different levels of crash injury severity as the output layer. Significant factors identified as influencing injury severity are seat belt use, alcohol/drug intoxication, age and gender, and vehicle role. Results suggested that weather conditions and time of crash are not influential. The authors concluded that no single factor appeared to be a key determinate of injury severity; yet, a factor could act as an enabler or obstacle when combined with other factors.

Chimba and Sando (2009)

Chimba and Sando (2009) compared ANN models and ordered probit (OP) models in the prediction power of highway traffic crash injury severity. The authors claimed that while many studies have applied a form of the ANNs technique to predict crash counts, few have applied the methodology to injury severity modeling. However, computer technology advancements make the ANN technique feasible for crash severity prediction. The study's objective was to present an approach for optimizing the number of hidden neurons, and then to compare the back-propagation ANN performance with the OP method. The authors accessed data for crashes occurring in 2003 on arterial segments of the Florida state highway system and obtained 1,271 records. The model presented various ANN outputs based on differing amounts of hidden neurons, epochs and learning rates, and results were compared to a trained network performance. When comparing the prediction accuracy of the ANN and OP models, results suggested that the ANN resulted in an approximate prediction accuracy of 83.3%, while the OP had a prediction accuracy of 65.5%. This suggests that a well-structured ANN can produce higher prediction performance relative to the OP approach. The authors concluded by suggesting future research consider multiple injury severity levels as the network outputs, as well additional input variables to determine injury severity.

Chapter 3 - Research Purpose

3.1 Research Purpose

As the literature review makes clear, researchers have employed a wide array of methodological techniques when examining crash data; and, each approach encompassed varying advantages and limitations with the potential to lead to complementary, conflicting and/or inaccurate results. Yet, few studies have directly compared the varying benefits and results of different modeling techniques (Ye and Lord, 2014).

Abdel-Aty (2003) compared ordered probit, multinomial logit and nested logit methods to model injury severity. Compared to the ordered probit, the multinomial logit methodology produced poorer results in all tested applications, which was evident from lower likelihood ratio indexes. Also compared to the ordered probit model, the best nested model of six developed multinomial logit models resulted in only a slight improvement in the goodness-of-fit measure and had a negligible effect on the classification accuracy. Due to the difficulty of determining the best nested model given the vast number of different possible nesting structures, the authors recommend the ordered probit as an easy to estimate and well performing model for assessing crash injury severity.

Haleem and Abdel-Aty (2010) compared ordered probit, binary probit and nested logit methodologies to aid in the selection of the best modeling technique for injury severity analysis for crashes occurring at unsignalized intersections. The authors developed two separate models to analyze the relationship between severe injuries (incapacitating injury and fatal injury), non-severe injuries (property damage only, possible injury, and non-incapacitating injury), and explanatory characteristics at three and four legged unsignaled intersections. Comparing the binary probit and the ordinal probit frameworks, they found that the aggregated binary probit model had a lower Akaike Information Criterion (AIC) and higher likelihood of convergence, indicating that the binary probit model better fit the data. The authors claimed that this finding suggested that the aggregate model performs better when analyzing injury severity, given a crash at an unsignalized intersection.

More recent efforts compared injury severity model structures (Abay, 2013a; Yasmin and Eluru, 2013; Ye and Lord, 2014). Abay (2013) investigated the choice of 'state of the art' injury severity models by examining the sensitivity of the model results to empirical inferences. The author estimated four models: standard fixed-parameter ordered logit (OL), random parameters ordered logit (RPOL), standard fixed-parameter multinomial logit (MNL), and mixed logit (MXL). Findings suggested that substantial differences in the marginal effect of the variables in the OL model compared with the RPOL and MXL models existed, and underestimation of the effects of important driver behaviors can lead to misinformed safety planners. For example, when compared to the

RPOL and MXL estimations, the OL model underestimated the effect of an older-aged pedestrian being struck by a driver proceeding straight-ahead, which could misguide policy intended to help vulnerable pedestrians.

Yasmin and Eluru (2013) explored methodological approaches used to assess driver injury severity in traffic crashes by comparing ordered response methodologies (ordered logit, generalized ordered logit, mixed generalized ordered logit) with methodologies that either neglect the natural ordering of the response outcome or require artificial constructs to consider ordering (multinomial logit, nested logit, ordered generalized extreme value logit, and mixed multinomial logit). The authors used a two-step approach to compare the unordered to the ordered models: step 1) established the superior model within each methodological framework using the likelihood ratio test; step 2) compared the superior models from each framework using a non-nested measure. The authors determined that neither the unordered or ordered frameworks outperformed the other at either the aggregate or disaggregate level. The authors concluded that their findings signified that the different approaches offer comparable prediction for the risk of crash injury severity.

Ye and Lord (2014) compared the sample size requirements for estimating multinomial logit, ordered probit and mixed logit models. The authors reported the mixed logit model to be more interpretive than the multinomial logit model, since the parameter effects can vary across crashes in the mixed logit model. Additionally, results indicated that the ordered probit model did not have the same interpretive power as the other methodologies, as the effects of the explanatory variables are restricted to impacting ordered probabilities using identical coefficients across the ordered outcomes.

The authors combined simulation data with the four-year crash records to compare sample size effects on the three models. Results suggested that the ordered probit model required the smallest samples and the mixed logit model required the largest samples. Overall results indicated that all three models improved in accuracy as sample size increased, the mixed logit and multinomial logit were more sensitive to smaller sample sizes, and the minimum sample size for the ordered probit, multinomial logit and mixed logit are approximately 2,000, 5,000, and 10,000 observations respectively.

While prior research has made substantial progress in crash injury severity modeling, “major methodological and data challenges have yet to be fully resolved” (Savolainen et al., 2011, p. 1674). Accordingly, addressing these challenges “must be a priority in future crash-injury research” (Savolainen et al., 2011, p.1674), and “not expanding the methodological frontier, and continuing to use methodological approaches with known deficiencies, has the potential to lead to erroneous and ineffective safety policies that may result in unnecessary injuries and loss of life” (Mannering and Bhat, 2014, p. 16).

To expand the methodological frontier and advance the future of crash injury research, this study will build upon the current body of literature by comparing four methodological techniques used in crash injury severity models and by creating model ensembles that combine popular, longstanding crash injury severity models with contemporary data analytic techniques to examine the accuracy and validity of simultaneously employing multiple methodologies. This research will estimate, compare, and ensemble (1) multinomial logit, (2) ordinal probit, (3) artificial neural networks and (4) decision tree models to attempt to gain greater insight into relationships in Missouri crash data and to examine how crash injury severity differs with numerous possible explanatory variables. By doing so, the combination of modeling techniques are expected to uncover more intricate relationships amongst explanatory variables, and provide better information for transportation planning, education and policy that will enhance transportation safety efforts.

3.2 Research Objectives

(1) Build four differing model types (multinomial logit, ordinal probit, artificial neural network and decision tree models), and assess the performance of each individual model by examining the relative accuracy of the model on a training subset and a testing subset of the data.

(2) Combine multinomial logit, ordinal probit, artificial neural network and decision tree models to build a model ensemble to test if the combination of the multiple methodologies enhances the classification accuracy of crash injury severity on a training subset and a testing subset of the data.

(3) Examine and compare the predictive importance of variables generated by each individual model and the model ensemble to determine the factors that have the greatest effect on crash injury severity outcomes.

(4) Gain greater insight into relationships in the crash data by examining how crash injury severity is affected by a wide range of possible explanatory variables.

(5) Evaluate findings relative to current Missouri driving policy and law to provide information for transportation planning, education and policy to enhance transportation safety efforts.

3.2.1 Research Questions

Q_1: What insights do the multinomial logit, ordinal probit, artificial neural network, decision tree and model ensemble each reveal from the data?

Q_2: What is the relative accuracy and discriminatory power of each model in comparison with the accuracy of the model ensemble?

Q_3: When adjacent severity outcomes are grouped, what is the relative discriminatory power of each model compared to the discriminatory power of the model ensemble?

Q_4: What findings are derived from the model with the greatest accuracy and/or discriminatory power, and do these findings support prior research?

Q_5: Do the findings support current Missouri public policy or point to needed revision?

Chapter 4 – Data and Methodology

4.1 Data

The Missouri State Highway Patrol (MoHWP) Traffic Division collects and preserves crash report data, and codes and classifies the reports for entry into the Statewide Traffic Accident Records System (STARS) database. The intent of the STARS program is to provide timely and accurate traffic crash information to support operation and management of traffic safety (Missouri Traffic Records Committee, 2002). MoHWP provided traffic, personal, and vehicle crash data files from 2002-2012 from the STARS database, which contained 3,902,742 individual records.

The MoHWP is responsible for training police officers on the proper collection, processing and completion of the STARS crash report through the use of the Missouri Uniform Crash Report form and field reporting procedures, and obligations for STARS reporting are specified in Missouri statue 43.250 (Missouri Traffic Records Committee, 2002). Law enforcement officers who investigate a vehicle crash must file crash reports to the Superintendent of the MoHWP within ten days of the investigation when a vehicle crash results in injury to or death of a person or when total property damage appears to be five hundred dollars or more to one vehicle (Missouri Traffic Records Committee, 2002). The Superintendent of the MoHWP appoints a standing committee to provide direction and coordination for improvement to STARS and the Missouri Uniform Crash Report. The following agencies have representation on the committee: AAA - Automobile Club of Missouri, Bridgeton Police Department, Cass County Sheriff's Office, Columbia Police Department, Federal Highway Administration, Federal Motor Carrier Safety Administration, Kansas City Police Department, Missouri Department of Health, Missouri Department of Revenue, Missouri Department of Transportation, Missouri Safety Center, Missouri Safety Council, Missouri State Highway Patrol, National Highway Traffic Safety Administration, Platte County Sheriff's Department, Poplar Bluff Police Department, Regional Justice Information System, St. Charles County Sheriff's Department, St. Joseph Police Department, St. Louis County Highway Department, St. Louis Metropolitan Police Department, Springfield Police Department, and Town and Country Police Department (Missouri Traffic Records Committee, 2002).

4.1.2 Data Description

This study uses three relevant datasets from the STARS database: accident level data, vehicle level data and personal level data. Each dataset, which is categorized in the *Missouri State Highway Patrol Record Specification* form, contains an array of information that is linked together using the accident number and person number.

MoHWP provided 151 variables grouped as crash time and date, notification and report time and date, agency and highway patrol information, crash severity, number injured and killed, number and type of vehicle, crash location, highway information, speed limit, driver characteristics, driver contributing circumstances, temporal factors, weather conditions, road characteristics, crash type, licensing state, license type, vehicle damage, vehicle action, restraint and helmet use, airbag deployment, pedestrian characteristics, and pedestrian contributing circumstances. The years 2002-2012 are combined from the three datasets into a single dataset containing 3,902,742 observations.

Drawing upon the reviewed literature, as illustrated in Table 4.1, the variables suggested to affect crash injury severity include: age, gender, number of occupants, speed limit, light conditions, weather conditions, road conditions and characteristics, and contributing circumstances.

Table 4.1: Variables Suggested by Reviewed Literature to Affect Crash Injury Severity

Variables	Reviewed Liturature
Age	Kuhnert et al. (2000); Abdelwahab and Abdel-Aty (2001); Bédard et al. (2002); Khattak et al. (2002); Abdel-Aty (2003); Khattak and Rocha (2003); Abdelwahab and Abdel-Aty (2004); Delen et al. (2006); Lu et al. (2006); Schneider et al. (2009); Haleem and Abdel-Aty (2010); Rifatt et al. (2011); Yasmin and Eluru (2013)
Gender	Kuhnert et al. (2000); Abdelwahab and Abdel-Aty (2001); Abdel-Aty and Abdelwahab (2003); Abdel-Aty and Abdelwahab (2004); Ulfarsson and Mannering (2004); Delen et al. (2006); Islam and Mannering (2006); Savolainen and Ghosh (2008); Schneider et al. (2009); Malyshkina and Mannering (2010b); Schneider and Salovainen (2011); Eustace et al. (2014)
Number of Occupants	Renski et al. (1999); Oh (2006)
Speed Limit	Renski et al. (1999); Khattak et al. (2002); Oh (2006); Gårder (2006); Malyshkina and Mannering (2010); Savolainen and Ghosh (2008); Haleem and Abdel-Aty (2010); Zhu and Srinivasan (2011); Yasmin and Eluru (2013)
Light Conditions	Klop and Khattak (1999); Rifatt and Tay (2009); Haleem and Abdel-Aty (2010); Wang et al. (2009); Haleem and Abdel-Aty (2010); Khattak et al. (2002)
Weather Conditions	Khattak et al. (1998); Abdel-Aty (2003); Wang et al. (2009)
Road Conditions & Characteristics	Khattak et al. (1998); Krull et al. (2000); Lu et al. (2006); Rifatt and Tay (2009); Quddus et al. (2010); Zhu and Srinivasan (2011)
Contributing Circumstances	Chang and Wang (2006)

As a result, the following variables have been included in the analysis:

Crash Injury Severity

The Missouri Traffic Records Committee (2001) measures the injury severity of a crash as follows

1. Fatality – when one or more person dies as the result of the crash within 30 days of the incident.
2. Injury - any crash in which a (1) disabling injury, (2) evident but not disabling injury, or (3) probable but not apparent injury is received by one or more people as a result of the incident.

3. Property Damage - any crash in which property was damaged, but no person was killed or injured as a result of the incident. A report for the STARS database is not required for property damage of less than $500.00.

Driver Characteristics

Age

Gender: Male, Female, Unknown

Total Number of People Involved

Contributing Circumstances

After a crash occurs, the crash investigator identifies at least one of the following contributing circumstances at the driver level : Vehicle Defects, Improperly Stopped, Speed - Exceed Limits, Too Fast for Conditions, Improper Passing, Violation Stop Sign/Signal, Wrong Side - Not Passing, Following Too Close, Improper Signal, Improper Backing, Improper Turn, Improper Lane Usage/Change, Wrong Way (One-Way), Improper Start from Park, Improperly Parked, Failed to Yield, Alcohol, Drugs, Physical Impairment, Distracted/Inattentive, Vision Obstructed, Driver Fatigue/Asleep*, Failed to Dim Lights*, Failed to Use Lights*, Improper Towing/Pushing*, Overcorrected*, Improper Riding/Clinging to Vehicle Exterior*, Failed to Secure Load/Improper Loading*, Animal(s) in Roadway, Object/Obstruction in Roadway*, Other, and Unknown.

Temporal Factors

Day of Week: Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, Saturday

Light Conditions: Daylight, Dark - Streetlights On, Dark - Streetlights Off, Dark - No Streetlights, Indeterminate, Unknown

*Contributing circumstance included in data collection in 2012.

Weather Conditions

Conditions: Clear, Cloudy, Rain, Snow, Sleet, Freezing, Fog/Mist, Indeterminate

Road Characteristics

Road Conditions: Other/Unknown, Dry, Wet, Snow, Ice, Mud, Slush, Standing Water, Moving Water, Dry

Road Alignment: Unknown, Curve, Straight

Road Profile: Unknown, Hill/Grade, Crest, Level

Road Surface: Unknown, Asphalt, Brick, Gravel, Dirt/Sand, Multi-Surface, Concrete

Speed Limit: 15mph, 20mph, 25mph, 30mph, 35mph, 40mph, 45mph, 50mph, 55mph, 60mph, 65mph, 70mph, Unknown

Crash Type

Type: Animal, Bicyclist/Pedalcyclist, Fixed Object, Other Object, Pedestrian, Train, Motor Vehicle in Transport, Motor Vehicle on Other Roadway, Parked Motor Vehicle, Non-Collision Overturn, Non-Collision, Other, Animal Drawn Vehicle/Animal Ridden Trans, Working Motor Vehicle, Fire / Explosion, Immersion, Jackknife, Fell/Jumped from MV, Cargo/Equipment Loss/Shift

Location

Crash Location: On Roadway, Off Roadway

4.1.2.1 Variable Frequencies

Initial data exploration uses cross tabulations to examine the frequency of injury severity, given a crash occurs, conditional on the values of individual explanatory variables. To be included in this analysis, observations must meet the following criteria:

- Crash occurs among the years 2002 to 2012.

- Crash occurs in the state of Missouri.
- The person involved in the crash is the driver of a motor vehicle or other transport device.
- The driver is found to have contributed to the crash.
- The driver's licensing state is Missouri.

When employing these criteria, the unit of analysis is a Missouri licensed motor vehicle driver who contributed to a reported crash in Missouri in 2002 through 2012. By selecting this sub-population, the analysis focuses on the circumstances effecting crash severity for drivers who contribute to the crash occurrence, while eliminating those drivers who were merely victims in the sense that they did not contribute to the crash. Additionally, evaluation of drivers licensed by the state of Missouri who are involved in a reported crash in the state of Missouri provides a commonality for comparison that allows for potential prescriptive training and policy recommendations.

When considering motor vehicle drivers with a Missouri issued driver's license who contributed to a reported crash, cross tabulation results identify 1,282,919 observations in the dataset with the crash severity distributed as 0.6% fatal, 28.1% injury and 71.3% property damage only. The frequencies of crash severity partitioned by each categorical explanatory variable are presented in Tables 4.2 through 4.13 below.

The MoHWP groups drivers ages into categories termed: Young Driver, a driver under the age of 21; Middle Driver, a driver between the ages of 21 and 54; Mature Driver, a driver 55 years of age or older. The sum of the number of Missouri licensed drivers for the years 2002 to 2012 by age group and by gender are presented in Tables 4.2

and 4.3 respectively. The numbers in parentheses in Tables 4.2 and 4.3 are the number of incidents per drivers' licenses year.

As illustrated in Table 4.2, the total number of crashes per driver licensed year decreases as the age group increases, as does the number of crashes per driver licensed year of each crash severity level. Additionally, as illustrated in Table 4.3, the total number of crashes per driver licensed year for male drivers is greater than for female drivers, which is also the case for each level of crash severity.

Table 4.2: Frequency of Crash Severity by Age Group

Driver Age Group	Fatal	Injury	Property Damage	Total	Drivers' Licensed Years[1]
Young (< 21 years-old)	1,477 (0.0005)	85,040 (0.0274)	206,732 (0.0666)	293,249 (0.0945)	3,101,902
Middle (≥21 and <55 years-old	4,875 (0.0002)	212,662 (0.0079)	534,448 (0.0198)	751,985 (0.0279)	26,968,574
Mature (≥55 years-old)	1,750 (0.0001)	60,999 (0.0046)	164,450 (0.0123)	227,199 (0.0170)	13,377,387
Unknown	1	1,897	8,588	10,486	0
Total	8,103	360,598	914,218	1,282,919	43,447,863

[1] Data obtained from US Department of Transportation, Federal Highway Administration (2015)

Table 4.3: Frequency of Crash Severity by Gender

Driver Gender	Fatal	Injury	Property Damage	Total	Drivers' Licensed Years[1]
Male	5,969 (0.0003)	203,373 (0.0091)	519,901 (0.0232)	729,243 (0.0325)	22,435,329
Female	2,133 (0.0001)	157,130 (0.0068)	389,201 (0.0168)	548,464 (0.0237)	23,172,730
Unknown	0	39	4,936	4,975	0
Missing	1	56	180	237	0
Total	8,103	360,598	914,218	1,282,919	45,608,059

[1] Data obtained from US Department of Transportation, Federal Highway Administration (2015)

Table 4.4: Frequency of Crash Severity by Contributing Circumstances

Contributing Circumstance	Fatal	Injury	Property Damage	Total
Vehicle Defects	132	9,124	26,079	35,335
Improperly Stopped on Roadway	33	1,750	4,929	6,712
Speed Exceed Limit	1,457	15,015	14,806	31,278
Too Fast for Conditions	2,253	74,516	138,927	215,696
Improper Passing	232	4,348	14,694	19,274
Violation of Stop Sign/Signal	420	23,589	33,184	57,193
Wrong Side - Not Passing	1,229	11,630	13,387	26,246
Following Too Close	167	53,943	166,735	220,845
Improper Signal	7	713	2,356	3,076
Improper Backing	15	1,772	39,412	41,199
Improper Turn	99	10,390	36,398	46,887
Improper Lane Usage/Change	1,517	31,257	84,691	117,465
Wrong Way (One-Way)	91	749	1,126	1,966
Improper Start from Park	4	667	3,181	3,852
Improperly Parked	2	226	1,215	1,443
Failed to Yield	983	75,623	170,798	247,404
Alcohol	2,107	30,180	35,372	67,659
Drugs	337	4,552	5,250	10,139
Physical Impairment	422	13,507	13,238	27,167
Inattention	1,734	107,057	290,602	399,393
Vision Obstructed	626	32,534	88,554	121,714
Driver Fatigue/Asleep	7	656	921	1,584
Failed To Dim Lights	0	2	11	13
Failed To Use Lights	1	40	49	90
Improper Towing/Pushing	0	11	55	66
Overcorrected	60	1,044	1,222	2,326
Improper Riding/Clinging to Vehicle Exterior	0	21	9	30
Failed To Secure Load/Improper Loading	0	25	402	427
Animal(s) in Roadway	11	765	3,002	3,778
Object/Obstruction in Roadway	2	153	654	809
Other	14	961	2,772	3,747
Total [1]	13,962	506,820	1,194,031	1,714,813

[1] The sum of the frequency of contributing circumstance can exceed the number of cases, since multiple citations of contributing circumstance may be present in a given crash.

Table 4.5: Frequency of Crash Severity by Day of Week

Day of Week	Fatal	Injury	Property Damage	Total
Sunday	1,175	38,591	78,527	118,293
Monday	1,009	50,335	132,289	183,633
Tuesday	977	52,131	138,591	191,699
Wednesday	1,037	52,871	141,930	195,838
Thursday	1,072	53,540	143,463	198,075
Friday	1,318	62,633	165,442	229,393
Saturday	1,502	50,421	113,767	165,690
Unknown	13	76	209	298
Total	8,103	360,598	914,218	1,282,919

Table 4.6: Frequency of Crash Severity by Light Condition

Light Condition	Fatal	Injury	Property Damage	Total
Indeterminate	56	3,944	12,465	16,465
Dark - Streetlights On	895	51,042	130,773	182,710
Dark - Streetlights Off	235	4,860	11,060	16,155
Dark - No Streetlights	2,401	39,362	57,931	99,694
Daylight	4,515	261,341	701,812	967,668
Missing	1	49	177	227
Total	8,103	360,598	914,218	1,282,919

Table 4.7: Frequency of Crash Severity by Weather Condition

Weather Condition	Fatal	Injury	Property Damage	Total
Cloudy	2,368	95,787	231,930	330,085
Rain	395	24,747	67,902	93,044
Snow	113	7,036	24,846	31,995
Sleet	16	1,160	3,360	4,536
Freezing	44	2,015	5,409	7,468
Fog/Mist	91	2,426	4,883	7,400
Indeterminate	27	1,403	10,303	11,733
Clear	5,045	225,786	564,684	795,515
Missing	4	238	901	1,143
Total	8,103	360,598	914,218	1,282,919

Table 4.8: Frequency of Crash Severity by Road Surface

Road Surface	Fatal	Injury	Property Damage	Total
Unknown	14	2,618	15,186	17,818
Asphalt	6,620	283,922	695,042	985,584
Brick	1	167	916	1,084
Gravel	325	9,674	15,914	25,913
Dirt or Sand	16	448	842	1,306
Multi Surface	152	5,713	15,297	21,162
Concrete	975	58,055	171,010	230,040
Missing	0	1	11	12
Total	8,103	360,598	914,218	1,282,919

Table 4.9: Frequency of Crash Severity by Road Conditions

Road Conditions	Fatal	Injury	Property Damage	Total
Other/Unknown	53	2,936	9,318	12,307
Wet	1,047	61,424	163,216	225,687
Snow	133	8,005	29,687	37,825
Ice	78	4,622	13,340	18,040
Dry	6,792	283,569	698,589	988,950
Missing	0	42	68	110
Total	8,103	360,598	914,218	1,282,919

Table 4.10: Frequency of Crash Severity by Road Alignment

Road Alignment	Fatal	Injury	Property Damage	Total
Unknown	10	1,873	13,835	15,718
Curve	2,941	68,059	129,811	200,811
Straight	5,152	290,666	770,572	1,066,390
Total	8,103	360,598	914,218	1,282,919

Table 4.11: Frequency of Crash Severity by Road Profile

Road Profile	Fatal	Injury	Property Damage	Total
Unknown	24	3,696	19,815	23,535
Hill/Grade	4,271	114,574	240,829	359,674
Crest	287	10,148	21,055	31,490
Level	3,520	231,985	631,679	867,184
Missing	1	195	840	1,036
Total	8,103	360,598	914,218	1,282,919

Table 4.12: Frequency and Percentage of Crash Severity by Crash Type

Crash Type	Fatal	Injury	Property Damage	Total
Animal	10 (0.3%)	490 (16.2%)	2,531 (83.5%)	3,031 (100%)
Bicyclist/Pedalcyclist	18 (0.8%)	1,867 (84.0%)	337 (15.2%)	2,222 (100%)
Fixed Object	3,368 (1.5%)	86,792 (37.6%)	140,431 (60.9%)	230,591 (100%)
Other Object	42 (0.8%)	1,124 (22.1%)	3,930 (77.1%)	5,096 (100%)
Pedestrian	205 (4.4%)	4,124 (88.5%)	331 (7.1%)	4,660 (100%)
Train	69 (19.8%)	133 (38.1%)	147 (42.1%)	349 (100%)
Motor Vehicle in Transport	3,312 (0.4%)	240,416 (25.6%)	694,141 (74.0%)	937,869 (100%)
Motor Vehicle on Other Roadway	82 (4.1%)	541 (27.1%)	1,374 (68.8%)	1,997 (100%)
Parked Motor Vehicle	85 (0.1%)	6,344 (10.2%)	56,050 (89.7%)	62,479 (100%)
Non-Collision Overturn	843 (3.1%)	16,718 (61.5%)	9,606 (35.4%)	27,167 (100%)
Non-Collision Other	66 (1.0%)	1,888 (27.5%)	4,918 (71.6%)	6,872 (100%)
Other	3 (0.5%)	161 (27.5%)	422 (72.0%)	586 (100%)
Total	8,103 (0.6%)	360,598 (28.1%)	914,218 (71.3%)	1,282,919 (100%)

Table 4.13: Frequency of Crash Severity by Crash Location

Crash Location	Fatal	Injury	Property Damage	Total
Crash On Roadway	4,090	255,949	709,414	969,453
Crash Off Roadway	4,013	104,649	204,804	313,466
Total	8,103	360,598	914,218	1,282,919

The study presents chi-square tests to determine if significant differences exist between the frequencies of crash outcomes across the different categories of the individual variables. Interesting observations from the chi-square tests and other relevant remarks regarding the data are as follows:

- A statistically significant difference among age groups and their relationship with crash injury severity exists at the 0.05 significance level (χ^2 = 428.641; p = 0.000), with fatal outcomes more prevalent for middle-aged drivers and mature drivers, injury outcomes more prevalent for young drivers and middle-aged drivers, and property damage outcomes more prevalent for mature drivers.
- The most often cited contributory factor is inattention (33.5%).
- The top three cited circumstances that contribute to a fatality are driving too fast for conditions (27.8%), alcohol (26.0%), and inattention (21.4%).
- **For younger drivers,** the contributing circumstances of following too close (χ^2 = 890.454; p = 0.000), inattention (χ^2 = 39.385; p = 0.000), driving too fast for conditions (χ^2 = 7,315.776; p = 0.000), speeding (χ^2 = 3,705.197; p = 0.000), driving on the wrong side of the road (χ^2 = 217.586; p = 0.000), overcorrecting (χ^2 = 91.432; p = 0.000), and vision obstructed (χ^2 = 483.381; p = 0.000) are more prevalent than for older drivers (21+ years-old) at a 0.05 significance level.
- **For mature drivers,** the contributing circumstances of failing to yield (χ^2 = 12,154.163; p = 0.000), improper backing (χ^2 = 1,692.303; p = 0.000), improper lane usage (χ^2 = 219.905; p = 0.000), improper signal (χ^2 = 43.305; p = 0.000), improper start (χ^2 = 13.036; p = 0.000), improper turn (χ^2 = 1,42.693; p = 0.000), improperly parked (χ^2 = 10.823; p = 0.001), improperly stopped (χ^2 = 57.518; p = 0.000), physical impairment (χ^2 = 2,584.381; p = 0.000), violation of stop-sign/signal (χ^2 = 577.468; p = 0.000), driving the wrong way on a one-way street (χ^2 = 17.955; p = 0.000), improper towing (χ^2 = 3.991; p = 0.000), and striking an

object in the roadway (χ^2 = 17.991; p = 0.000) are more prevalent than for younger drivers (<55 years-old) at a 0.05 significance level.

- A statistically significant difference between genders with respect to crash injury severity exists at the 0.05 significance level (χ^2 = 2828.094; p = 0.000), with fatal outcomes and property damage outcomes more prevalent for male drivers and injury outcomes more prevalent for female drivers.
- The contributing circumstances of overcorrected (χ^2 = 5.598; p = 0.018), inattention (χ^2 = 34.496; p = 0.000), improper turn (χ^2 = 6.306; p = 0.012), and failed to yield (χ^2 = 67.332; p = 0.000) are more prevalent for female drivers.
- The contributing circumstances of speeding (χ^2 = 1332.012; p = 0.000), driving too fast for conditions (χ^2 = 5.900; p = 0.015) improper passing (χ^2 = 20.698; p = 0.000), improper lane usage (χ^2 = 4.942; 0.026), alcohol intoxication (χ^2 = 198.025; 0.000) and drug use (χ^2 = 6.061; p = 0.014) are more prevalent for male drivers.

4.2 Methodology

The study employs IBM SPSS 22.0 and IBM SPSS Modeler 15.0 to develop and ensemble multinomial logit, ordinal probit, artificial neural network, and decision tree models to predict the effect of certain factors on crash injury severity. Descriptions of the abovementioned models are as follows.

4.2.1 Multinomial Logit Model

The multinomial logit model is an unordered methodological approach used to predict the probability of three or more categorical dependent outcomes, given a set of independent variables. This approach assumes independence of irrelevant alternatives

(IIA) in which the presence or absence of alternative dependent outcomes does not impact the relative probability of modeled dependent outcomes. Many research studies have chosen the multinomial logit approach to account for underreporting when assessing crash injury severity (since not all crashes are reported, the ability to accurately assess data is limited and can lead to a biased estimates when using crash prediction models) (Ye and Lord, 2011). Multinomial logit models do not consider the natural ordering of outcomes (if present) and might be considered less parsimonious than ordered models. However, they offer greater explanatory power relative to ordered models due to the additional exogenous effects that may be explored (Eluru, 2013); for example, the effect of changing environmental conditions on the likelihood of an outcome, while all other variables are held constant.

The multinomial logit model is presented below (Savolainen et al. 2011).

$$P_n(i) = \frac{\mathrm{EXP}[\beta_i^T \bullet \mathrm{X}_{in}]}{\sum_i \mathrm{EXP}\,[\beta_i^T \bullet \mathrm{X}_{in}]}$$

where

β_i = a vector of estimable parameters

X_{in} = a vector of observable characteristics that may impact the probability of crash severity outcome i for observation n

$P_n(i)$ = the probability of the crash severity outcome i for observation n

The estimation is completed using maximum likelihood methods, and uses the likelihood ratio test to assess if a statistically significant difference exists between the estimated model and a model in which all of the parameter coefficients are zero. Additionally, the number and percentage of correct predictions may be used to evaluate prediction accuracy. Finally, model effectiveness is evaluated using the proportional by chance accuracy criteria, which is calculated by summing the squared proportion that each group represents of the sample (White, 2013) and comparing this “by chance” accuracy to model forecast accuracy.

4.2.2 Ordered Logit and Probit Models

When alternative categorical outcomes are ordinal in nature and share common trend and unobservable effects, unordered response models can produce inconsistent estimates (Abay, 2013). Therefore, when the value of the response category has a meaningful sequential order (e.g. level of injury severity), ordered probit and ordered logit models may be used to account for the ordinal nature of the dependent variable. Estimation is usually accomplished using maximum likelihood methods, and the estimated relationship can be tested by using probability scores as the predicted values of the ordinal categorical outcomes. The ordered logit and probit models produce similar results; however, differences do occur since estimations are derived from assumed differing error distributions (logit – cumulative standard logistic distribution and probit – cumulative standard normal distribution). The ordered probit model has been chosen for this analysis, since it is the more popular of the two approaches used in prior literature.

Drawing upon Abdel-Aty (2003) the ordered probit model has the following form:

$$P_n(1) = \varphi(\alpha_1 - \beta_1 X_n)$$

$$P_n(j) = \varphi\left(\alpha_j - \beta_j X_n\right) - \varphi\left(\alpha_{j-1} - \beta_{j-1} X_n\right), j = 2, \dots, J-1$$

$$P_n(J) = 1 - \sum_{j=1}^{J-1} P_n(j)$$

where

φ = the cumulative standard normal distribution

α_j = the alternative specific constant

β_j = a vector of estimable coefficients

X_n = a vector of measurable characteristics

$P_n(j)$ = the probability that subject n belongs to category j

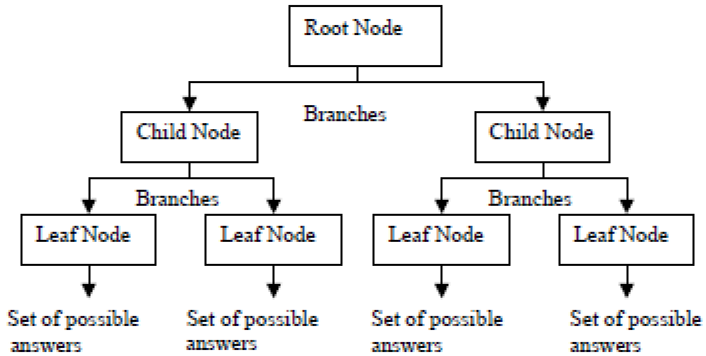
The predicted outcome is the j-value with the largest probability.

The ordered probit model assumes that the vector of estimable coefficients in the model do not vary for each categorical outcome, and the Brant test of parallel lines is used to test whether this assumption (i.e. the proportional odds assumption or, alternatively, the parallel lines assumption) holds true. A significant test statistic indicates that the parallel lines assumption has been violated.

4.2.3 Decision Tree Model

Decision tree models may be used for classification of occurrences into pre-specified groups, for prediction of values of a dependent variable based on values of independent variables, and for data exploration in model building. The tree is built by applying decision rules sequentially that split a larger heterogeneous population into smaller more homogeneous subsets (termed nodes) based on the single, most predictive input factor (Eustace et al., 2014). Subset purity is measured and evaluated using the Gini coefficient as the measure of purity to determine the best split for the subset (Mingers, 1989a), and factors deemed statistically homogenous, with respect to the target outcome, are combined (Trnka, 2010). Splitting continues for each node until no more splits are possible or until pre-defined stopping parameters (e.g. maximum tree depth or minimum number of records in branch) are reached.

Figure 4.1: Structure of a Decision Tree (Bayam et al., 2005)



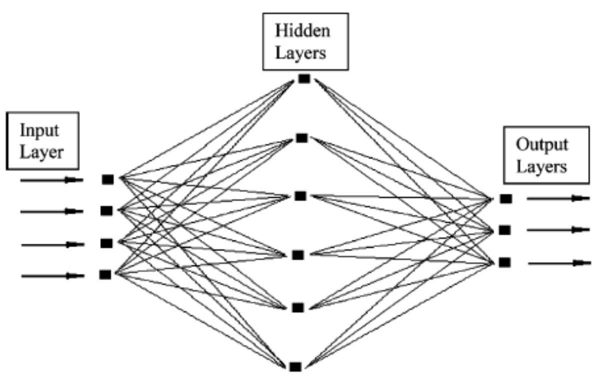
Decision trees have several advantages over other models, which include nonlinear relationships between variables do not affect performance, the data partitioning yields insights into input / output relationships, each path of the decision tree contains an estimated risk factor, missing values are accommodated automatically, and the output is simple to understand and interpret. However, overfitting of the model can occur if the learning algorithm fits data that is irrelevant (i.e. noise), which results in a model that may not be generalizable (Bayam et al., 2005). Fortunately, to avoid overfitting and improve generalization, pruning may be used to remove lower-level splits that do not significantly contribute the generalized accuracy of the model (Mingers, 1989b).

Various decision tree algorithms, including Classification and Regression Tree (CART) and Chi-square Automatic Interaction Dedication (CHAID), build and prune decision trees in differing ways. CART creates binary trees by splitting records at each node, and builds larger trees that are then pruned back to mitigate overfitting. CHAID creates wider, non-binary trees (often with many terminal nodes connected to a single branch) and automatically prunes the decision tree to avoid overfitting of the model (Bayam et al., 2005). Model fit is evaluated by testing the hypotheses that a difference between the classification accuracy (i.e. percentage of correct classifications) of the testing set and the training set is present. If a significant difference exists, then overfitting is suggested.

4.2.4 Artificial Neural Network

In large data sets, artificial neural networks (ANN) are useful in exploring complex nonlinear relationships. The model may be estimated without hypothesizing relationships between the dependent and independent variables a priori (Abdelwahab and Abdel-Aty, 2001), uses minimal assumptions, and acquires relationship understanding through learning or training processes that rely upon information from previous observations to predict new observations (Savolinen et al., 2011). ANN consists of three layers: an input layer that represents the input variables, hidden layer(s) that uncover patterns between the input and output variables, and an output layer that contains the outcome variables (Bayam et al., 2005).

Figure 4.2: Structure of a Multilayer Perception Neural Network (Bayam et al., 2005)



The multilayer perception (MLP) network, a type of ANN, has been found to be "a robust function approximator for prediction and classification problem[s]" (Delen et al., 2006, p. 437). The MLP involves a general mapping procedure and is comprised of many simple processors each with a small amount of local memory. The three layers, as illustrated in Figure 4.2, include input layers with *K* nodes and a bias node, hidden layers with *J* nodes and a bias node, and output layers with *I* nodes and no bias node (Abdelwahab and Abdel-Aty, 2001).

The MLP network estimation is completed in two phases: a training phase that uses a collection of patterns for learning in order to train the network, and a testing phase that compares the output from the trained network to the desired output in order to test for classification accuracy (Abdelwahab and Abdel-Aty, 2002). The MLP is trained using a back-propagation algorithm, and allows only feed-forward connections (Abdelwahab and Abdel-Aty, 2001) that use directed arrows as coefficients (i.e. weights) (Delen et al., 2006).

ANN models, including MLP networks, are advantageous in capturing the relationship between factors and outcomes by possessing the following characteristics (Abdelwahab and Abdel-Aty, 2001):

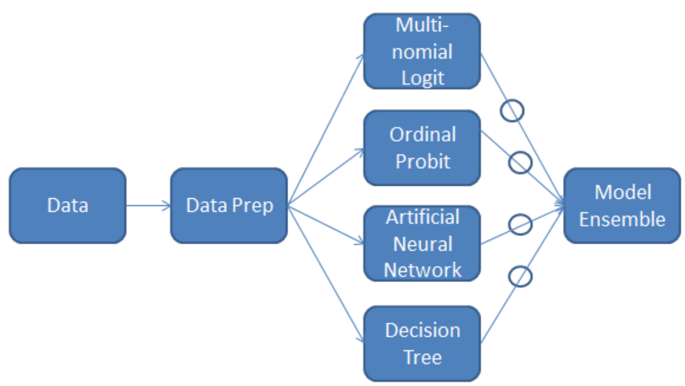
- Nonlinear input-output mapping: ANNs learn nonlinear mapping directly from training data.
- Generalization: ANNs fit the desired function that allows for generalization.
- Adaptability: ANNs can adjust connection weights and network structure to optimize behaviors.
- Fault tolerance: The large numbers of connections produced by ANNs allow for redundancy and each node relies on local information.

Unfortunately, too many hidden layers can result in overfitting and too few can result in high statistical bias (Bayam et al., 2005). Additionally, this approach does not provide a straightforward translation of the weights of the links, and it does have greater computational burden over the aforementioned methodologies (Bayam et al., 2005).

4.2.5 Model Ensemble

Advances in data mining techniques utilize ensemble learning to (1) reduce the impact of inaccurate model selection, (2) properly represent data distributions, and (3) enhance predictive performance (Dietterich, 2000; Polikar, 2006). As illustrated in Figure 4.3, ensemble-based systems draw upon multiple experts by creating and combining the outputs of individual models, with the intent to produce a combination of models that has greater performance (e.g. prediction) over any single model (Polikar, 2006).

Figure 4.3: Model Ensemble Illustration



To obtain greater accuracy relative to the individual models, diversity in ensemble learning must be present (Hansen and Salamon, 1990); and, can be created by combining different modeling types (Polikar, 2006). As a result, it is instinctual that if proper diversity is attained and each model produces different errors, then a strategic combination of the models will reduce the total error (Polikar, 2006). Diversity may be achieved by using differing modeling types and/or using different subsets of data (Polikar, 2006).

The basic procedure to ensemble models employs the following logic:

Step I: Create multiple models of differing types and evaluate each model.

Step II: Construct and evaluate an ensemble of these models.

A. When the constituent model results concur, use the unanimous prediction.
B. When the constituent model results conflict, use a scoring method to combine predictions.
    a. Choose one of several scoring strategies (Kittler et al., 1998; Polikar, 2006).
        i. Algebraic combiners: minimum rule, maximum rule, sum rule, product rule, median rule, and mean rule
        ii. Voting based methods: majority voting and weighted majority voting
        iii. Probability voting: highest probability and highest mean probability
        iv. Other: Softmax smoothing, Borda count, behavior knowledge space, and Dempster-Schafer rule.
    b. If voting is tied, select value using either random selection or highest confidence.

The dataset is randomly partitioned into a training set and a holdout subset, i.e. a testing set, to test for model accuracy. The accuracy of the final model ensemble is compared with the accuracy of the constituent models used in the ensemble by examining the confusion matrices (i.e. confidence matrices). Additionally, the diversity of opinion amongst the models used in the ensemble will be measured to assess the extent that predictions vary across the base models. Finally, the area under the ROC curve (AUC) is used to assess the models' ability to distinguish between the outcome groups (i.e. levels of injury severity) to examine the quality of each model relative to randomly choosing an outcome (i.e. not using a model at all and assigning outcomes at random).

Chapter 5 – Analysis

5.1 Examination of Individual Models

Multinomial logit, ordinal probit, decision tree and artificial neural network models are estimated to predict the effect of certain factors on crash injury severity, and then the performance the individual models is assessed by examining the relative discriminatory power of each model on a training subset and a testing subset of the data.

5.1.1 Multinomial Logit

A multinomial logit regression model is estimated to analyze the factors that affect crash injury severity. Using the unit of analysis defined in Chapter 4, observations in the data set include crashes in which the person involved was the driver of a motor vehicle who contributed to a reported crash in Missouri in the years 2002 through 2012, and held a valid driver's license issued by the state of Missouri at the time of the crash. A main-effects model that includes the covariate and factor direct effects, but does not include interaction effects between variables, is estimated. The base category is set to property damage only, and maximum-likelihood is used to estimate the parameters of the model.

Initial model runs suggested that a perfect prediction (quasi-separation) existed for the three categorical severity outcomes with respect to the variables of (1) contributing circumstances, (2) road conditions, (3) road surface, (4) weather conditions, (5) light conditions, (6) crash type, and (7) day of the week. The quasi-separation is resolved by combining certain variables and categories with similar magnitudes and by removing certain categories and variables. For the variables classified as Contributing Circumstances, *Improper Signal*, *Improper Start from Park*, *Improperly Parked*, *Driver Fatigue/Asleep*, *Failed to Dim Lights*, *Failed to Use Lights*, *Improper Towing/Pushing*, *Improper Riding/Clinging to the Vehicle Exterior*, *Failed to Secure Load/Improper Loading*, *Object/Obstruction in the Roadway* are combined with the *Other* variable, and the variable *Unknown* is removed. For the variable *Road Conditions*, the categories of Ice/Frost, Mud, Slush, Standing Water, and Moving Water are combined with the category of Other/Unknown. For the variable *Road Surface*, the categories of Brick, Dirt/Sand, and Multi-Surface are combined into one category. For the variable *Speed Limit*, the categories of 15mph and 20mph are combined, 25mph and 30mph are combined, 35mph and 40mph are combined, 45mph and 50mph are combined, 55mph and 60mph are combined, and 65mph and 70mph are combined. For the variable *Light Conditions*, the categories of Indeterminate and Unknown are combined. For the variables *Age* and *Gender*, the category of Unknown is excluded. The variables of *Day of the Week* and *Crash Type* are removed from the analysis. Finally, 2,195 cases with missing values are removed. Using this criterion, the final multinomial model is estimated using the variables identified in Table 5.1; and, the number of observations and distribution across injury severities for the sample are shown in Table 5.2.

Table 5.1: Variables Included in Multinomial Model

Driver Characteristics	
Age	Young (<21 years-old); Middle (≥21 and <55 years-old); Mature (≥ 55 years-old); Unknown
Gender	Male; Female; Unknown
Vehicle Occupants	
Total Number of Occupants	1 to 149
Contributing Circumstances	
Alcohol	Present = 1; Not Present = 0
Animal(s) in Roadway	Present = 1; Not Present = 0
Distracted/Inattentive	Present = 1; Not Present = 0
Drugs	Present = 1; Not Present = 0
Failed to Yield	Present = 1; Not Present = 0
Following Too Close	Present = 1; Not Present = 0
Improper Backing	Present = 1; Not Present = 0
Improper Lane Usage/Change	Present = 1; Not Present = 0
Improper Passing	Present = 1; Not Present = 0
Improper Turn	Present = 1; Not Present = 0
Improperly Stopped	Present = 1; Not Present = 0
Other	Present = 1; Not Present = 0
Overcorrected	Present = 1; Not Present = 0
Physical Impairment	Present = 1; Not Present = 0
Speed - Exceeds Limit	Present = 1; Not Present = 0
Too Fast for Conditions	Present = 1; Not Present = 0
Vehicle Defects	Present = 1; Not Present = 0
Violation Stop Sign/Signal	Present = 1; Not Present = 0
Vision Obstructed	Present = 1; Not Present = 0
Wrong Side - Not Passing	Present = 1; Not Present = 0
Wrong Way (One Way)	Present = 1; Not Present = 0
Location	
Crash Location	On Roadway; Off Roadway
Road Characteristics	
Road Conditions	Other/Unknown; Wet; Snow; Ice: Dry
Road Alignment	Unknown; Curve; Straight
Road Profile	Unknown; Hill/Grade; Crest; Level
Road Surface	Unknown; Asphalt; Gravel; Brick/Dirt/Sand/Multi-Surface, Concrete
Speed Limit	15 or 20mph; 25 or 30mph; 35 or 40mph; 45 or 50mph; 55 or 60mph; 65 or 70mph; Unknown
Environmental Factors	
Weather Conditions	Cloudy; Rain; Snow; Sleet; Freezing Rain; Fog/Mist; Indeterminate; Clear
Light Conditions	Indeterminate; Dark-Streetlights On; Dark-Streetlights Off; Dark-No Streetlights; Daylight
Dependent Variable	
Injury Severity	Fatal; Injury; Property Damage Only

Table 5.2: Frequency of Crash Severity for Selected Dataset

Injury Severity	Frequency
Fatal	8,096
Injury	358,162
Property Damage	899,205
Total	**1,265,463**

The dataset is randomly partitioned into a training set (75%; n=948,679) to estimate the model, and a testing set (25%; n=316,784) to assess model accuracy, generalizability, and overfitting. The data partitioning was completed prior to estimating all models, so that identical observations are used for training of the each of the four categories of models (multinomial logit, ordered probit, decision tree, and artificial neural network). If an estimated model performs similarly on the training set and the testing set, it is inferred that the estimated model is not overfit to the dataset.

For the multinomial model estimated on the training set, the overall goodness of fit test, presented in Table 5.3, with 948,679 observations yields a χ^2 = 130,650.385 with 112 degrees of freedom and a p-value of 0.000. Table 5.4 presents the pseudo R-Square values for the training set; Table 5.5 presents the standard errors and p-values for each independent variable for the training set; Table 5.6 presents the parameter estimates and equation specific significance tests for the training set of the model with the baseline category of "property damage only"; and, Tables 5.7 and 5.8 present the model coincidence matrices (also referred to as the classification table) for the training and testing sets.

Table 5.3: Multinomial Model Fitting Information

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	769,957.259			
Final	639,530.874	130,650.385	112	.000

Table 5.4: Multinomial Model Pseudo R-Square

Pseudo R-Square

Cox and Snell	.098
Nagelkerke	.137
McFadden	.082

Table 5.5: Multinomial Model Likelihood Ratio Test

Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	639530.874	.000	0	.
Alcohol	644336.640	4839.766	2	.000
Drugs	640063.587	536.713	2	.000
Failed to Yield	643534.816	4007.942	2	.000
Following Too Close	640332.406	805.532	2	.000
Improper Backing	647124.804	7597.930	2	.000
Improper Lane Usage	639881.061	354.186	2	.000
Improper Passing	639724.796	197.922	2	.000
Improper Turn	639724.538	197.664	2	.000
Improperly Stopped	639549.721	22.847	2	.000
Distracted/Inattentive	640077.383	550.508	2	.000
Physical Impairment	645118.004	5591.130	2	.000
Speed – Exceeds Limit	646673.615	7146.740	2	.000
Too Fast for Conditions	643412.597	3885.723	2	.000
Vehicle Defects	639587.934	61.060	2	.000
Violation Stop Sign/Signal	646156.218	6629.344	2	.000
Wrong Side – Not Passing	641663.543	2136.669	2	.000
Wrong Way (One Way)	639800.023	273.149	2	.000
Overcorrected	639676.792	149.918	2	.000
Total Number of Occupants	667721.349	28194.475	2	.000
Animal(s) in Roadway	639712.871	185.997	2	.000
Other	639557.920	31.046	2	.000
Vision Obstructed	639623.763	96.889	2	.000
Crash Location On/Off Roadway	641906.921	2380.047	2	.000
Road Conditions	641744.538	2229.664	8	.000
Road Alignment	639698.527	175.653	4	.000
Road Profile	640752.994	1234.120	6	.000
Weather Conditions	639666.371	163.497	14	.000
Light Conditions	640124.753	609.879	8	.000
Speed Limit	658125.198	18618.323	12	.000
Age Groups	640135.580	612.706	4	.000
Gender	640283.150	756.276	2	.000
Road Surface	640527.963	1013.089	8	.000

Table 5.6: Multinomial Model Parameter Estimates

Crash Severity		B	Std. Error	Wald	Sig.	Exp(B)
Fatal	Intercept	-7.321	.165	1979.362	.000	
	Alcohol	1.095	.032	1172.772	.000	2.990
	Drugs	.969	.062	241.740	.000	2.635
	Failed to Yield	.313	.041	59.297	.000	1.368
	Following Too Close	-1.795	.081	489.339	.000	.166
	Improper Backing	-2.161	.261	68.479	.000	.115
	Improper Lane Usage	.261	.031	69.245	.000	1.299
	Improper Passing	.156	.072	4.756	.029	1.169
	Improper Turn	-.730	.103	50.493	.000	.482
	Improperly Stopped	-.008	.178	.002	.965	.992
	Distracted/Inattentive	-.082	.031	7.146	.008	.921
	Physical Impairment	.947	.056	288.868	.000	2.577
	Speed – Exceeds Limit	2.337	.035	4472.594	.000	10.355
	Too Fast for Conditions	.518	.032	264.997	.000	1.679
	Vehicle Defects	-.641	.091	49.857	.000	.527
	Violation of Stop Sign/Signal	.960	.054	320.788	.000	2.612
	Wrong Side – Not Passing	1.477	.036	1650.889	.000	4.380
	Wrong Way (One Way)	1.881	.122	239.254	.000	6.561
	Overcorrected	.830	.141	34.430	.000	2.293
	Total Number of Occupants	.252	.004	5030.091	.000	1.287
	Animal(s) in Roadway	-1.677	.306	29.975	.000	.187
	Other	-.770	.168	21.088	.000	.463
	Vision Obstruction	.146	.045	10.456	.001	1.158
	Crash Location = On Roadway	-.307	.029	110.307	.000	.736
	Crash Location = Off Roadway	0	.	.	.	.
	Road Conditions = Other/Unknown	-.465	.148	9.864	.002	.628
	Road Conditions = Wet	-.650	.047	193.334	.000	.522
	Road Conditions = Snow	-1.337	.115	134.333	.000	.263
	Road Conditions = Ice	-1.197	.126	89.510	.000	.302
	Road Conditions = Dry	0	.	.	.	.
	Road Alignment = Unknown	-.558	.344	2.641	.104	.572

Road Alignment = Curve	.253	.027	90.032	.000	1.288
Road Alignment = Straight	0	.	.	.	.
Road Profile = Unknown	-.527	.220	5.714	.017	.590
Road Profile = Hill/Grade	.607	.024	615.832	.000	1.834
Road Profile = Crest	.456	.065	48.903	.000	1.578
Road Profile = Level	0	.	.	.	.
Weather Conditions = Cloudy	.104	.028	13.840	.000	1.110
Weather Conditions = Rain	-.019	.069	.075	.784	.981
Weather Conditions = Snow	-.232	.125	3.435	.064	.793
Weather Conditions = Sleet	-.539	.262	4.222	.040	.584
Weather Conditions = Freezing Rain	-.001	.161	.000	.995	.999
Weather Conditions = Fog/Mist	.326	.114	8.263	.004	1.386
Weather Conditions= Indeterminate	.560	.208	7.280	.007	1.751
Weather Conditions = Clear	0	.	.	.	.
Light Conditions = Indeterminate	.036	.138	.068	.795	1.037
Light Conditions = Dark – Streetlights On	.156	.040	15.044	.000	1.169
Light Conditions = Dark – Streetlights Off	.345	.073	22.456	.000	1.413
Light Conditions = Dark – No Streetlights	.549	.030	329.547	.000	1.731
Light Conditions = Daylight	0	.	.	.	.
Speed Limit =15 or 20 mph	-.273	.214	1.635	.201	.761
Speed Limit = 25 or 30 mph	.370	.161	5.267	.022	1.447
Speed Limit = 35 or 40 mph	1.101	.158	48.489	.000	3.007
Speed Limit = 45 or 50 mph	1.718	.159	116.366	.000	5.574
Speed Limit = 55 or 60 mph	2.500	.157	254.312	.000	12.177
Speed Limit = 65 or 70 mph	2.578	.159	263.028	.000	13.175
Speed Limit = Unknown	0	.	.	.	.
Age Group = Young Driver (<21)	-.923	.038	587.074	.000	.397
Age Group = Middle Drivers (≥ 22 and <55)	-.614	.030	414.859	.000	.541

	Age Group = Mature Driver(≥ 55 and ≤ 98)	0	.	.	.	.
	Gender = Male	.348	.026	174.405	.000	1.416
	Gender = Female	0	.	.	.	.
	Road Surface = Unknown	-.715	.276	6.721	.010	.489
	Road Surface = Asphalt	.285	.036	62.852	.000	1.330
	Road Surface = Gravel	.033	.069	.225	.635	1.033
	Road Surface = Brick, Dirt, Sand, Multi-Surface	.008	.086	.009	.923	1.008
	Road Surface = Concrete	0	.	.	.	.
Injury	Intercept	-1.944	.017	13769.026	.000	
	Alcohol	.623	.009	4345.180	.000	1.864
	Drugs	.454	.022	429.469	.000	1.574
	Failed to Yield	.425	.007	4038.495	.000	1.530
	Following Too Close	-.023	.007	11.114	.001	.977
	Improper Backing	-1.749	.026	4687.989	.000	.174
	Improper Lane Usage	-.124	.008	251.958	.000	.883
	Improper Passing	-.248	.019	178.316	.000	.780
	Improper Turn	-.144	.012	141.771	.000	.866
	Improperly Stopped	.142	.029	23.163	.000	1.152
	Distracted/Inattentive	.128	.006	530.220	.000	1.136
	Physical Impairment	1.027	.014	5644.775	.000	2.792
	Speed – Exceeds Limit	.892	.013	4901.107	.000	2.439
	Too Fast for Conditions	.448	.007	3836.542	.000	1.566
	Vehicle Defects	-.021	.013	2.511	.113	.979
	Violation of Stop Sign/Signal	.805	.010	6755.705	.000	2.237
	Wrong Side – Not Passing	.479	.014	1174.046	.000	1.614
	Wrong Way (One Way)	.634	.051	157.153	.000	1.885
	Overcorrected	.529	.045	139.322	.000	1.698
	Total Number of Occupants	.210	.001	24688.622	.000	1.233
	Animal(s) in Roadway	-.501	.043	134.734	.000	.606
	Other	-.048	.021	5.288	.021	.953
	Vision Obstruction	.071	.007	91.165	.000	1.074
	Crash Location = On Roadway	-.296	.006	2363.152	.000	.744
	Crash Location = Off Roadway	0	.	.	.	.

Road Conditions = Other/Unknown	-.172	.024	52.223	.000	.842
Road Conditions = Wet	-.207	.008	671.580	.000	.813
Road Conditions = Snow	-.669	.018	1404.447	.000	.512
Road Conditions = Ice	-.488	.020	582.832	.000	.614
Road Conditions = Dry	0	.	.	.	.
Road Alignment = Unknown	-.243	.035	49.354	.000	.785
Road Alignment = Curve	.039	.006	43.793	.000	1.040
Road Alignment = Straight	0	.	.	.	.
Road Profile = Unknown	-.166	.023	52.079	.000	.847
Road Profile = Hill/Grade	.109	.005	534.030	.000	1.115
Road Profile = Crest	.157	.013	143.084	.000	1.170
Road Profile = Level	0	.	.	.	.
Weather Conditions = Cloudy	.011	.005	3.923	.048	1.011
Weather Conditions = Rain	-.053	.011	23.047	.000	.948
Weather Conditions = Snow	-.133	.019	49.425	.000	.876
Weather Conditions = Sleet	-.147	.037	15.641	.000	.863
Weather Conditions = Freezing Rain	-.031	.029	1.183	.277	.969
Weather Conditions = Fog/Mist	.039	.027	2.076	.150	1.040
Weather Conditions= Indeterminate	-.169	.035	23.447	.000	.844
Weather Conditions = Clear	0	.	.	.	.
Light Conditions = Indeterminate	.005	.020	.059	.808	1.005
Light Conditions = Dark – Streetlights On	.020	.006	10.167	.001	1.020
Light Conditions = Dark – Streetlights Off	-.067	.019	12.480	.000	.935
Light Conditions = Dark – No Streetlights	.147	.008	334.397	.000	1.158
Light Conditions = Daylight		.	.	.	.
Speed Limit =15 or 20 mph	-.241	.020	152.506	.000	.786
Speed Limit = 25 or 30 mph	.177	.014	157.898	.000	1.193
Speed Limit = 35 or 40 mph	.541	.014	1540.020	.000	1.718
Speed Limit = 45 or 50 mph	.596	.015	1652.840	.000	1.815

Speed Limit = 55 or 60 mph	.874	.014	3819.589	.000	2.396
Speed Limit = 65 or 70 mph	.581	.016	1349.088	.000	1.788
Speed Limit = Unknown	0	.	.	.	.
Age Group = Young Driver (<21)	-.019	.007	8.198	.004	.981
Age Group = Drivers (≥ 22 and <55)	-.001	.006	.018	.894	.999
Age Group = Mature Driver(≥ 55 and ≤ 98)	0	.	.	.	.
Gender = Male	-.097	.004	524.506	.000	.908
Gender = Female	0	.	.	.	.
Road Surface = Unknown	-.006	.026	.055	.814	.994
Road Surface = Asphalt	.142	.006	646.160	.000	1.152
Road Surface = Gravel	.085	.015	31.675	.000	1.089
Road Surface = Brick, Dirt, Sand, Multi-Surface	-.135	.016	68.398	.000	.874
Road Surface = Concrete	0	.	.	.	.

a. The reference category is: Property Damage Only

As illustrated in Table 5.5, the likelihood ratio tests indicate that all variables are significant in the model at the 0.000 significance level. The Fatality equation in Table 5.6 suggests that the likelihood that a crash results in a fatality increase as the total number of occupants increases, speed limits increase, and the contributory circumstances of speed exceeding the limit, driving the wrong way on a one-way, driving on the wrong side of the road when not passing, alcohol use, drug use, violating a stop sign or signal, and driving while physically impaired are noted. Furthermore, the results suggest that the likelihood that a crash results in a fatality is lower when the driver is young (less than 21 years old), and the contributory circumstances of improper backing, following too close, striking an animal/animal obstruction, snow, and ice are noted.

Additionally, the Injury equation in Table 5.6 suggests that injuries are more likely for crashes when the number of occupants increases, and the contributory circumstances of alcohol, physical impairment, driving the wrong way on a one-way street, speed exceeding the limit, violation of a stop sign or signal, and increased speed limits are noted. The results also indicate that injuries are less likely for crashes where the contributory circumstances of improper backing, animal obstruction, and snow are noted.

The coincidence matrices for the training and testing sets, presented in Tables 5.7 and 5.8, illustrate how well the model correctly classifies cases. The matrices indicate that the multinomial model has an overall classification accuracy rate of 72.0% for both the training set and the testing set, which suggests that the model is not overfit to the training dataset.

Table 5.7: Multinomial Model Coincidence Matrix for the Training Set

Classification

	Predicted			
Observed	Fatal	Injury	Property Damage	Percent Correct
Fatal	21	2,486	3,516	0.3%
Injury	48	38,754	229,663	14.4%
Property Damage	15	29,912	644,264	95.6%
Overall Percentage	0.0%	7.5%	92.5%	72.0%

Table 5.8: Multinomial Model Coincidence Matrix for the Testing Set

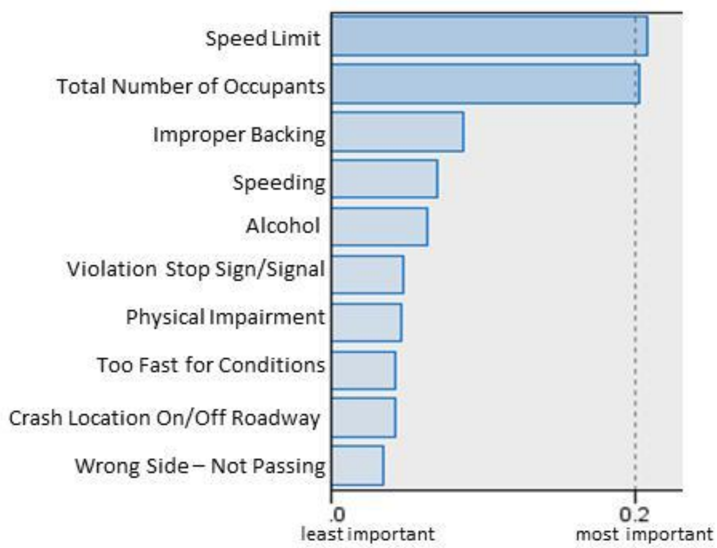
Classification

	Predicted			
Observed	Fatal	Injury	Property Damage	Percent Correct
Fatal	12	855	1,206	0.6%
Injury	11	12,755	76,931	14.2%
Property Damage	5	9,698	215,311	95.7%
Overall Percentage	0.0%	7.4%	92.6%	72.0%

The factors with the greatest predictor importance for crash injury severity (i.e. the relative importance of each predictor in estimating the model) are calculated from the testing partition. The model determines predictor importance by computing the reduction in variance of the target attributable to each predictor via a sensitivity analysis. For details of the sensitivity analyses employed, see Chapter 29 of the *IBM SPSS Modeler 15 Algorithms Guide* (2012), Saltelli et al. (2004) and Saltelli (2002).

The predictor importance chart shows the top predictive factors and their relative importance values, which are normalized to sum to unity. Figure 5.1 presents the top ten factors suggested to have greatest importance in estimating the multinomial model.

Figure 5.1: Multinomial Model Predictor Importance



Lift curves are often used to illustrate the improvement that a model provides over a "random" guess of the dependent variable, to compare the accuracy of predictions among multiple models, and to help identify which model most accurately forecasts outcomes for subsets of cases (Vuk and Curk, 2006). The points on a lift curve are computed by determining the ratio between the number of correct results of a particular outcome predicted by the model and the expected number of correct results of that outcome using no model for segments of the population (Fawcett, 2006). To create a lift curve, the cases are assorted in descending order of the estimated probability of an outcome, and the chart is constructed with the cumulative proportion of the total number of cases on the x-axis and the ratio of the cumulative number of true positives to the cumulative random number of true positives on the y-axis (Shmueli et al., 2011). The chart illustrates the observations from a selected outcome (e.g. fatality, injury, or property damage only) that are classified correctly, referred to as the true positives (Shmueli et al., 2011). A good classifier will have a high lift when only a small number of cases are selected, and will decrease to unity as the number of cases selected increases (Shmueli et al., 2011).

Figures 5.2, 5.3, and 5.4 present lift charts for the multinomial model for fatal, injury and property damage only outcomes respectively. The red lines represent the ratio of the expected number of positive fatal outcomes (Figure 5.2), the expected number of positive injury outcomes (Figure 5.3), and the expected number of property damage only outcomes (Figure 5.4) to their sample proportions that would be predicted if the outcomes were simply selected at random (unity). Tables 5.9, 5.10, and 5.11 provide the lift values for the fatal, injury, and property damage only lift charts for the training and testing sets and the number of expected, observed, cumulative expected and cumulative observed cases for the testing sets for each decile.

Inspection of the figures and tables indicates that the multinomial logit model provides significant and similar lifts for each severity outcome for both the training and testing data partitions. Further inspection reveals greater lift for fatal outcomes than for injury outcomes with injury outcomes also providing greater lift than property damage only outcomes across both the training and testing data partitions.

Figure 5.2: Multinomial Logit Lift Chart for Fatal Outcomes

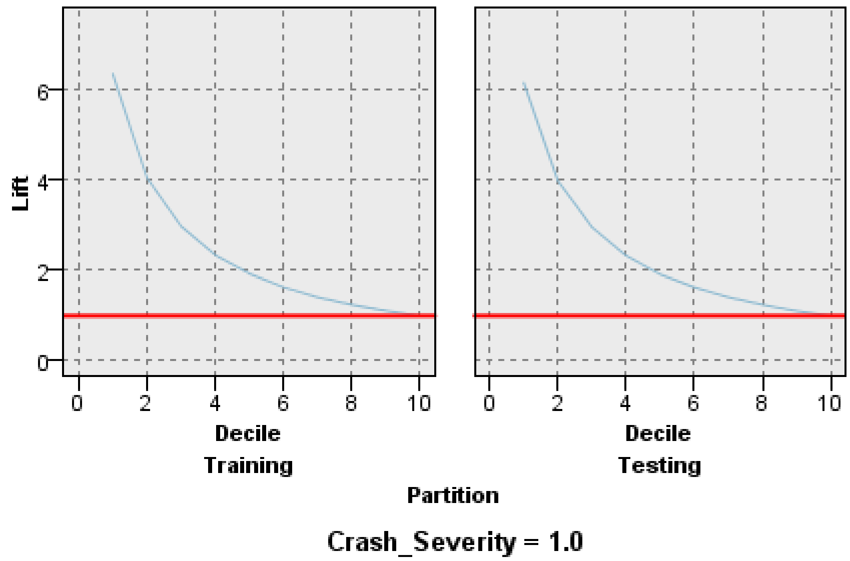


Table 5.9: Lift Values, Expected and Observed Counts per Decile for Fatal Outcomes

Decile	Lift Training Set	Lift Testing Set	Expected Outcomes Testing Set	Observed Outcomes Testing Set	Cumulative Expected Testing Set	Cumulative Observed Testing Set
1	6.3625	6.1651	1,223.50	1,278	1,223.50	1,278
2	4.0561	3.9894	320.77	376	1,544.27	1,654
3	2.9797	2.9571	173.01	185	1,717.28	1,839
4	2.3390	2.3251	105.56	89	1,822.84	1,928
5	1.9299	1.9141	69.87	56	1,892.71	1,984
6	1.6324	1.6305	48.35	44	1,941.06	2,028
7	1.4139	1.4134	33.62	23	1,974.68	2,051
8	1.2448	1.2446	22.10	13	1,996.78	2,064
9	1.1109	1.1079	12.43	3	2,009.21	2,067
10	1.0	1.0	4.70	6	2,013.91	2,073

Figure 5.3: Multinomial Logit Lift Curve for Injury Outcomes

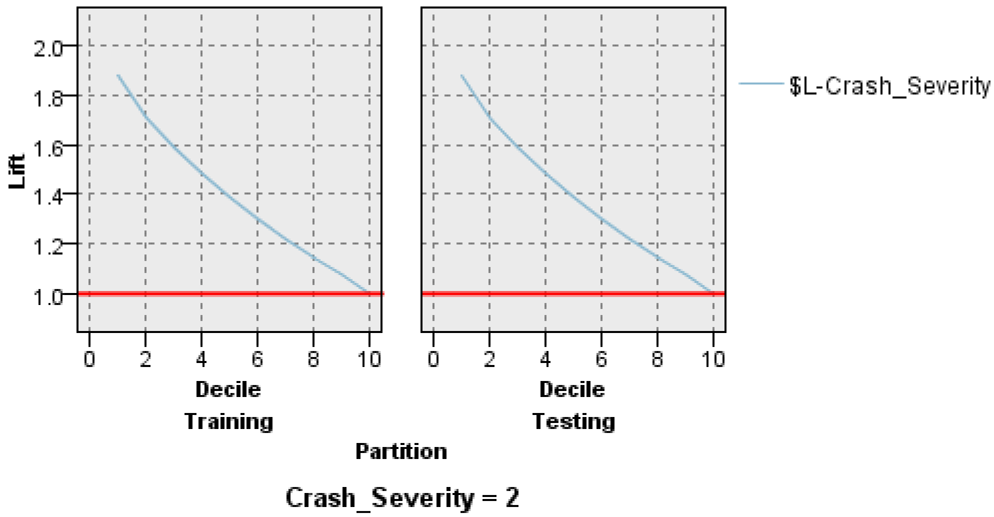


Table 5.10: Lift Values, Expected and Observed Counts per Decile for Injury Outcomes

Decile	Lift Training Set	Lift Testing Set	Expected Outcomes Testing Set	Observed Outcomes Testing Set	Cumulative Expected Testing Set	Cumulative Observed Testing Set
1	1.8761	1.8786	17,445.63	16,850	17,445.63	16,850
2	1.71	1.7197	13,131.65	13,998	30,577.28	30,848
3	1.5896	1.5947	11,200.40	12,064	41,777.68	42,912
4	1.4847	1.4921	9,757.94	10,623	51,535.62	53,535
5	1.3877	1.3955	8,754.91	9,053	60,290.53	62,588
6	1.3019	1.3067	7,799.85	7,737	68,090.38	70,325
7	1.2199	1.2246	6,951.64	6,564	75,042.02	76,889
8	1.1466	1.1482	6,205.71	5,508	81,247.73	82,397
9	1.0775	1.0784	5,256.24	4,660	86,503.97	87,057
10	1.0	1.0	3,062.78	2,640	89,566.75	89,697

Figure 5.4: Multinomial Logit Lift Curve for Property Damage Only Outcomes

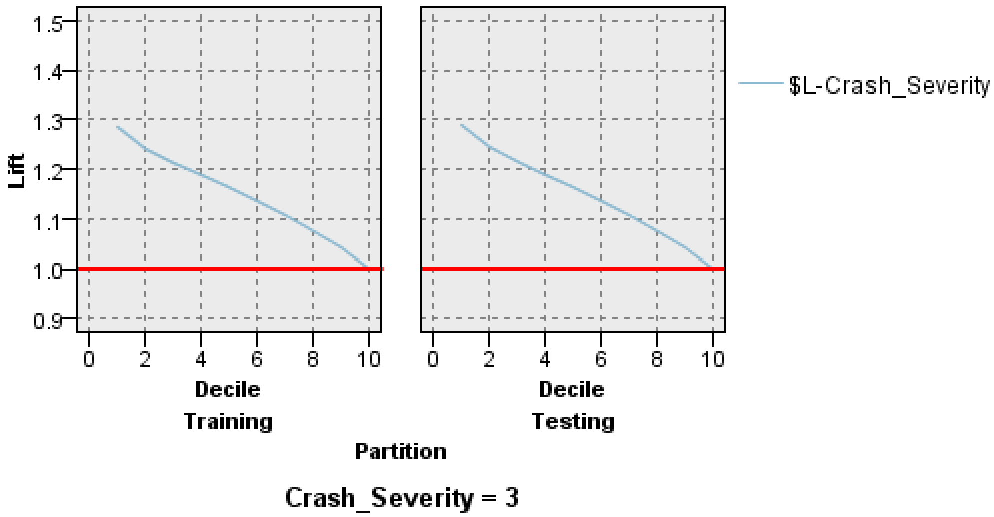


Table 5.11: Lift Values, Expected and Observed Counts per Decile for Property Damage Only Outcome

Decile	Lift Training Set	Lift Testing Set	Expected Outcomes Testing Set	Observed Outcomes Testing Set	Cumulative Expected Testing Set	Cumulative Observed Testing Set
1	1.286	1.2899	28,601.61	29,024	28,601.61	29,024
2	1.2417	1.2446	26,391.23	26,990	54,992.84	56,014
3	1.2123	1.217	25,430.22	26,139	80,423.06	82,153
4	1.1882	1.1912	24,669.59	25,064	105,092.65	107,217
5	1.1621	1.1653	23,794.97	23,882	128,887.62	131,099
6	1.1356	1.1379	22,818.29	22,525	151,705.91	153,624
7	1.1074	1.1083	21,772.02	20,939	173,477.93	174,563
8	1.0763	1.0769	20,264.89	19,287	193,742.82	193,850
9	1.043	1.0432	1,819.68	17,418	195,562.50	211,268
10	1	1	13,263.86	13,746	208,826.36	225,014

According to Fawcett (2006), when an outcome is rare (the distribution of outcomes is highly skewed) and the proportion of outcomes can change, model evaluation based solely on the true positive rate (lift charts) may not reveal the true discriminatory power of a model in a sample since the lift depends on the ratio of positives to negatives in the sample. Receiver Operating Characteristic (ROC) curves are an alternative construct employed to assess a model's capability to discriminate amongst outcomes at various thresholds (Provost and Fawcett, 1997; Fawcett, 2006). ROC curves are constructed by plotting the true positive rate (the sensitivity) against a false positive rate (1-the specificity) for subsets of the observations, and are calculated as follows (Fawcett, 2006).

$$True\ Positive\ Rate\ = \frac{positives\ correctly\ classified}{total\ positives}$$

$$False\ Postive\ Rate = \frac{negatives\ incorrectly\ classified}{total\ negatives}$$

Following Fawcett (2006), ROC curves are constructed to assess the multinomial model's capability to (1) predict a fatal outcome relative to property damage and injury only outcomes and to (2) predict a property damage only outcome relative to fatal and injury outcomes. These curves help evaluate the model's prediction of the outcome with the greatest severity, a fatality outcome, against the two non-fatal outcomes, as well as to evaluate the model's prediction capability of the least severe outcome, a property damage only outcome, versus the two more severe outcomes, fatality and injury outcomes. Figures 5.5 and 5.6 present the ROC curves and illustrate that the multinomial model better predicts fatal versus non-fatal outcomes and non-injury versus injury outcomes than if no model is used and the outcomes are randomly assigned.

By calculating the area under the ROC curve (AUC), this study quantifies the significance of the findings of the ROC curve. The AUC is a widely recognized measure of discriminatory power (Worster et al., 2006) and quality of probabilistic classifiers (Vuk and Curk, 2006). The AUC measures the classifiers' performance across the entire range of potential outcome distributions (Vuk and Curk, 2006), and is equal to the likelihood of assigning a higher probability that injury or death will occur for randomly selected cases where injury or death does occur than for cases where injury or death does not occur (Fawcett, 2006). A maximal AUC value of 1.0 suggests a perfectly discriminating model and an AUC value of 0.5 suggests no discriminative value (Worster et. al 2006); and, no accurate classifier should have an AUC of less than 0.5 (Fawcett, 2006). The AUC for the multinomial model's performance are 0.883 for the predicted probability of a fatal outcome relative to a nonfatal outcome (presented in Tables 5.12) and 0.695 for a non-injury outcome relative to an injury outcome (presented in Tables 5.13), both of which are different from 0.5 at asymptotically significant levels of 0.000 suggesting that the multinomial model has good discriminatory power.

Figure 5.5: Multinomial Logit ROC Curve Fatal Outcome using the Testing Set

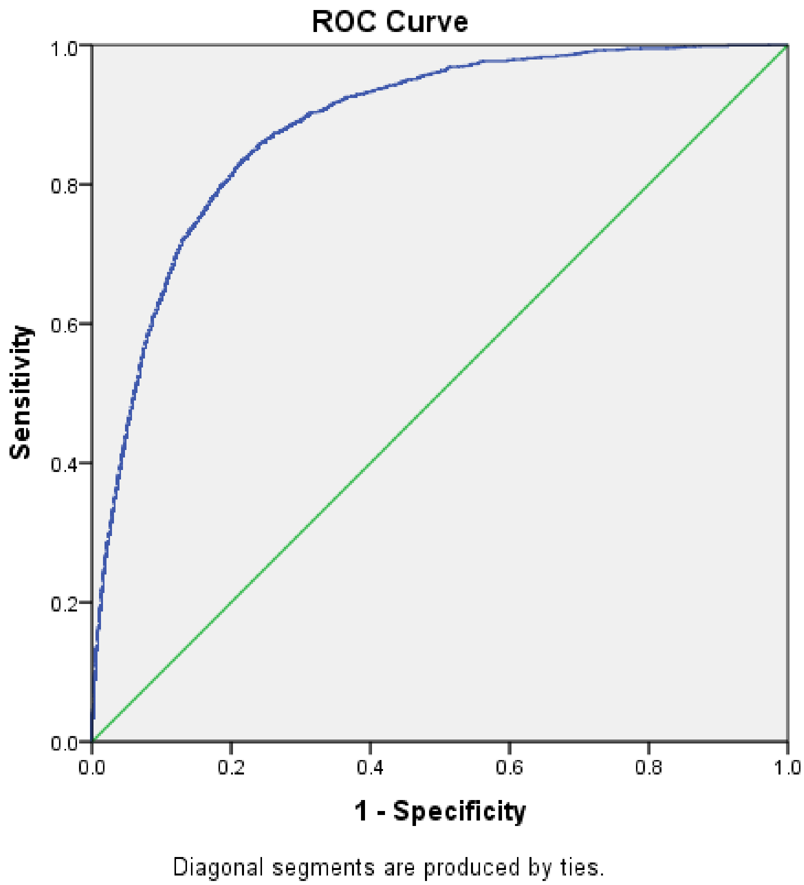


Table 5.12: AUC for Multinomial Logit Prediction of Fatal Outcome using the Testing Set

Area Under the Curve

Test Result Variable(s): Multinomial Propensity Fatal

Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
.883	.003	.000	.876	.889

The test result variable(s): Multinomial Propensity Fatal has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Figure 5.6: Multinomial Logit ROC Curve Property Damage Only Outcome using the Testing Set

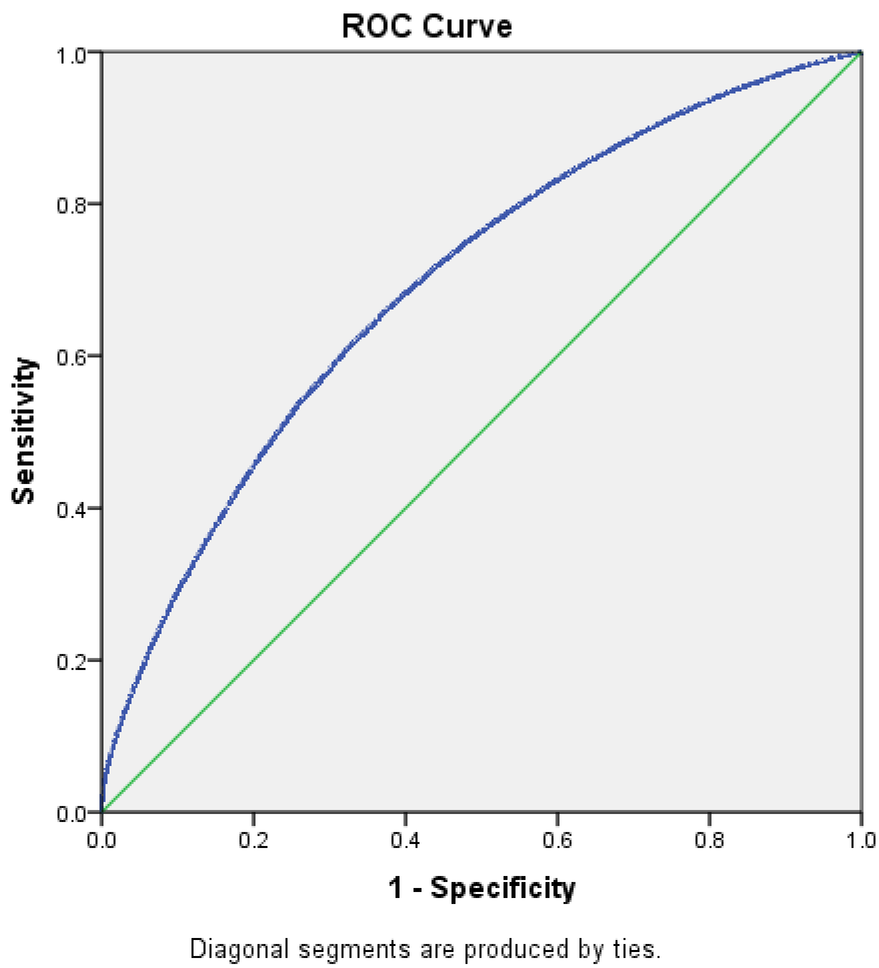


Table 5.13: AUC for Multinomial Logit Prediction of Property Damage Only Outcome using the Testing Set

Area Under the Curve

Test Result Variable(s): Multinomial Propensity PD

Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
.695	.001	.000	.693	.697

The test result variable(s): Multinomial Propensity PD has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Important findings for the Multinomial Logit Model include:

- Classification accuracy rate equals 72.0% for both the training set and the testing set.
- AUC for a fatal outcome equals 0.883 for the testing set.
- AUC for a property damage only outcome equals 0.695 for the testing set.
- The AUC scores are both significantly greater than 0.5, indicating significant discriminatory power.
- The three most important predictors of crash severity are speed – exceeds limit, total number of occupants involved, and improper backing.

5.1.2 Ordered Probit

To utilize the information in the natural ordering of the crash injury severity outcomes, an ordered probit regression model is developed with the outcome thresholds (property damage only, injury and fatality) assumed to be a natural ascending order. The development of the ordered probit model uses the case selection criteria and factors employed in the final multinomial logit model, and the model is estimated using the maximum likelihood method. The proportional odds assumption (also referred to as the parallel regressions assumption or the parallel lines assumption) is tested, since this single equation model invokes this assumption. The null hypothesis for this test is that the values of the coefficients of the independent variables are the same across response categories (Long, 1997; Williams, 2008). The Brant test of parallel lines for the estimated ordered probit model produces a chi-square of 6,544.677 with 59 degrees of freedom which is significant at a level of less than 0.000, as illustrated in Table 5.14. Therefore, the null hypothesis is rejected. Rejecting the null hypothesis can lead to inconsistent model estimation (Eluru et al. 2008); and therefore, this approach is not carried forward.

Table 5.14: Test of Parallel Lines

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	633158.558			
General	626613.881[b]	6544.677[c]	59	.000

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Probit.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

5.1.3 Decision Tree

Decision tree models can yield additional insights into the relationships between the explanatory variables and crash injury severity. As described in Chapter 4, decision tree algorithms, including CART and CHAID techniques, build and prune decision trees in differing methods to mitigate against possible overfitting. CART builds larger trees that are then pruned back to mitigate overfitting, while CHAID automatically prunes the decision tree to avoid overfitting of the model (Bayam et al., 2005). Both CART and CHAID trees are estimated, the discriminatory performance of each algorithm is evaluated, and the model with the greatest discriminatory power is identified and carried forward as a constituent ensemble model. The models' performances are compared by calculating and evaluating the classification accuracy and the AUC values for each model.

The CART algorithm nodal splitting criteria are set to a minimum absolute value of 100 records in a parent branch and a minimum of 50 records in a child branch as the stopping criteria; the Gini coefficient is used as the impurity measure for the categorical targets; the maximum tree depth is set to 15 branches; and, the tree is pruned by merging leaves on the same branch using a value of one as the maximum difference in risk in standard errors. The estimation of the CART model considers the explanatory variables included in the final multinomial logit regression model, identified in Table 5.1, to analyze crash injury severity on three levels: property damage only, injury and fatality, and uses the predetermined partitioned dataset to test the classification accuracy of the model and to examine for overfitting The final CART decision tree model finds 23 variables significant (indicated in Table 5.15), includes 948,679 observations in the training set and 316,784 in the testing set, and results in an analysis accuracy of 72.32% and 72.30% for the training set and the testing set respectively (presented in Tables 5.16 and 5.17).

Table 5.15: Explanatory Variables used in Estimation of CART model

Speed – Exceed Limits	Alcohol	Road Alignment
Too Fast for Conditions	Physical Impairment	Road Conditions
Violation Stop Sign/Signal	Overcorrected	Road Profile
Wrong Side – Not Passing	Animal	Weather Conditions
Improper Backing	Other	Light Conditions
Improper Turn	Total Number of Occupants	On/Of Roadway
Improper Lane Usage	Speed Limit	Vision Obstructed
Failed to Yield	Road Surface	

Table 5.16: CART Coincidence Matrix for the Training Set

Classification

Observed	Predicted			
	Fatal	Injury	Property Damage	Percent Correct
Fatal	0	1,760	4,263	0.0%
Injury	0	33,743	234,722	12.6%
Property Damage	0	21,837	652,654	96.8%
Overall Percentage	0.0%	6.0%	94.0%	72.32%

Table 5.17: CART Coincidence Matrix for the Testing Set

Classification

Observed	Predicted			
	Fatal	Injury	Property Damage	Percent Correct
Fatal	0	606	1,4676	0.0%
Injury	0	11,170	78,527	12.5%
Property Damage	0	7,140	217,874	96.8%
Overall Percentage	0.0%	6.0%	94.0%	72.30%

The CHAID algorithm nodal splitting criteria is set to a minimum absolute value of 100 records in a parent branch and a minimum of 50 records in a child branch, and the maximum tree depth is set to 15 branches. The Pearson measure is used as the chi-square measure for categorical targets, and the significance level for both splitting and merging is set to 0.05. The estimation of the CHAID model considers the explanatory variables identified in Table 5.1, and uses the predetermined partitioned dataset to test the classification accuracy of the model and to examine for overfitting. The final CHAID decision tree model suggests 30 variables are significant (indicated in Table 5.18), includes 948,679 observations in the training set and 316,784 in the testing set, and results in an analysis accuracy of 73.06% and 73.0% for the training set and the testing set respectively (presented in Tables 5.19 and 5.20).

Table 5.18: Explanatory Variables used in Estimation of CHAID Model

Alcohol	Improperly Stopped	Wrong Way (One-Way)	Road Alignment
Drugs	Distracted/Inattentive	Total Number of Occupants	Road Profile
Failed to Yield	Physical Impairment	Improper Turn	Weather Conditions
Following Too Close	Speed – Exceed Limits	Other	Light Conditions
Improper Backing	Too Fast for Conditions	Vision Obstructed	Speed Limit
Improper Lane Usage	Vehicle Defects	On Off Roadway Crash	Age Groups
Improper Passing	Violation Stop Sign/Signal	Road Conditions	Gender
Wrong Side – Not Passing	Road Surface		

Table 5.19: CHAID Coincidence Matrix for the Training Set

Classification

Observed	Predicted			
	Fatal	Injury	Property Damage	Percent Correct
Fatal	0	3,175	2,848	0.0%
Injury	0	63,279	205,186	23.6%
Property Damage	0	44,398	62,793	93.4%
Overall Percentage	0.0%	11.7%	88.3%	73.06%

Table 5.20: CHAID Coincidence Matrix for the Testing Set

Classification

Observed	Predicted			
	Fatal	Injury	Property Damage	Percent Correct
Fatal	0	1,084	989	0.0%
Injury	0	21,011	68,686	23.4%
Property Damage	0	14,758	210,256	93.4%
Overall Percentage	0.0%	11.6%	88.4%	73.0%

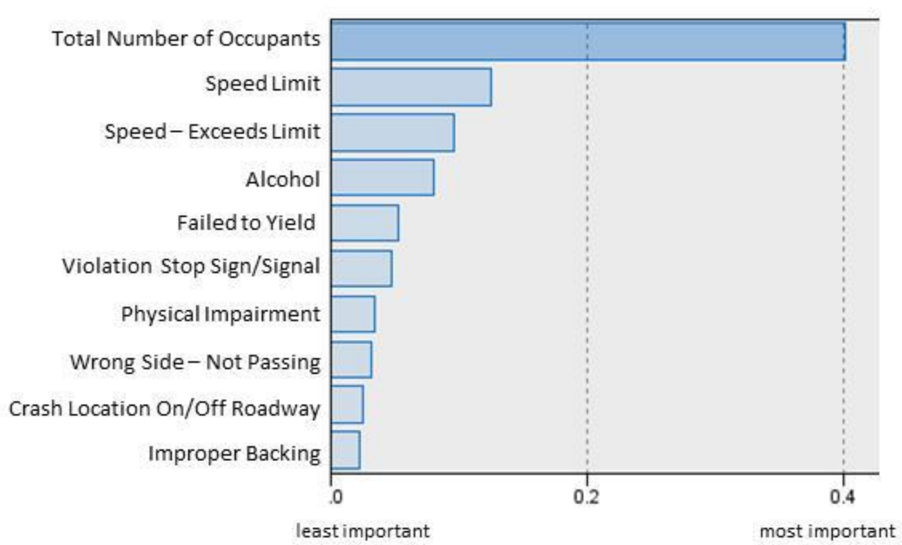
As described in section 5.1.1, the AUC measures a classifiers' performance across the entire range of outcome distributions (Vuk and Curk, 2006), and is equal to the probability that a classifier will rate a randomly chosen positive outcome higher than a randomly chosen negative outcome (Fawcett, 2006). The AUC results for the CART and CHAID's capabilities to predict a fatal outcome relative to non-fatal outcomes are 0.761 and 0.898 for the testing set, respectively. The AUC results for the CART and CHAID's capabilities to predict a property damage only outcome relative to injury outcomes are 0.667 and 0.717 for the testing set, respectively. As a result of its lesser classification accuracy and AUC values, as illustrated in Table 5.21, the CHAID algorithm is carried forward, so as to consider the best decision tree approach for the ultimate model ensemble.

Table 5.21: Accuracy Comparison of CHAID and CART Models

Decision Tree Approach	Classification Accuracy Training Set	Classification Accuracy Testing Set	AUC Value Fatal vs. Nonfatal Training Set	AUC Value Fatal vs. Nonfatal Training Set	AUC Value Non-injury vs. Injury Training Set	AUC Value Non-injury vs. Injury Training Set
CHAID	73.06%	73.00%	0.899	0.898	0.717	0.717
CART	72.32%	72.30%	0.759	0.761	0.667	0.667

The factors with the greatest predictor importance for crash injury severity for the CHAID decision tree are calculated. The predictor importance chart shows the top predictive factors and their relative values, which are normalized to sum to unity. Figure 5.7 presents the top ten factors suggested to have greatest importance in estimating the CHAID model. The CHAID model findings suggest the variable *total number of occupants* to be the most important variable for predicting crash injury severity, which splits the tree into three initial branches: ≤1 occupant, >1 and <3 occupant(s), and ≥3 occupants. Appendices 1, 2, and 3 present partial branches for each of these splits.

Figure 5.7: CHAID Model Predictor Importance



Figures 5.8, 5.9, and 5.10 present lift charts for the CHAID decision tree for fatal, injury, and property damage only outcomes for the training and testing partitions. The red lines represent the ratio of the expected number of positive fatal outcomes (Figure 5.8), the expected number of positive injury outcomes (Figure 5.9), and the expected number of property damage only outcomes (Figure 5.10) to their sample proportions that would be predicted if the outcomes were simply selected at random (unity). Tables 5.22, 5.23, and 5.24 provide the lift values for the fatal, injury, and property damage only lift charts for the training and testing sets and the number of expected, observed, cumulative expected and cumulative observed cases for the testing sets for each decile.

Inspection of the figures and tables indicates that the CHAID model provides significant and similar lifts for each severity outcome for both the training and testing data partitions. Further inspection reveals greater lift for fatal outcomes than for injury outcomes with injury outcomes also providing greater lift than property damage only outcomes across both the training and testing data partitions.

Figure 5.8: CHAID Lift Chart for Fatal Outcomes

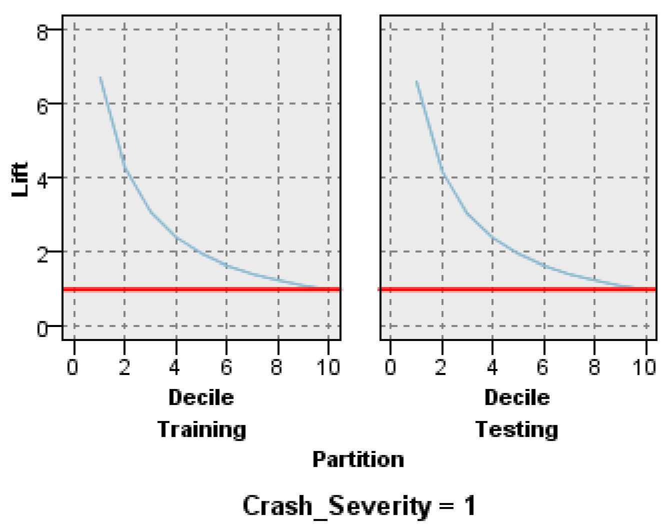


Table 5.22: Lift Values, Expected and Observed Counts per Decile for Fatal Outcomes

Decile	Lift Training Set	Lift Testing Set	Expected Outcomes Testing Set	Observed Outcomes Testing Set	Cumulative Expected Testing Set	Cumulative Observed Testing Set
1	6.6900	6.5877	1,384.33	1,365	1,384.33	1,365
2	4.2623	4.1703	366.18	364	1,750.51	1,729
3	3.0679	3.0418	139.44	164	1,889.95	1,893
4	2.3858	2.3704	69.04	72	1,958.99	1,965
5	1.9478	1.9370	36.24	43	1,995.23	2,008
6	1.6414	1.6373	20.48	28	2,015.71	2,036
7	1.4121	1.4113	8.35	12	2,024.06	2,048
8	1.2397	1.2390	4.20	6	2,028.26	2,054
9	1.1065	1.1062	0.00	8	2,028.26	2,062
10	1.0	1.0	0.00	11	2,028.26	2,073

Figure 5.9: CHAID Lift Chart for Injury Outcomes

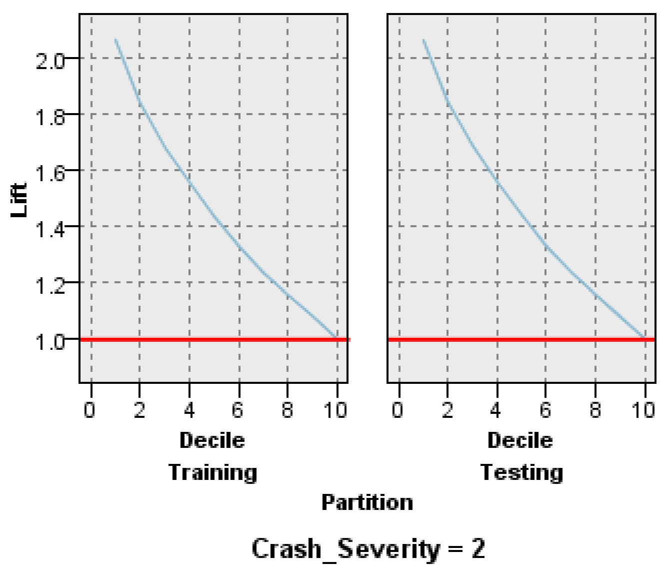


Table 5.23: Lift Values, Expected and Observed Counts per Decile for Injury Outcomes

Decile	Lift Training Set	Lift Testing Set	Expected Outcomes Testing Set	Observed Outcomes Testing Set	Cumulative Expected Testing Set	Cumulative Observed Testing Set
1	2.0630	2.0602	18,560.10	18,471	18,560.10	18,471
2	1.8391	1.8441	14,520.59	14,616	33,080.69	33,087
3	1.6803	1.6849	12,193.40	12,280	45,274.09	45,367
4	1.5564	1.5577	10,602.20	10,522	55,876.29	55,889
5	1.4374	1.4400	8,578.08	8,701	64,454.37	64,590
6	1.3286	1.3324	6,983.42	7,112	71,437.79	71,702
7	1.2337	1.2375	5,979.40	5,977	77,417.19	77,679
8	1.1577	1.1592	5,530.62	5,508	82,947.81	83,187
9	1.0827	1.0834	4,281.36	4,268	87,229.17	87,455
10	1.0	1.0	2,239.90	2,242	89,469.07	89,697

Figure 5.10: CHAID Lift Chart for Property Damage Only Outcomes

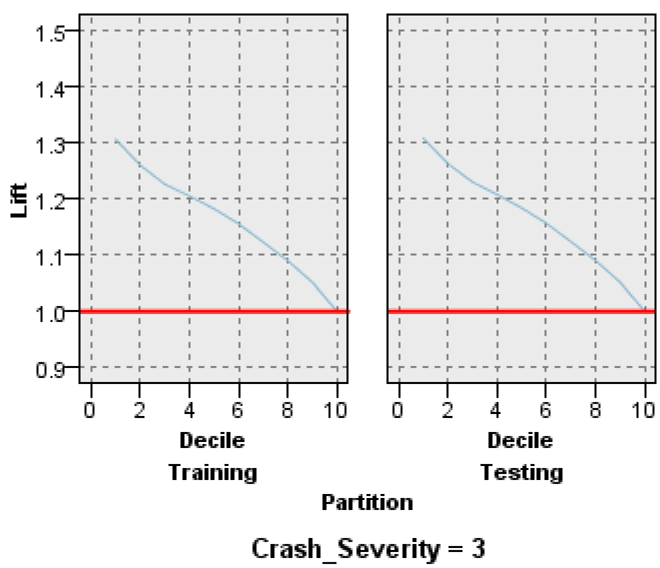


Table 5.24: Lift Values, Expected and Observed Counts per Decile for Property Damage Only Outcome

Decile	Lift Training Set	Lift Testing Set	Expected Outcomes Testing Set	Observed Outcomes Testing Set	Cumulative Expected Testing Set	Cumulative Observed Testing Set
1	1.3049	1.3071	29,424.03	29,415	29,424.03	29,415
2	1.2593	1.2620	27,379.19	27,372	56,803.22	56,787
3	1.2254	1.2291	26,127.65	26,190	82,930.87	82,977
4	1.2045	1.2069	25,680.37	25,654	108,611.24	108,631
5	1.1818	1.1832	24,625.92	24,483	133,237.16	133,114
6	1.1549	1.1558	23,002.35	22,937	156,239.51	156,051
7	1.1224	1.1232	20,882.18	20,876	177,121.69	176,927
8	1.0889	1.0896	19,273.18	19,210	196,394.87	196,137
9	1.0508	1.0510	16,773.86	16,698	213,168.73	212,835
10	1.0	1.0	12,118.83	12,179	225,287.56	225,014

As described in section 5.1.1, the ROC curves are constructed to visualize and evaluate the model's capability to predict (1) a fatal outcome relative to property damage and injury only outcomes and (2) a property damage only outcome relative to fatal and injury outcomes. Figures 5.11 and 5.12 present the ROC curves and illustrate that the CHAID decision tree better predicts fatal versus non-fatal outcomes and non-injury versus injury outcomes than if no model was used and the outcomes were randomly assigned.

By calculating the area under the ROC curve (AUC), this study quantifies the significance of the findings of the ROC curve. As earlier described, the maximal AUC value of 1.0 suggests a perfect classifier (Worster et al., 2006); and, no useful classifier should have an AUC of less than 0.5, the AUC for a random classifier (Fawcett, 2006). The AUC for the CHAID decision tree's performance are 0.898 for the predicted probability of a fatal outcome relative to a nonfatal outcome (presented in Table 5.25), and 0.717 for a non-injury outcome relative to an injury outcome (presented in Table

5.26), both of which are significantly different from 0.5 at the 0.000 level and suggest that the CHAID model has good discriminatory power.

Figure 5.11: CHAID Decision Tree ROC Curve Fatal Outcome using the Testing Set

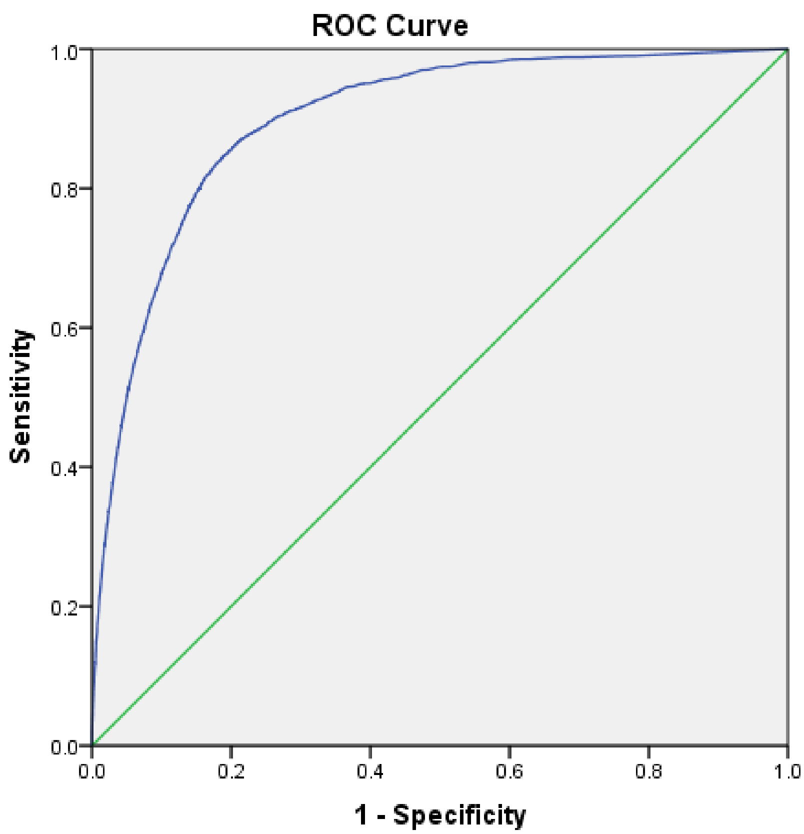


Table 5.25: AUC for CHAID Decision Tree Prediction of Fatal Outcome using the Testing Set

Area Under the Curve

Test Result Variable(s): CHAID Propensity Fatal

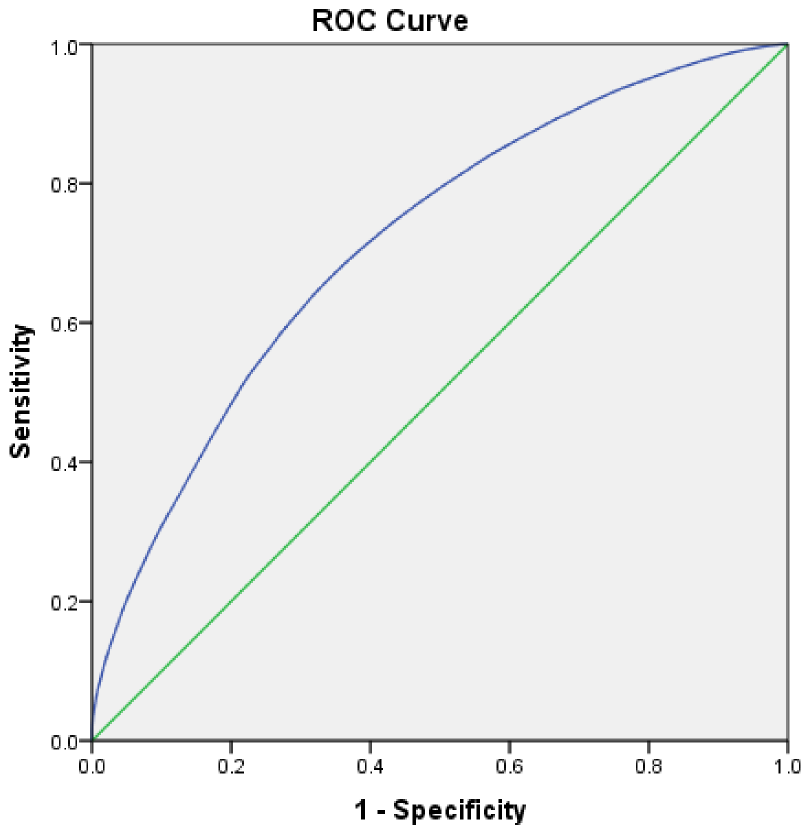
Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
.898	.003	.000	.892	.904

The test result variable(s): CHAID Propensity Fatal has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Figure 5.12: CHAID Decision Tree ROC Curve Property Damage Only Outcome using the Testing Set



Diagonal segments are produced by ties.

Table 5.26: AUC for CHAID Decision Tree Prediction of Property Damage Only Outcome using the Testing Set

Area Under the Curve

Test Result Variable(s): CHAID Propensity PD

Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
.717	.001	.000	.715	.719

The test result variable(s): CHAID Propensity PD has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Important findings for the CHAID Decision Tree include:

- Classification accuracy rate equals 73.06% and 73.0% for the training set and the testing set respectively.
- AUC for a fatal outcome equals 0.898 for the testing set.
- AUC for a property damage only outcome equals 0.717 for the testing set.
- The AUC estimates are significantly greater than 0.5, indicating significant discriminatory power.
- The top three most important predicators of crash severity are the total number of occupants, speed limit, and speed – exceeds limit.

5.1.4 Artificial Neural Network

Prior literature has found the Multilayer Perceptron (MLP) algorithm, a type of ANN, to be a robust estimator (Delen et al., 2006) and useful in the analysis of crash injury severity (Abdelwahab and Abdel-Aty, 2001; Abdel-Aty and Abdelwahab, 2004a). Following previous research, this study develops MLP networks to assess crash injury severity, given the independent variables identified in Table 5.1.

As described in Chapter 4, the MLP network operates in two phases: a training phase that uses a collection of patterns for learning in order to train the network, and a testing phase that compares the output from the trained network to the desired output to test for classification accuracy (Abdelwahab and Abdel-Aty, 2002). The MLP is trained using a back-propagation algorithm, and allows only feed-forward connections (Abdelwahab and Abdel-Aty, 2001) that use directed arrows as coefficients (i.e. weights) (Delen et al., 2006). The partitioned data is used to estimate the MLP to create an input layer, hidden layers, and output layers to explain relationships between variables as described in Chapter 4 section 4.2.4. The parameters are set so that hidden layers are automatically computed, the overfit prevention is 30.0%, and the confidence is based on the probability of the predicted value. The final training model includes 948,679 observations, has 1 hidden layer, 11 neurons (indicated in Table 5.27), and a classification accuracy of 72.84% for the training set and 72.89% for the testing set (presented in Tables 5.28 and 5.29).

Table 5.27: Explanatory Variables (Neurons) used in the ANN

Speed – Exceeds Limit	Speed Limit	Physical Impairment
Violation Stop Sign/Signal	Wrong Side – Not Passing	Alcohol
Weather Conditions	Improper backing	Light conditions
Total Number of Occupants	Bias	

Table 5.28: ANN Coincidence Matrix for the Training Set

Classification

	Predicted			
Observed	Fatal	Injury	Property Damage	Percent Correct
Fatal	7	2,942	3,074	0.1%
Injury	24	59,801	208,640	22.3%
Property Damage	9	42,952	631,230	93.6%
Overall Percentage	0.0%	11.1%	88.9%	72.84%

Table 5.29: ANN Coincidence Matrix for the Testing Set

Classification

	Predicted			
Observed	Fatal	Injury	Property Damage	Percent Correct
Fatal	0	991	1,082	0.0%
Injury	8	20,091	69,598	22.4%
Property Damage	5	14,187	210,822	93.7%
Overall Percentage	0.0%	11.1%	88.9%	72.89%

Figure 5.13 presents the effect diagram, which displays the network of independent variables to the crash injury severity outcomes; and, Table 5.30 presents the coefficients table, which displays the coefficient estimates that indicate the relationship among variables between one layer and the next layer.

Figure 5.13: ANN Effect Diagram

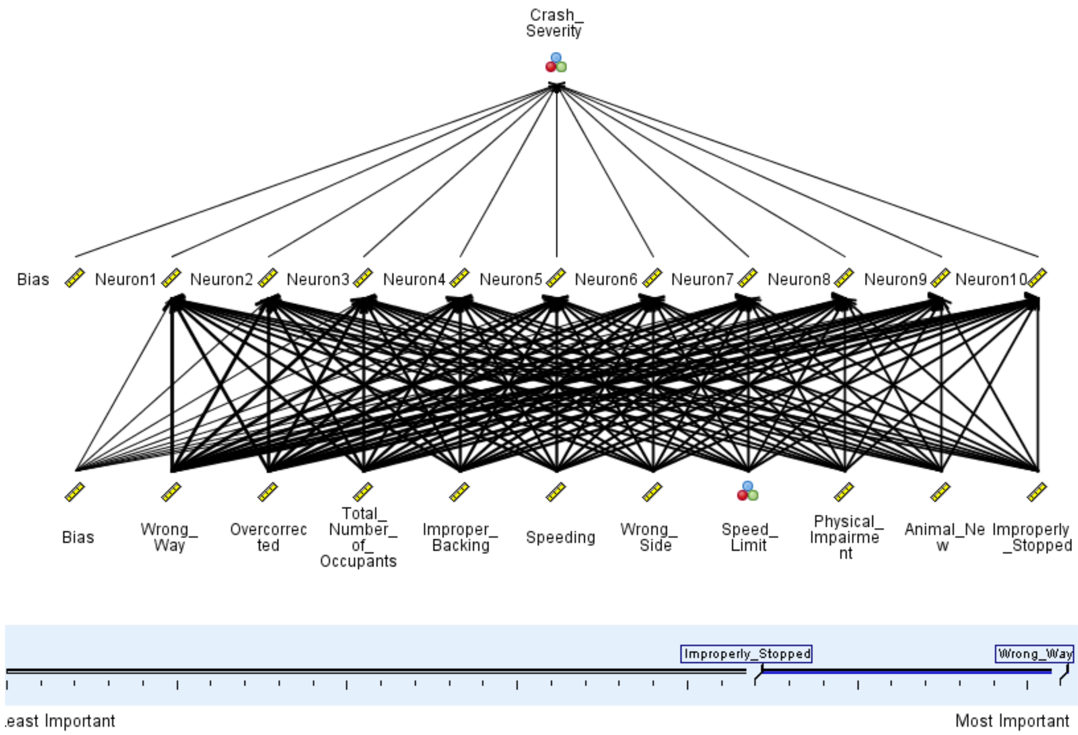
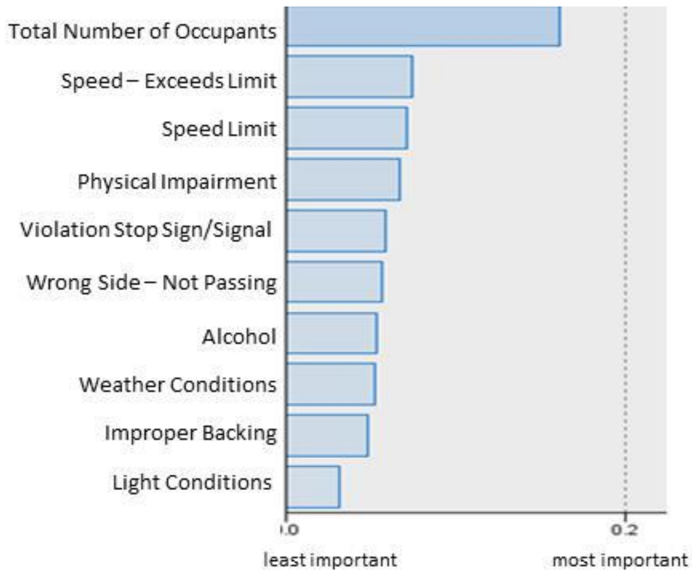


Table 5.30: ANN Coefficients Table

Y	V4
15.1111	Bias
14.2222	Wrong Way
13.3333	Overcorrected
12.4444	Total Number of Occupants
11.5556	Improper Backing
10.6667	Speed – Exceeds Limit
9.7778	Wrong Side
2.6667	Physical Impairment
1.7778	Animal
0.8889	Improperly Stopped
14.6667	Bias
13.3333	Hidden layer activation
12.000	Hidden layer activation
10.6667	Hidden layer activation
9.3333	Hidden layer activation
8.000	Hidden layer activation
6.6667	Hidden layer activation
5.3333	Hidden layer activation
4.000	Hidden layer activation
2.6667	Hidden layer activation
1.3333	Hidden layer activation
8.8889	Speed Limit=05-20 mph
8.000	Speed Limit=25-30 mph
7.1111	Speed Limit=35-40 mph
6.2222	Speed Limit=45-50 mph
5.3333	Speed Limit=55-60 mph
4.4444	Speed Limit=65-70 mph
3.5556	Speed Limit=Unknown
12.000	Crash Severity=Fatal
8.000	Crash Severity=Injury
4.000	Crash Severity=Property Damage

The predictor importance chart shows the top predictive factors and their relative importance values, which are normalized to sum to unity. Figure 5.14 presents the top ten factors suggested to have greatest importance in estimating the ANN model.

Figure 5.14: ANN Predictor Importance



Figures 5.15, 5.16, and 5.17 present lift charts for the ANN for fatal, injury, and property damage only outcomes in the training and testing sets. The red lines represent the ratio of the expected number of positive fatal outcomes (Figure 5.15), the expected number of positive injury outcomes (Figure 5.16), and the expected number of property damage only outcomes (Figure 5.17) to their sample proportions that would be predicted if the outcomes were simply selected at random (unity). Tables 5.31, 5.32, and 5.33 provide the lift values for the fatal, injury, and property damage only lift charts for the training and testing sets and the number of expected, observed, cumulative expected and cumulative observed cases for the testing sets for each decile.

Figure 5.15: ANN Lift Curve for Fatal Outcomes

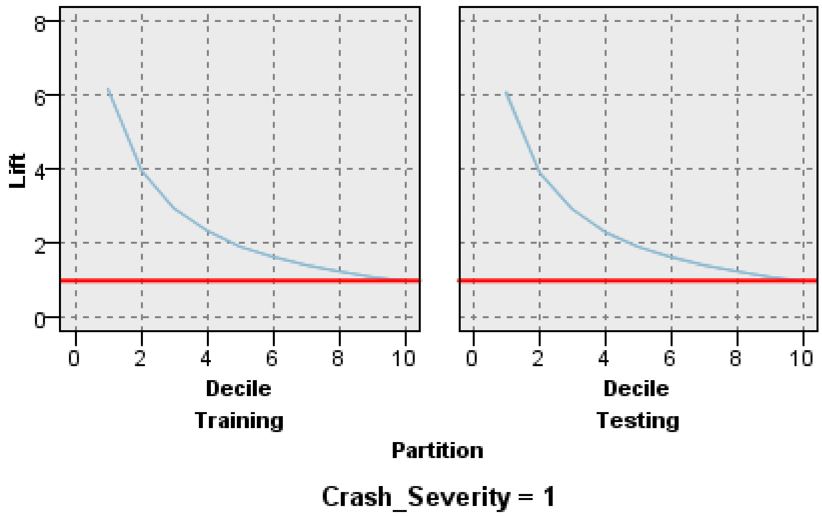


Table 5.31: Lift Values, Expected and Observed Counts per Decile for Fatal Outcome

Decile	Lift Training Set	Lift Testing Set	Expected Outcomes Testing Set	Observed Outcomes Testing Set	Cumulative Expected Testing Set	Cumulative Observed Testing Set
1	6.1382	6.0734	1,235.38	1,259	1,235.38	1,259
2	3.9598	3.9074	287.29	361	1,522.67	1,620
3	2.9404	2.9104	143.42	190	1,666.09	1,810
4	2.3269	2.3022	84.15	99	1,750.24	1,909
5	1.9047	1.8977	60.24	58	1,810.48	1,967
6	1.6199	1.6064	43.89	31	1,854.37	1,998
7	1.4094	1.4031	28.38	38	1,882.75	2,036
8	1.2417	1.2398	18.45	20	1,901.20	2,056
9	1.1089	1.1079	12.27	11	1,913.47	2,067
10	1.0	1.0	5.27	6	1,918.74	2,073

Figure 5.16: ANN Lift Curve for Injury Outcomes

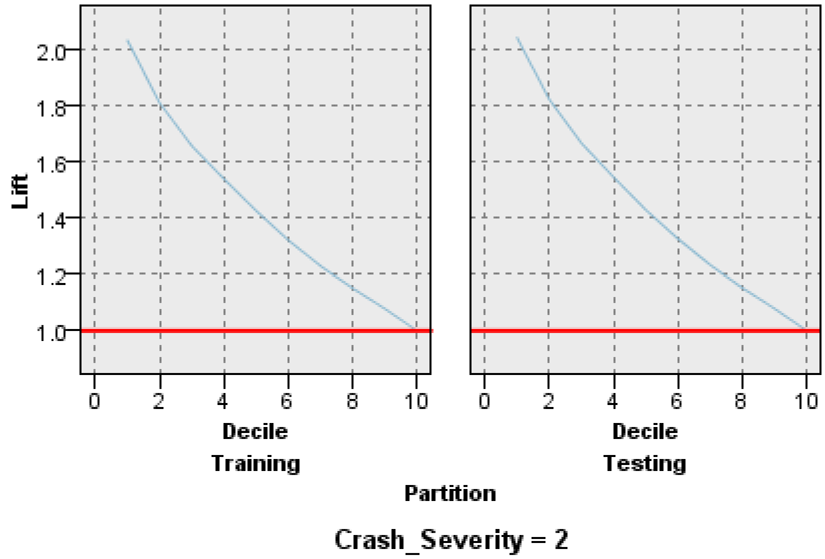


Table 5.32: Lift Values, Expected and Observed Counts per Decile for Injury Outcome

Decile	Lift Training Set	Lift Testing Set	Expected Outcomes Testing Set	Observed Outcomes Testing Set	Cumulative Expected Testing Set	Cumulative Observed Testing Set
1	2.0296	2.0395	18,358.16	18,282	18,358.16	18,282
2	1.8072	1.8194	14,316.38	14,357	32,674.54	32,639
3	1.6551	1.6646	12,013.70	12,155	44,688.24	44,794
4	1.5374	1.5433	10,551.38	10,578	55,239.62	55,372
5	1.4245	1.4276	8,528.21	8,653	63,767.83	64,025
6	1.3200	1.3246	7,051.50	7,261	70,819.33	71,286
7	1.2287	1.2326	6,026.16	6,108	76,845.49	77,394
8	1.1503	1.1514	5,137.58	5,226	81,983.07	82,620
9	1.078	1.0786	4,373.28	4,455	86,356.35	87,075
10	1.0	1.0	2,717.40	2,622	89,073.75	89,697

Figure 5.17: ANN Lift Curve for Property Damage Only Outcomes

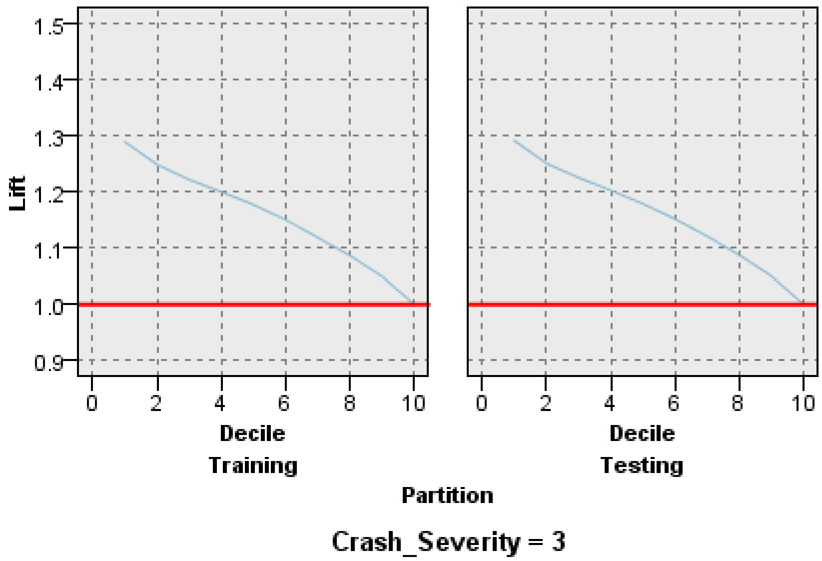


Table 5.33: Lift Values, Expected and Observed Counts per Decile for Property Damage Only Outcome

Decile	Lift Training Set	Lift Testing Set	Expected Outcomes Testing Set	Observed Outcomes Testing Set	Cumulative Expected Testing Set	Cumulative Observed Testing Set
1	1.2883	1.2905	28,953.17	29,037	28,953.17	29,037
2	1.2479	1.2499	27,288.78	27,218	56,241.95	56,255
3	1.2209	1.2245	26,515.58	26,405	82,757.53	82,660
4	1.1993	1.2022	25,614.42	25,541	108,371.95	108,201
5	1.1766	1.1781	24,562.55	24,344	132,934.50	132,545
6	1.1496	1.1513	23,048.67	22,884	155,983.17	155,429
7	1.1182	1.1204	20,964.76	21,049	176,947.93	176,478
8	1.0860	1.0872	19,507.26	19,235	196,455.19	195,713
9	1.0495	1.0498	16,966.67	16,894	213,421.86	212,607
10	1	1	12,366.69	12,407	225,788.55	225,014

Inspection of the figures and tables indicates that the ANN model provides significant and similar lifts for each severity outcome for both the training and testing data partitions. Similar to the multinomial and CHAID models, further inspection reveals greater lift for fatal outcomes than for injury outcomes with injury outcomes also providing greater lift than property damage only outcomes across both the training and testing data partitions.

ROC curves are constructed for the training set to visualize and evaluate the network's capability to predict (1) a fatal outcome relative to property damage and injury only outcomes and to predict (2) a property damage only outcome relative to fatal and injury outcomes. Figures 5.18 and 5.19 present the ROC curves and illustrate that the ANN better predicts fatal versus non-fatal outcomes and non-injury versus injury outcomes than if no model was used and the outcomes were randomly assigned.

AUC values are calculated; and, as earlier described, the maximum AUC value of 1.0 suggests a perfect classifier (Worster et al., 2006) and any useful classifier should have an AUC of greater than 0.5 (Fawcett, 2006). The AUC values for the ANN model are 0.859 for the predicted probability of a fatal outcome relative to a nonfatal outcome (presented in Table 5.34) and 0.706 for a non-injury outcome relative to an injury outcome (presented in Table 5.35), both of which are significantly different from 0.5 at the 0.000 level suggesting that the ANN model has good discriminatory power.

Figure 5.18: ANN ROC Curve Fatal Outcome using the Testing Set

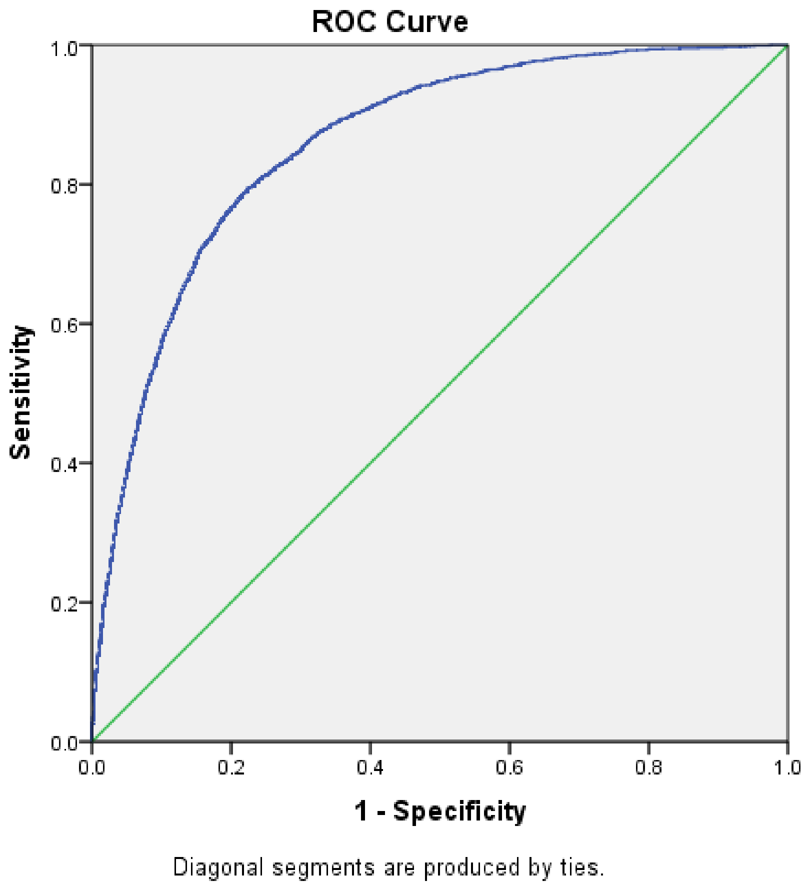


Table 5.34: AUC for ANN Prediction of Fatal Outcome using the Testing Set

Area Under the Curve

Test Result Variable(s): ANN Propensity Fatal

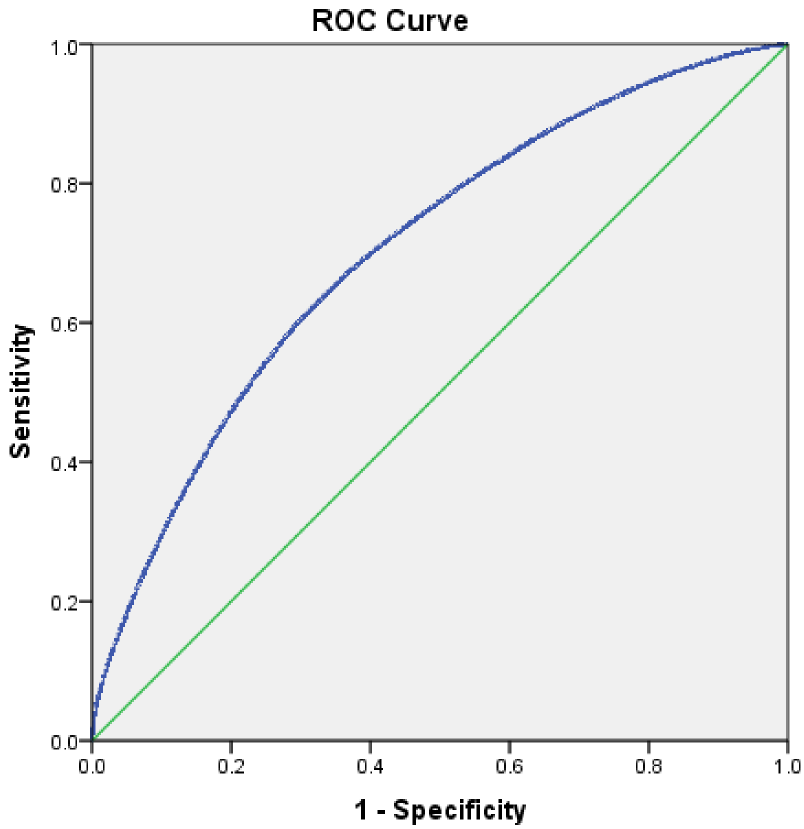
Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
.859	.004	.000	.852	.867

The test result variable(s): ANN Propensity Fatal has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Figure 5.19: ANN ROC Curve Property Damage Only Outcome using the Testing Set



Diagonal segments are produced by ties.

Table 5.35: AUC for ANN Prediction of Property Damage Only Outcome using the Testing Set

Area Under the Curve

Test Result Variable(s): ANN Propensity PD

Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
.706	.001	.000	.704	.708

The test result variable(s): ANN Propensity PD has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Important findings from the ANN analyses include:

- Classification accuracy rate equals 72.84% for the training set and 72.89% for the testing set.
- AUC for a fatal outcome equals 0.859 for the testing set.
- AUC for a property damage only outcome equals 0.706 for the testing set.
- Both AUC scores are significantly greater than 0.5, indicating above-chance accuracy.
- The top three most important predicators of crash severity are total number of occupants, speed – exceeds limit, and speed limit.

5.2 Ensembles of Models

As described in Chapter 4 section 2.5, recent advances in data mining techniques utilize ensemble learning to (1) reduce the impact of inaccurate model selection, (2) better represent data distributions, and (3) enhance predictive performance (Dietterich, 2000; Polikar, 2006). The fundamental procedure to create an ensemble of models employs the following logic:

- Step I: Create multiple models of differing types and evaluate each model.
- Step II: Compute an ensemble score value derived from these models using a combinatory rule.
- Step III: Evaluate the performance of the model ensemble using the combinatory rule.

The final multinomial logit, CHAID decision tree, and ANN models are used to score the model ensemble using three common combinatory rules (Kittler et al., 1998): Majority Voting, Weighted-Majority Voting, and Max Rule. The study assesses the accuracy and discriminatory power of each model ensemble by examining the confidence matrices, the ROC curves, and the AUC values of each ensemble against the training set (75%) and testing set (25%) data partitions also described in Chapter 4.

5.2.1 Majority Voting

The first ensemble, the Majority Voting scoring method, combines the individual model forecasts of crash severity for an observation by tallying the number of times each possible severity value is forecast and selecting the value with the highest total as the ensemble forecast (Kittler et al., 1998). If the voting is tied, the scoring method uses the value with the highest confidence. This ensemble model results in a classification accuracy of 73.02% for the training set and 72.99% for the testing set as presented in Tables 5.36 and 5.37.

Table 5.36: Majority Voting Ensemble Coincidence Matrix for the Training Set

Classification

Observed	Predicted			
	Fatal	Injury	Property Damage	Percent Correct
Fatal	2	2,910	3,111	0.0%
Injury	1	53,810	214,654	20.0%
Property Damage	2	35,260	638,929	94.8%
Overall Percentage	0.0%	9.7%	90.3%	73.02%

Table 5.37: Majority Voting Ensemble Coincidence Matrix for the Testing Set

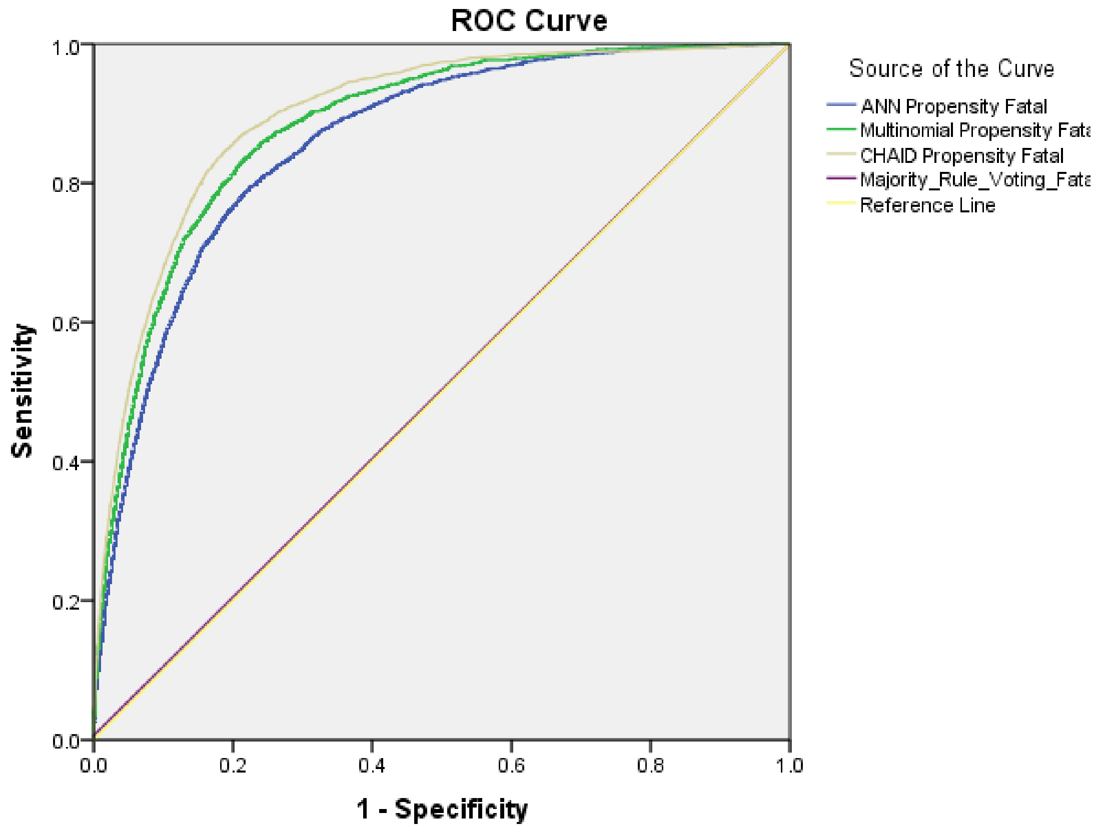
Classification

Observed	Predicted			
	Fatal	Injury	Property Damage	Percent Correct
Fatal	1	1,010	1,062	0.0%
Injury	0	17,869	71,828	19.9%
Property Damage	1	11,657	213,356	94.8%
Overall Percentage	0.0%	9.6%	90.4%	72.99%

ROC curves are constructed to visualize and evaluate the Majority Voting Ensemble's capability to predict (1) a fatal outcome relative to property damage and injury only outcomes and to predict (2) a property damage only outcome relative to fatal and injury outcomes. Figures 5.20 and 5.21 present the ROC curves and illustrate that this ensemble approach does not significantly better predict fatal versus non-fatal outcomes and non-injury versus injury outcomes than if no model was used and the predicted outcomes were randomly assigned.

AUC values are calculated; and, as earlier described, a maximum AUC value of 1.0 suggests a perfect classifier (Worster et al., 2006) and any useful classifier should have an AUC significantly greater than 0.5 (Fawcett, 2006). The AUC value for the Majority Voting Ensemble is found to be 0.503 for the predicted probability of a fatal outcome relative to a nonfatal outcome (presented in Table 5.38), which is not significantly different from 0.5, and 0.605 for the predicted probability for a non-injury outcome relative to an injury outcome (presented in Table 5.39), which is significantly different from 0.5 at the 0.000 level, but much lower than the AUC for each constituent model. These relatively low AUC values suggest that, overall, the Majority Voting Ensemble does not have good discriminatory power, and that when the distribution of outcomes is highly skewed as they are here, Majority Voting is not a useful combinatory rule.

Figure 5.20: Majority Voting Ensemble ROC Curve Fatal Outcome using the Testing Set



Diagonal segments are produced by ties.

Table 5.38: AUC for Majority Voting Ensemble Prediction of Fatal Outcome using the Testing Set

Area Under the Curve

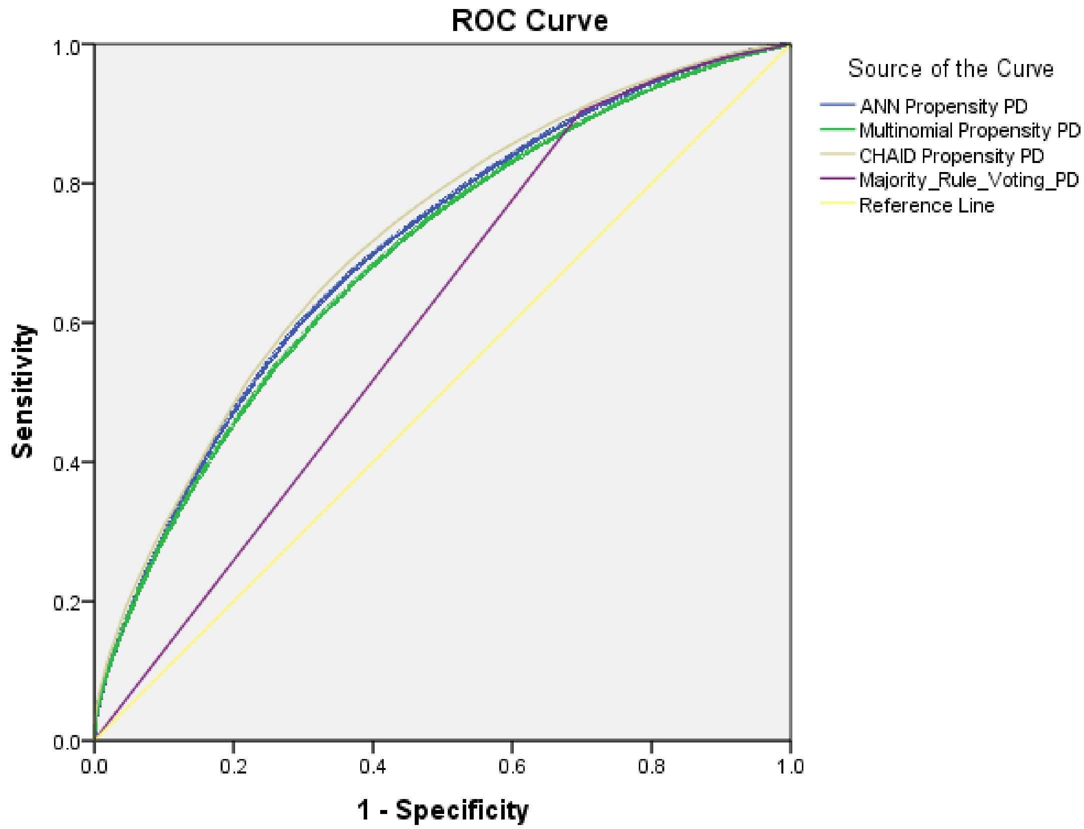
Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
ANN Propensity Fatal	.859	.004	.000	.852	.867
Multinomial Propensity Fatal	.883	.003	.000	.876	.889
CHAID Propensity Fatal	.898	.003	.000	.892	.904
Majority_Rule_Voting_Fatal	.503	.006	.627	.491	.516

The test result variable(s): ANN Propensity Fatal, Multinomial Propensity Fatal, CHAID Propensity Fatal , Majority_Rule_Voting_Fatal has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Figure 5.21: Majority Voting Ensemble ROC Curve Property Damage Only Outcome using the Testing Set



Diagonal segments are produced by ties.

Table 5.39: AUC for Majority Voting Ensemble Prediction of Property Damage Only Outcome using the Testing Set

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
ANN Propensity PD	.706	.001	.000	.704	.708
Multinomial Propensity PD	.695	.001	.000	.693	.697
CHAID Propensity PD	.717	.001	.000	.715	.719
Majority_Rule_Voting_PD	.605	.001	.000	.602	.607

The test result variable(s): ANN Propensity PD, Multinomial Propensity PD, CHAID Propensity PD, Majority_Rule_Voting_PD has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

5.2.2 Weighted-Majority Voting

When using the Weighted-Majority Voting combinatory rule, the constituent model votes are weighted based on the confidence of each model for each severity prediction, the weights are summed, and the outcome with the highest total is selected (Littlestone and Warmuth, 1994). The confidence for the final prediction is the sum of the weights for the selected outcome divided by the number of models included in the ensemble (Littlestone and Warmuth, 1994); and, if the voting is tied, the outcome is randomly selected. This scoring method has a classification accuracy of 73.02% for the training set and 72.99% for the testing set (presented in Tables 5.40 and 5.41).

Table 5.40: Weighted-Majority Voting Ensemble Coincidence Matrix for the Training Set

Classification

	Predicted			
Observed	Fatal	Injury	Property Damage	Percent Correct
Fatal	2	2,910	3,111	0.0%
Injury	1	53,810	214,654	20.0%
Property Damage	2	35,260	638,929	94.8%
Overall Percentage	0.0%	9.7%	90.3%	73.02%

Table 5.41: Weighted-Majority Voting Ensemble Coincidence Matrix for the Testing Set

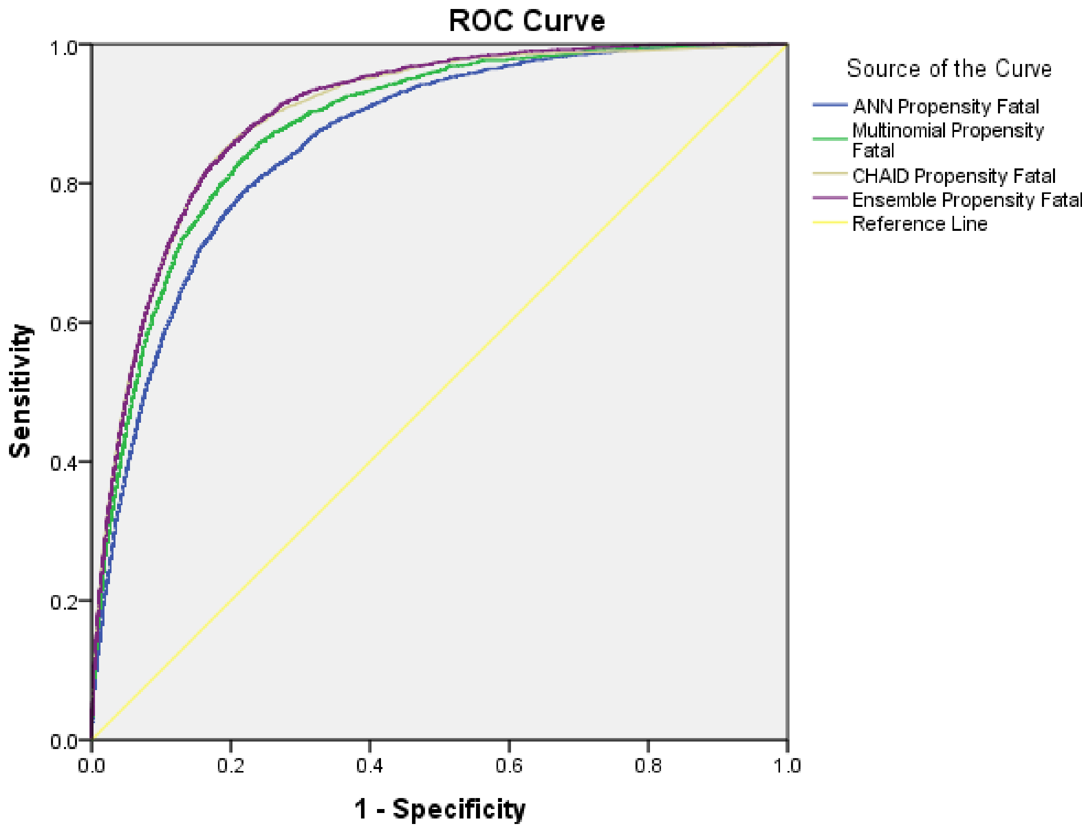
Classification

	Predicted			
Observed	Fatal	Injury	Property Damage	Percent Correct
Fatal	1	1,010	1,062	0.0%
Injury	0	17,869	71,828	19.9%
Property Damage	1	11,657	213,356	94.8%
Overall Percentage	0.0%	9.6%	90.4%	72.99%

ROC curves are constructed to visualize and evaluate the ensemble's capability to predict (1) a fatal outcome relative to property damage and injury only outcomes and to predict (2) a property damage only outcome relative to fatal and injury outcomes. Figures 5.22 and 5.23 present the ROC curves and illustrate that this ensemble combinatory rule significantly better predicts fatal versus non-fatal outcomes and non-injury versus injury outcomes than if no model was used and the predicted severity outcomes were randomly assigned. Additionally, the ensemble ROC curve for the prediction of fatal outcomes versus non-fatal outcomes is everywhere above the individual model ROC curves, signifying that the ensemble better predicts fatal versus non-fatal outcomes than all of the individual modeling approaches. Yet, for the prediction of non-injury outcomes versus injury outcomes, the ensemble ROC curve intersects the CHAID decision tree ROC curve. This suggests that the ensemble better predicts non-injury versus injury outcomes than the individual modeling approaches, with the exception of the CHAID decision tree.

The AUC values for the Weighted-Majority Voting Ensemble are 0.901 for the predicted probability of a fatal outcome relative to a nonfatal outcome (presented in Table 5.42) and 0.706 for a non-injury outcome relative to an injury outcome (presented in Table 5.43). Both AUC values are significantly different from 0.5 at the 0.000 level, which suggests that the Weighted-Majority Voting Ensemble has good discriminatory power. It is also evident that the ensemble has a higher AUC value than the individual models when predicting the probabilities of a fatal outcome relative to a nonfatal outcome; yet, the ensemble has a slightly lower AUC value than the CHAID decision tree when predicting a non-injury outcome relative to an injury outcome.

Figure 5.22: Weighted-Majority Voting Ensemble ROC Curve Fatal Outcome using the Testing Set



Diagonal segments are produced by ties.

Table 5.42: AUC for Weighted-Majority Voting Ensemble Prediction of Fatal Outcome using the Testing Set

Area Under the Curve

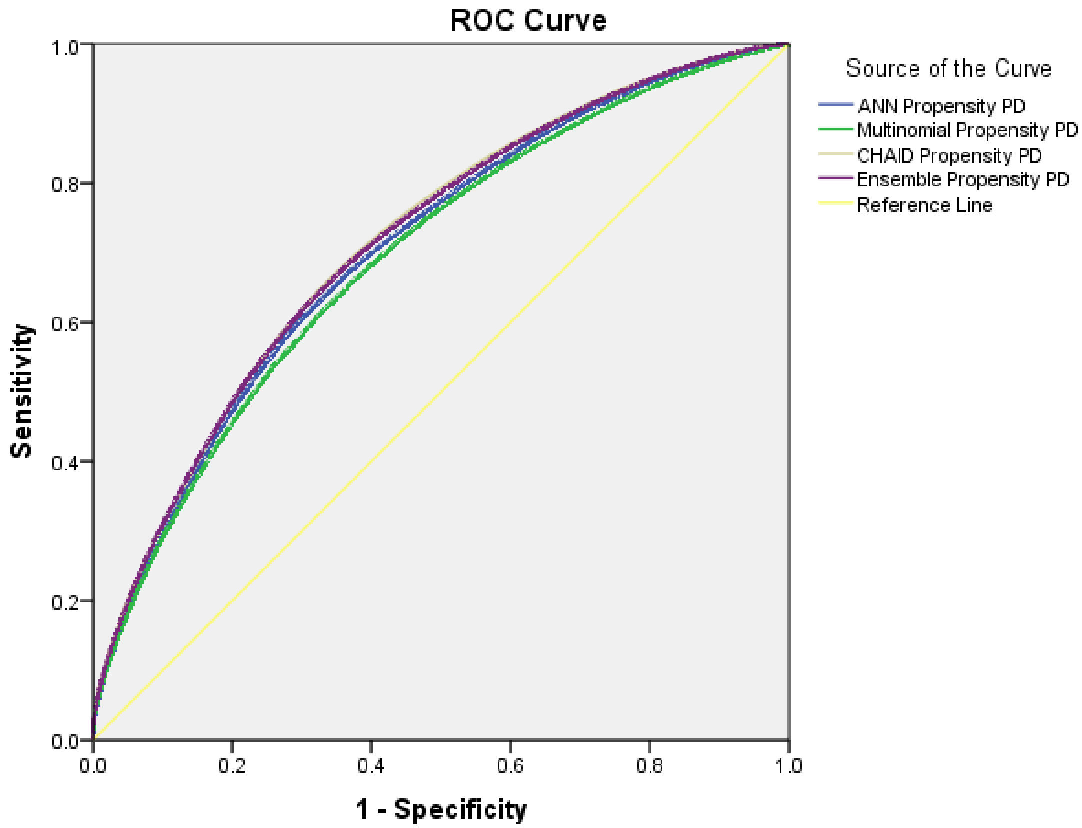
Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
ANN Propensity Fatal	.859	.004	.000	.852	.867
Multinomial Propensity Fatal	.883	.003	.000	.876	.889
CHAID Propensity Fatal	.898	.003	.000	.892	.904
Ensemble Propensity Fatal	.901	.003	.000	.895	.907

The test result variable(s): ANN Propensity Fatal, Multinomial Propensity Fatal, CHAID Propensity Fatal , Ensemble Propensity Fatal has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Figure 5.23: Weighted-Majority Voting Ensemble ROC Curve Property Damage Only Outcome using the Testing Set



Diagonal segments are produced by ties.

Table 5.43: AUC for Weighted-Majority Voting Ensemble Prediction of Property Damage Only Outcome using the Testing Set

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval Lower Bound	Asymptotic 95% Confidence Interval Upper Bound
ANN Propensity PD	.706	.001	.000	.704	.708
Multinomial Propensity PD	.695	.001	.000	.693	.697
CHAID Propensity PD	.717	.001	.000	.715	.719
Ensemble Propensity PD	.715	.001	.000	.713	.717

The test result variable(s): ANN Propensity PD, Multinomial Propensity PD, CHAID Propensity PD, Ensemble Propensity PD has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

5.2.3 Max Rule

When using the max rule combinatory rule (also referred to as the highest confidence wins rule) to create the model ensemble, the rule selects the individual constituent model with the highest propensity value of all predicted values to generate the prediction value for the model ensemble (Kittler et al., 1998). This scoring method has a classification accuracy of 72.84% for the training set and 72.83% for the testing set (presented in Tables 5.44 and 5.45).

Table 5.44: Max Rule Ensemble Coincidence Matrix for the Training Set

Classification

Observed	Predicted			
	Fatal	Injury	Property Damage	Percent Correct
Fatal	4	2,800	3,219	0.1%
Injury	3	47,365	221,097	17.6%
Property Damage	5	30,492	643,694	95.5%
Overall Percentage	0.0%	8.5%	91.5%	72.84%

Table 5.45 Max Rule Ensemble Coincidence Matrix for the Testing Set

Classification

Observed	Predicted			
	Fatal	Injury	Property Damage	Percent Correct
Fatal	3	962	1,108	0.1%
Injury	2	15,807	73,888	17.6%
Property Damage	1	10,124	214,889	95.5%
Overall Percentage	0.0%	8.5%	91.5%	72.83%

ROC curves are constructed to visualize and evaluate the ensemble's capability to predict (1) a fatal outcome relative to property damage and injury only outcomes and to predict (2) a property damage only outcome relative to fatal and injury outcomes. Figures 5.24 and 5.25 present the ROC curves and illustrate that the ensemble significantly better predicts fatal versus non-fatal outcomes and non-injury versus injury outcomes than if no model was used and the outcomes were randomly predicted. Moreover, the ensemble ROC curves for prediction of fatal outcomes versus non-fatal outcomes and injury outcomes versus non-injury outcomes are ubiquitously above all of the individual model ROC curves, again with the exception of the CHAID decision tree. This suggests that the ensemble better predicts fatal versus non-fatal outcomes and non-injury versus injury outcomes than the individual modeling approaches, with the exception of the CHAID model.

AUC values are calculated for the Max Rule Ensemble, which equal 0.898 for the predicted probability of a fatal outcome relative to a nonfatal outcome (presented in Table 5.46) and 0.711 for a non-injury outcome relative to an injury outcome (presented in Table 5.47). Both AUC values are significantly different from 0.5 at the 0.000 level, which suggests that the Max Rule Ensemble has good discriminatory power. Additionally, it is evident that this ensemble has higher AUC values than all of the individual models, with the exception of the CHAID model.

Figure 5.24: Max Rule Ensemble ROC Curve Fatal Outcome using the Testing Set

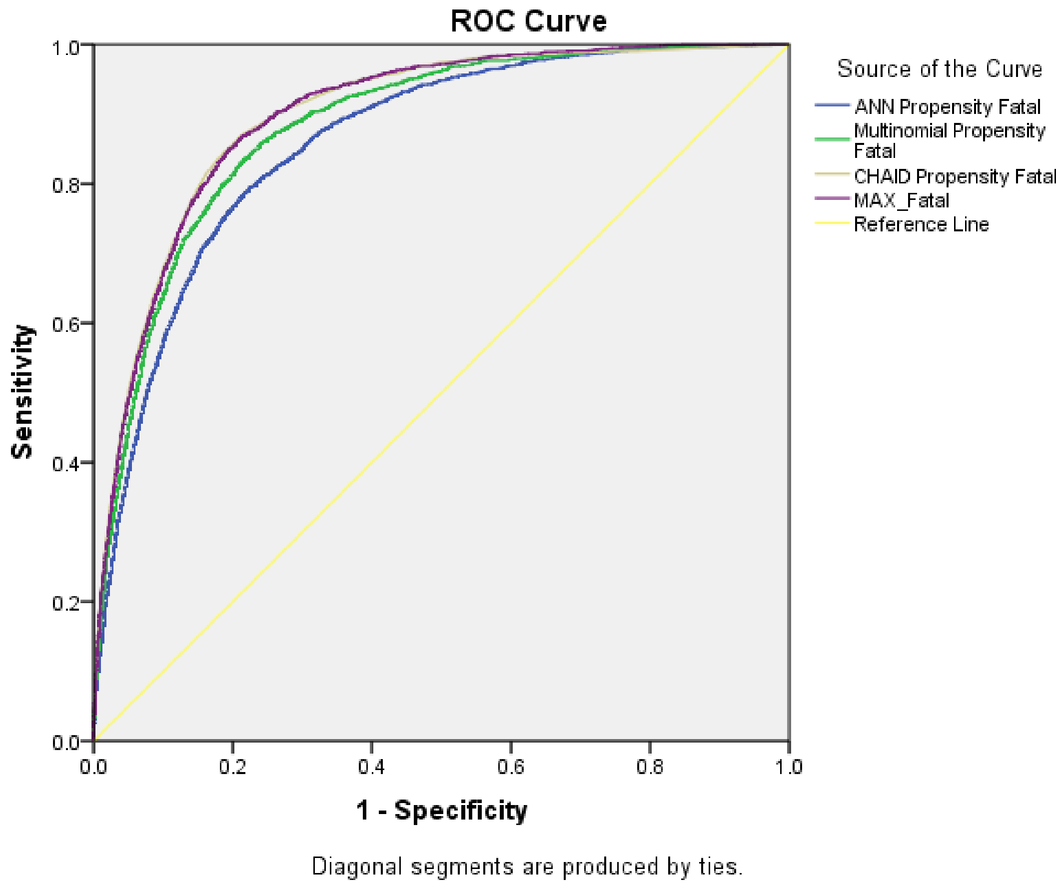


Table 5.46: AUC for Max Rule Ensemble Prediction of Fatal Outcome using the Testing Set

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
ANN Propensity Fatal	.859	.004	.000	.852	.867
Multinomial Propensity Fatal	.883	.003	.000	.876	.889
CHAID Propensity Fatal	.898	.003	.000	.892	.904
MAX_Fatal	.898	.003	.000	.892	.904

The test result variable(s): ANN Propensity Fatal, Multinomial Propensity Fatal, CHAID Propensity Fatal , MAX_Fatal has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

Figure 5.25: Max Rule Ensemble ROC Curve Property Damage Only Outcome using the Testing Set

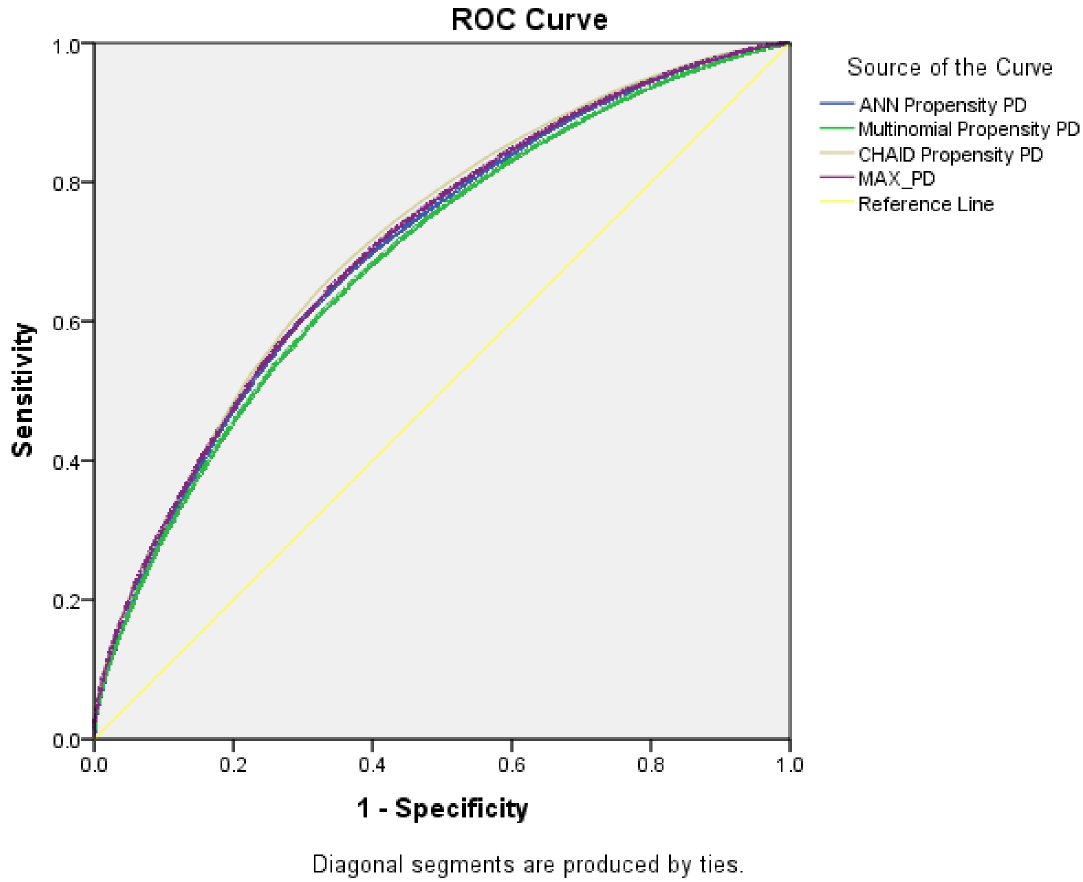


Table 5.47: AUC for Max Rule Ensemble Prediction of Property Damage Only Outcome using the Testing Set

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
ANN Propensity PD	.706	.001	.000	.704	.708
Multinomial Propensity PD	.695	.001	.000	.693	.697
CHAID Propensity PD	.717	.001	.000	.715	.719
MAX_PD	.711	.001	.000	.709	.713

The test result variable(s): ANN Propensity PD, Multinomial Propensity PD, CHAID Propensity PD, MAX_PD has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5

5.2.4 Summary of Ensemble Findings

Important findings for the model ensembles include:

- All ensemble approaches have similar classification accuracy for the training set and for the testing set as illustrated in Table 5.48.
- The Weighted-Majority Voting Ensemble approach results in the highest AUC values for both fatal versus nonfatal outcomes (0.901) and injury versus non-injury outcomes (0.715) as presented in Table 5.48.
- The AUC scores for the Weighted-Majority Voting Ensemble and Max Rule are both significantly greater than 0.5, which indicates above-chance accuracy.
- The relatively low AUC values suggest that the Majority Voting Ensemble model does not have good discriminatory power; and, when the distribution of outcomes is as highly skewed as it is here, Majority Voting is not a useful ensembling method.
- The ROC curves for the Weighted-Majority Voting Ensemble and Max Rule Ensemble for the prediction of fatal versus non-fatal outcomes are above or equal to all the individual model ROC curves, signifying that these ensemble models predict fatal versus non-fatal outcomes better than or equal to the individual modeling approaches.
- The ROC curves for the Weighted-Majority Voting Ensemble and Max Rule Ensemble for the prediction of non-injury versus injury outcomes is ubiquitously above the individual models' ROC curves, with the exception of the CHAID decision tree. This suggests that the ensemble models better predict non-injury

versus injury outcomes than the individual modeling approaches, excluding the CHAID model.

Table 5.48: Accuracy and AUC Comparison of Ensemble Models

Ensemble Approach	Classification Accuracy Training Set	Classification Accuracy Testing Set	AUC Value Fatal vs. Nonfatal Testing Set	AUC Value Injury vs. Non-injury Testing Set
Majority Voting	73.02%	72.99%	0.503	0.605
Weighted-Majoring Voting	73.02%	72.99%	0.901	0.715
Max Rule	72.84%	72.83%	0.898	0.711

5.3 Relative Model Discriminatory Power

Table 5.49 presents the classification accuracy and AUC values for each of the individual models used for the model ensemble and for the three model ensemble techniques. The study compares AUC values to determine if there is a significant difference between the models' abilities to predict (1) a fatal outcome relative to property damage and injury only outcomes and to predict (2) a property damage only outcome relative to fatal and injury outcomes. Since the models are derived from and evaluated against the same set of training and test cases and are therefore likely to be correlated, the differences between area under the two ROC curves is assessed by calculating a critical ratio *z*, defined by Hanley and McNeil (1983) as:

$$z = \frac{A_1 - A_2}{\sqrt{SE_1^2 + SE_2^2 - 2rSE_1SE_2}}$$

where

A_i = AUC Value for model 1 and model 2 $\quad i = 1, 2$

SE_i = Standard Error for model 1 and model 2 $\quad i = 1, 2$

r = Estimated correlation coefficient between A_1 and A_2. This ratio is asymptotically distributed as a standard normal random variable and permits a test of the significance of the difference between the two areas under the curves.

Table 5.49: Individual Model and Model Ensemble Comparison

Model Approach	Classification Accuracy Training Set	Classification Accuracy Testing Set	AUC Value Fatal vs. Nonfatal Testing Set	AUC Value Injury vs. Non-injury Testing Set
Multinomial Logit	72.00%	72.00%	0.883	0.695
CHAID Decision Tree	73.06%	73.00%	0.898	0.717
ANN	72.84%	72.89%	0.859	0.706
Majority Voting Ensemble	73.02%	72.99%	0.503	0.605
Weighted-Majoring Voting Ensemble	73.02%	72.99%	0.901	0.715
Max Rule Ensemble	72.84%	72.83%	0.898	0.711

Results suggest a statistically significant difference between the AUC values of the CHAID model and the Multinomial Logit model for both fatal versus non-fatal outcomes ($z = 5.66$; $p < 0.0001$) and injury versus non-injury outcomes ($z = 33.95$; $p < 0.0001$). Additionally, there is a significant difference between the AUC values of the CHAID model and the ANN model for both fatal versus non-fatal outcomes ($z = 12.41$; $p < 0.0001$) and injury versus non-injury outcomes ($z = 21.57$; $p < 0.0001$). Among the individual model approaches examined, the CHAID decision tree is clearly best at predicting crash injury severity.

The study compares the model ensemble approaches with statistically significant AUC values, Weighted-Majority Voting and Max Rule, to determine if there are significant differences between the two ensembles' prediction capabilities. Results indicate that there is not a significant difference between the AUC values of the Weighted-Majority Voting Ensemble and Max Rule Ensemble for fatal versus non-fatal outcomes ($z = 1.67$; $p = 0.0949$), while there is a significant difference in AUC values for injury versus non-injury outcomes ($z = 8.16$; $p < 0.0001$).

The study then compares the CHAID AUC values to the Weighted-Majority Voting Ensemble AUC values to determine if there are significant differences between the prediction capabilities of the best individual model and the best ensemble model. Results suggest that there is not a significant difference between the AUC values of the CHAID model and the Weighted-Majority Voting Ensemble for fatal versus non-fatal outcomes ($z = 1.67$; $p = 0.0949$), yet there is a statistically significant difference between the AUC values for injury versus non-injury outcomes ($z = 4.08$; $p < 0.0001$) with the CHAID model providing better discriminatory power.

Of the modeling approaches examined, the CHAID decision tree renders the greatest accuracy and discriminatory power for predicting crash injury severity due to its greater classification accuracy and higher AUC values. Additionally, relative to the other modeling approaches, the CHAID method uncovers more complex interactions between predictor factors and also benefits by straightforward interpretability. As a result of these findings, the study uses the CHAID model to assess if findings support prior research and the current Missouri rules of the road in order to offer policy recommendations in Chapter 6.

Chapter 6 – Discussion

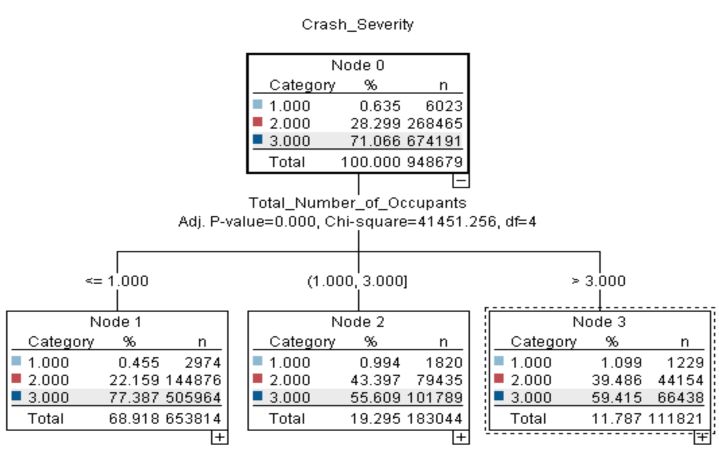
6.1 Model Findings and Insights

To illustrate the insights afforded by the CHAID decision tree, provide a context within which to evaluate reductions in motor vehicle crash risk, and examine possible changes in Missouri driving statues, decision rules focusing on the variables with the greatest predictor importance in the CHAID model (presented in Figure 5.7) are examined. As described in Chapter 4.2.3, the algorithm constructs the CHAID decision tree by sequentially applying decision rules that split a larger heterogeneous population into smaller more homogeneous subsets (termed nodes) based on the single, most predictive input factor (Eustace et al., 2013).

Number of Occupants

The CHAID model identifies *total number of occupants* as the best predictor to form the first branch of the decision tree, partitioning the training set into three branches characterized as single occupant, two or three occupants, or more than three occupants.

Figure 6.1: First Branch of CHAID Decision Tree – *Total Number of Occupants*

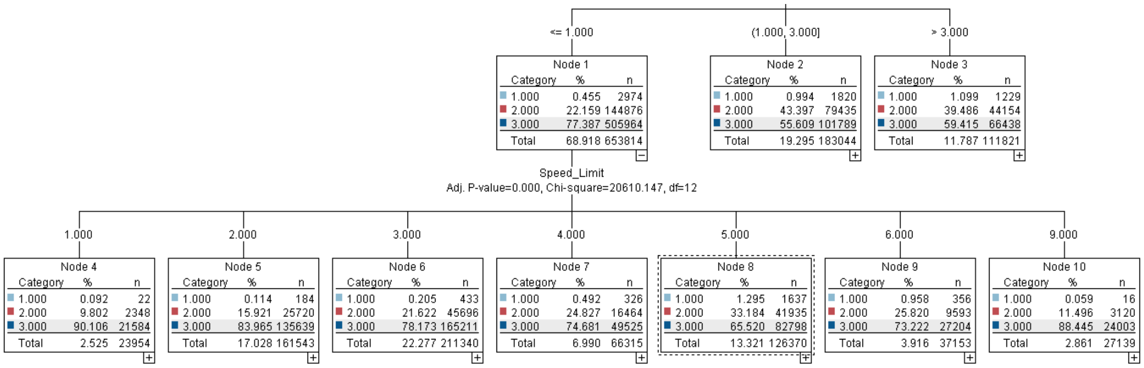


As illustrated in Figure 6.1, the probability that a fatal outcome (Category 1) will occur increases as the number of occupants involved in the crash increases - 0.455% for single occupant crashes, 0.994% for crashes involving two or three occupants, and 1.099% for crashes involving more than three occupants. Interestingly, the probability that an injury outcome (Category 2) will occur does not necessarily increase as the number of occupants increase. When increasing the total number of occupants from a single occupant to two or three occupants, the likelihood of an injury outcome increases from 22.159% to 43.397%; yet, when increasing the number of occupants to more than three occupants, the likelihood of an injury outcome decreases to 39.486%. Both findings indicate nonlinearity, and illustrate the importance of using the CHAID decision tree for analysis of non-linear effects.

Speed Limit

The CHAID model identifies speed limit as the second most important predictor variable, serves as the second branch for single occupant crashes. As illustrated in Figure 6.2, for single occupant crashes, the probability of a fatal or injury outcome increases for speed limit zones of up to 55mph and 60mph. Yet, a change from 55mph and 60mph to 65mph and 70mph decreases the likelihood that the outcome will be fatal or injurious, which could be contributed to the type of roads in which this speed limit is typically present in Missouri (e.g. interstates). This finding further solidifies the importance of using CHAID decision trees to analyze non-linear effects.

Figure 6.2: Single Occupant Crash Branch Two – Speed Limit



Zone 1 = 05mph and 20mph; zone 2 = 25mph and 30mph; zone 3 = 35mph and 40mph; zone 4 = 45mph and 50mph; zone 5 = 55mph and 60mph; zone 6 = 65mph and 70mph; and zone 9 = Unknown

Speeds - Exceed limit

Crashes involving the third most important predictor of crash injury severity, driving at speeds that exceed the posted limit, are more likely to cause of fatal and injury outcomes for each partition of number of occupants. For single occupant crashes, driving at speeds that exceed the limit in zones of 35mph or 40mph and 65mph or 70mph increases the chance of a fatal outcome from 0.133% to 3.689% and from 0.760% to 4.746% respectively. For crashes with two or three occupants, driving at speeds that exceed the limit in zones of 35mph or 40mph and 45mph or 50mph increases the chance of a fatal outcome from 0.233% to 4.671% and 0.568% to 6.534% respectively. Finally, for crashes with more than three occupants, driving at speeds that exceed the limit increases the chance of a fatal outcome occurring as speed limit zones increase: 25mph or 30mph = 3.409%; 35mph or 40mph = 6.902%; 45mph or 50mph = 8.543%; 65mph or 70mph = 13.223%.

Additionally, the results reveal important interactions between speeding and other circumstances. For example, for single occupant crashes, a young driver (under the age of 21) driving at speeds that exceed the limit in a speed limit zone of 25mph to 30mph and 65mph to 75mph has a lesser chance of a fatal outcome (0.676% and 3.049%) than older drivers (2.063% and 1.105% respectively for middle aged drivers and mature drivers in 25mph/30mph zones and 5.714% for both older groups in 65mph/75mph zones). For crashes with two or three occupants, driving at speeds that exceed the limit in a speed zone of 35mph or 45mph during dark, but lit conditions increases the likelihood of a fatal outcome from 2.607% to 8.108%, yet decreases the likelihood of an injury outcome of 70.142% to 66.366% when compared to driving at speeds that exceed the limit during other lighting conditions.

Alcohol

Crashes that occur while driving under the influence of alcohol, the fourth most important predictor, also have greater crash severity regardless of the number of occupants involved in the crash; yet, its importance is more prevalent for crashes involving multiple occupants. As presented in Appendix 2 and 3, the presence of alcohol represents the second split in the decision tree for two and three occupant crashes, where alcohol presence increases the probability of a fatal outcome and an injury outcome from 0.778% to 5.175% and 42.411% to 62.486% respectively, and for more than three occupant crashes, where alcohol presence increases the probability of a fatal outcome and an injury outcome from 0.856% to 7.023% and 38.676% to 59.273% respectively.

Additionally, results reveal dangerous interaction effects between alcohol and other variables. For example, for single occupant crashes, driving under the influence of alcohol in a speed limit zone of 65mph or 70mph increases the probability of a fatal outcome from 0.820% to 3.053% and of an injury outcome from 24.742% to 42.215%, compared with similar circumstances when alcohol is not present. When adding speeding to alcohol use at such high speeds, the risk of a fatal outcome and an injury outcome increase to 6.024% and 56.024% respectively.

For crashes involving two or three occupants, a crash occurring when alcohol is present increases the probability of a fatal outcome from 0.763% to 5.181% and the probability of an injury outcome from 42.380% to 62.327% compared to crashes when alcohol is not present. Moreover, adding speeding when on a hill or a crest to this scenario increases the probability of a fatal outcome and injury outcome to 20.882% and 65.429% respectively.

When a crash involves three or more occupants, the probability of a fatal outcome increases from 0.866% to 7.103% and an injury outcome increases from 38.752% to 60.276% when alcohol is present; when speeding is included, the chance of a fatal and an injury outcome increase to 17.221% and 65.558% respectively. Finally, when adding a dark light condition (with no streetlights or streetlights off) to this scenario, the chance of a fatal outcome increases to 26.627% and an injury outcome increases to 62.130%.

Failing to Yield

Crashes involving the fifth most important predictor of crash injury severity, failing to yield, are also more likely to cause fatal and injury outcomes and failure to yield has important interaction effects with other characteristics. For instance, when failing to yield is present and a single occupant on-roadway crash in a speed limit zone 65mph or 70mph occurs, the chance of a fatal or injury outcome increases from 0.471% and 19.260% to 0.972% and 25.791% respectively than if failing to yield is not present. For crashes with two or three occupants, drivers who fail to yield in a speed limit zone of

65mph or 70mph have a greater chance of a fatal outcome (4.708%) and injury outcome (53.861%) than if the driver yielded properly.

Violation of Stop Sign/Signal

Crashes involving a violation of a stop sign or signal, the sixth most important predictor, have a greater risk of a fatal or injury outcome in all decision rules identified and dangerous interactions are evident. For instance, for crashes with more than three occupants, mature drivers driving in a speed limit zone of 25mph, 30mph, or unknown and violating a stop sign or signal have a greater chance of a fatal outcome (1.866%) than their younger counterparts (0.325%). Additionally, for crashes with more than three occupants, driving at speeds that exceed the posted limit of 35mph or 40mph and violating a stop sign or signal has a greater chance of a fatal outcome (16.471%) than if speeding does not a occur (0.697%).

Physical Impairment

Crashes involving physical impairment, the seventh most important predictor of crash severity, are also more likely to cause fatal and injury outcomes. This factor is particularly prevalent in single occupant crashes, which may be attributed to other occupants' awareness of physical conditions and discouraging a physically impaired driver from operating the vehicle. Additionally, results reveal a dangerous interaction between mature drivers driving while physically impaired and speed limit. For instance, for single occupant crashes, mature drivers who are physically impaired and driving in a speed limit zone of 65mph or 70mph have a 3.551% of a fatal outcome and a 44.299% chance of an injury outcome, given a crash occurs.

Wrong Side – Not Passing

Crashes involving driving on the wrong side of the road are more likely to cause a fatal outcome in all instances. For example, for single occupant crashes, driving on the wrong side of the road in a speed limit zone of 55mph or 60mph results in 4.900% chance of a fatal outcome and a 35.844% injury outcome. For crashes with more than three occupants, an on-road crash while driving on the wrong side of the road in a speed limit zone of 55mph or 60mph results in a 9.432% chance of a fatal outcome and a 49.332% chance of an injury outcome.

Crash Location On/Off Roadway

Crash location, the ninth most important predictor for crash severity, does not consistently increase or decrease crash severity. In some situations, on-roadway crashes have a greater severity risk while in others off-roadway crashes have a greater severity risk, which further supports the importance of analyzing interaction effects. For instance, for single occupant crashes, driving at speeds that exceed the posted limit of 45mph or 50mph and having an off-roadway crash increases the chance of a fatal outcome from 0.255% to 1.233% and an injury outcome from 21.649% to 36.96%. For crashes with more than three occupants, when driving in a speed limit zone of 55mph or 60mph and alcohol is present, an on-roadway crash has a greater chance of a fatal outcome than an off-roadway crash (9.412% and 8.892%). Yet, under the same scenario when driving in a speed limit zone of 65mph or 70mph, an on-roadway crash has a lesser chance of a fatal outcome than an off-roadway crash (6.278% and 10.227%). Interestingly, the greatest likelihood of a non-property damage outcome (84.11%) occurs when the driver is under the influence of alcohol, driving in a speed limit zone of 55mph or 60mph and has an off-roadway crash that involves more than three occupants (presented in Appendix 4).

Improper Backing

Crashes involving improper backing, the final most important predictor of severity, are less likely to cause a fatal or injury crash. For all crashes, improperly backing in speed limit zones of 05mph to 20mph has a lesser probability of a fatal outcome. For single occupant crashes, the most likely non-injury crash (99.485% property damage only-Category 3) occurs when the driver improperly backing in a speed limit zone of 25 mph or 30 mph on a road with straight or unknown alignment and has an off-roadway crash (presented in Appendix 5).

6.1.1 Comparison of Findings with Prior Research

Expanding upon the discussion above, these findings are both consistent with and differ from findings of prior research. Similar key factors for crash severity prediction are recognized in the literature including the number of occupants involved in the crash, driver age, alcohol intoxication, speed, lighting conditions, weather conditions, and road characteristics.

Number of Occupants

The CHAID model indicates that as the total number of occupants involved in a crash increases, so does the probability that a fatal outcome will occur. This result is consistent with prior research findings that crash injury severity probabilities increase as the number of vehicle passengers increase (Renski et al., 1999; Oh, 2006).

Speed Limit/Speed - Exceed Limit

This study's results also are consistent with previous research findings that higher speed limits significantly increase the risk of severe injury outcomes (Renski et al., 1999; Khattak et al., 2002; Oh, 2006; Gårder, 2006; Malyshkina and Mannering, 2010; Savolainen and Ghosh, 2008; Haleem and Abdel-Aty, 2010; Zhu and Srinivasan, 2011; Yasmin and Eluru, 2013). For example, for single occupant crashes, lower driving speed limits are found to decrease the probability of a fatal outcome. Moreover, for multiple occupant crashes, as speed limits increase, the chance of a fatal outcome increases.

Additionally, model results which suggest that driving at speeds that exceed the limit have a greater risk of injury are consistent with prior research (Khattak et al., 1998; Renski et al., 1999; Khattak et al., 2002; Khattak and Rocha, 2003; Gårder, 2006; Oh, 2006; Savolainen and Ghosh, 2008; Schneider et al., 2009; Haleem and Abdel-Aty, 2010; Malyshkina and Mannering, 2010; Zhu and Srinivasan, 2011; Yasmin and Eluru, 2013). For instance, for crashes with two or three occupants, driving at a speed that exceeds the posted limit of 20mph to 50mph increases the chance of a fatal outcome. For crashes with more than three occupants, driving at speeds that exceed the speed limit increases the chance of a fatal outcome occurring as speed limits increase.

Importantly, in agreement with prior research (Yan and Radwan, 2006; Eustace et al., 2014), this study also identifies interaction effects between speed limit/speeding and other factors. For example, single occupant on-roadway crashes that occur when driving at speeds that exceed the posted limit of 45mph or 50mph increase the chance of a fatal outcome from 0.212% to 4.449% and an injury outcome from 21.429% to 43.52% than if speeding was not present. It is also suggested that for two or three occupant crashes, males driving at speeds that exceed the posted limit of 45mph or 50mph have an greater chance of a fatal outcome (7.950%) relative to their female counterparts (1.010%). Finally, for crashes involving two or three occupants, a 20.870% chance of a fatal outcome and a 68.216% of an injury outcome results when driving at speeds that exceed the limit while under the influence of alcohol.

Driver Age

Results from this study are consistent with prior research findings that age is a significant factor in predicting injury severity (Delen et al., 2006; Kuhnert et al., 2000), yet this study does not find age to have as great an importance for crash severity outcomes as previous findings. Importantly, though, this study agrees with prior research's assertion that the effect of young drivers on injury severity is circumstantial (Khattak and Rocha, 2003; Lu et al., 2006; Haleem and Abdel-Aty, 2010; Bernard and Sweeney II, 2015). For example, CHAID model results suggests that for single occupant crashes with a young driver (under the age of 21) driving at speeds that exceed the posted limit of 25mph or 30mph is more likely to cause a fatal crash (0.676%) than for older drivers. Yet, a young driver driving at speeds that exceed the posted limit of 35mph or 40mph during dark, unlit conditions is more likely to cause a fatal outcome (5.128%) and an injury outcome (37.5%) than their middle aged counterparts.

Agreeing with prior research (Bédard et al., 2002; Khattak et al., 2002; Abdelwahab and Abdel-Aty, 2002; Abdel-Aty, 2003; Schneider et al., 2009; Rifaatt et al., 2011; Yasmin and Eluru, 2013), the model suggests mature drivers have a circumstantial increased likelihood for greater injury severity. For example, in a crash involving three or more occupants, mature adults driving in a speed limit zone of 25mph, 30mph, or unknown and violating a stop sign or signal have a greater chance of a fatal outcome (1.866%) than their younger counterparts (0.325%). Yet, for single occupant crashes with middle aged drivers driving at speeds who exceed the posted limit of 35mph or 40mph are more likely to have a fatal outcome (4.517%) and an injury outcome (44.4%) than that of other age groups (2.109% fatal and 37.316% injury).

Alcohol

Study results are consistent with previous literature that alcohol use is a significant factor for predicting crash injury severity, and the presence of alcohol increases the likelihood of injury or fatality (Khattak et al., 1998; Renski et al., 1999; Krull et al., 2000; Bédard et al., 2002; Khattak et al., 2002; Kockelman and Kweon, 2002; Abdel-Aty, 2003; Zajac and Ivan, 2003; Donnell and Mason, 2004; Delen et al, 2006; Islam and Mannering, 2006; Rifaatt and Tay, 2009; Schneider et al., 2009; Wang et al., 2009; Moudon et al., 2011; Rifaatt et al., 2011; Yasmin and Eluru, 2013). For example, when a crash involves a single occupant in a speed limit zone of 65mph or 70mph and alcohol is a contributing circumstance, the probability of a fatal outcome dramatically increases from 0.891% to 32.555% and the probability of an injury outcome increases from 24.645% to 42.057% than if no alcohol is present. Additionally, when a crash involves two or three occupants and alcohol is a contributing factor, the likelihood of a fatality increases from 0.763% to 5.181% and the likelihood of an injury outcome increases from 42.380% to 62.327%. Finally, when a crash involves more than three occupants and alcohol is present, the probability of a fatal outcome increases from 0.886% to 7.103% and the probability of an injury outcome increases from 38.752% to 60.276%.

Additional Comparison

Lighting Conditions

Model results are also consistent with previous research which concludes that crashes that occur during dark, unlit conditions have greater injury severity (Klop and Khattak, 1999; Khattak et al., 2002; Rifaatt and Tay, 2009; Haleem and Abdel-Aty, 2010). For example, a single occupant crash involving a young driver or a mature driver driving in a speed limit zone of 35mph or 40mph during dark, unlit conditions are more likely to have a fatal outcome (5.128%) and an injury outcome (37.5%) than if driving during other lighting conditions. Additionally, for crashes involving three or more occupants, driving under the influence of alcohol at speeds that exceed the limit results in a 17.38% chance of a fatal outcome, yet adding a light condition of dark and no streetlights to this scenario increases the chance of a fatal outcome to 24.675%. Findings also suggest that for crashes involving two or three occupants, driving at speeds that exceed the limit in a speed zone of 35mph to 45mph during dark, but lit conditions has a likelihood of a fatal outcome of 8.108% and an injury outcome of 66.366%.

Weather Conditions

Model results with respect to the effects of weather conditions on severity outcomes help clarify previous research findings. The CHAID model suggests that in certain circumstances adverse weather can either increase likely crash severity (as reported by Wang et al., 2009; Abdel-Aty, 2003), yet in other circumstances decrease likely crash severity (as reported by Khattak et al., 1998). Single occupant crashes that occur during cloudy, rainy, freezing, or clear weather conditions are more likely to cause fatal and injury outcomes than snow, sleet, fog, mist, and indeterminate conditions when the speed limit zone is unknown. Additionally, two or three occupant on-roadway crashes that occur when the driver is driving too fast for conditions in a speed limit zone of 55mph or 60mph during dark but lit lighting conditions during weather conditions of cloudy, rainy, snowy and freezing are more likely to cause an injury outcome than during sleet, foggy, indeterminate and clear conditions. Yet, a two or three occupant crash that occurs during snowy or freezing weather conditions is more likely to cause an injury outcome but less likely to cause a fatal outcome than other weather conditions when a young driver is driving too fast for conditions on wet or unknown road conditions in a speed limit zone of 25mph or 30mph.

Road Characteristics

Finally, model results suggest that road conditions do not have high predictor importance, which differs from prior findings that road conditions have a great influence on crash severity (Lu et al., 2006).

6.2 Implications of Findings

6.2.1 Risk Assessment

To provide a context for understanding the relative reduction in overall risks associated with reducing the frequency of driver behaviors that importantly contribute to the likelihood of different crash severity outcomes, historic outcomes are examined to determine annual upper and lower bounds on the changes in the number of drivers involved in fatal, injury or property damage only crashes if selected contributory circumstances might be individually entirely eliminated. Due to the limitations of the modeling software, the annual bounds are estimated using the training set data and are calculated for each severity outcome by dividing the number of outcomes in the training set by the number of effective years in the training dataset (11 * 0.75).

Considering the contributing circumstances that have the greatest predictor importance for severe crash outcomes, lower and upper bounds for changes in the annual number of drivers involved in each of the three severity outcomes are determined by 1) removing the contributing circumstance for each driver and assuming the crash still occurs with severity outcome probabilities now determined by the outcome probabilities of the complementary node (a ceteris paribus lower bound) and 2) removing the contributing circumstance and alternatively assuming that the driver is not involved in a crash at all (an upper bound). This bounding technique presumes that no casual relationships exist among contributing circumstances in estimating the lower bounds and, alternatively, that the removed contributing circumstance was solely responsible for causing the accidents in estimating the upper bounds.

Table 6.1 presents the lower and upper bounds of the reductions in the annual numbers of drivers involved in fatalities, injury, and property damage outcomes associated with the six most important contributing circumstances.

Table 6.1: Estimated Annual Reductions in the Number of Drivers Involved in Each Severity Outcome if a Contributing Circumstance is Eliminated

Contributing Circumstance	Fatal		Injury		Property Damage Only		N[1]
	Estimated Lower Bound	Estimated Upper Bound	Estimated Lower Bound	Estimated Upper Bound	Estimated Lower Bound[2]	Estimated Upper Bound	
Speed - Exceed Limit	107	133	477	1,344	-801	1,325	2,802
Alcohol	135	191	841	2,741	-1,418	3,187	6,119
Failed to Yield	43	88	1412	6,779	-1,455	15,268	22,135
Violation - Stop Sign/Signal	16	39	692	2,133	-708	2,956	5,128
Wrong-Side	67	110	157	1,065	-224	1,212	2,388
Physical Impairment	11	36	427	1,215	-437	1,190	2,442

As illustrated in Table 6.1, the elimination of the specific contributing circumstance clearly changes the distribution of the number of drivers involved in the three outcomes. For example, alcohol involvement has significant detrimental effects on the number of Missouri drivers involved in fatal outcomes. When eliminating alcohol as a contributing circumstance and assuming the crash then does not occur, 191 fewer annual driver contributions towards fatal crashes might be prevented. When eliminating alcohol as a contributing circumstance and assuming the crash still does occur, the estimated severity outcomes are redistributed and at least 135 fatal accident outcomes per year might be avoided. It is apparent that many fatalities, injuries, and property damage outcomes might be prevented by completely eliminating these contributing circumstances; therefore, the findings from this study are compared with the current Missouri driving policy in order to identify possible driving statue modifications that could have a significant impact on improving public safety.

[1] N = Number of estimated cases per year.
[2] A negative value for property damage only outcome represents an increase for the least severe outcome, given the assumption that the crash still occurs.

6.2.2 Implications of Findings for Missouri Driver Guide - Rules of the Road

Key findings presented in section 6.1 have important implications for possible changes in the current Missouri Driver Guide - Rules of the Road. Drawing upon these findings, policy recommendations are identified and discussed for the contributing circumstances that greatly increase the likelihood of more severe outcomes of motor vehicle crashes: total number of occupants, speed limit, driving at speeds that exceed the limit, driver age, and alcohol use.

Number of Occupants

As earlier described, model results strongly suggest that as the number of occupants involved in a crash increases, so does the probability of a more severe outcome. While seatbelt use is not considered as a predictor of injury severity in this study as there is no data regarding the seatbelt usage of all vehicle occupants, prior research has found the use of seatbelt restraints reduces the probability of fatal and injury outcomes (Shibata and Fukuda, 1994; Farmer et al., 1997; Bédard et al., 2002; Ulfarsson and Mannering, 2004; Chang and Yeh, 2006; Islam and Mannering, 2006; Kononen et al., 2011; Amarasingha and Dissanayake, 2013; Yasmin and Eluru, 2013). According to the National Highway Traffic Safety Administration, seatbelt usage reduced the number of fatalities by approximately 13,000 in 2009; and approximately 4,000 more fatal outcomes would have be avoided if all occupants had been properly restrained (Department of Transportation (US), 2010). Current Missouri seatbelt-use policy requires only the driver and front-seat passengers to use seatbelts; and, findings suggest revising the Missouri Driver Guide - Rules of the Road to require all vehicle occupants to be properly restrained since doing so reduces the risk of injury or fatality for possibly unrestrained passengers thereby reducing the likelihood of an injury or fatality crash outcome.

Speed Limit/Speed - Exceed Limit

The Missouri Driver Guide states that "speed limit signs indicate the maximum speed allowed by law, and do not mean that all parts of the road can be safely driven at those speeds under all conditions. The speed limit is the maximum allowable speed in ideal conditions" (p. 37); and, it is recommended that driving speed be adjusted as appropriate for changes in road conditions and characteristics, visibilities, other road users, and weather conditions. As previously suggested the interaction of speed limit and driving at speeds that exceed the limit increase the likely severity of crash outcomes, which is confirmed by the aforementioned statements made by. For example, driving at speeds that exceed the posted limit of 35mph to 45mph during dark, but lit conditions has an increased likelihood of a fatal outcome than when speeding during other lighting conditions. As a result, it is recommended that patrol units be aware that dark conditions increase the probability of severe outcomes and adjust accordingly.

Additionally, the likelihood of a fatal crash is higher when driving on the wrong side of the road in speed limit zones of 45mph to 60mph and when failing to yield in a speed limit zone of 65mph or 70mph than if these contributing circumstances are not present. Following successful application in North Carolina and California, many states have adopted innovative strategies to reduce wrong-way driving such as lowering the height of "Do Not Enter" and "Wrong Way" signs, increasing the size of signage, locating signage on both sides of the exit travel lane, changing lighting and minor ramp geometrics, and illuminating "Wrong Way" signs that flash when a wrong-way vehicle is detected (Zhou and Rouholamin, 2014). As a result, the study may infer that in higher speed limit zones preventive measures to reduce driving on the wrong side of the road and failing to yield, such prominent signage, are of great importance.

Driver Age

Current Missouri law requires that all first time drivers obtain an instruction permit followed by an intermediate license before graduating to a full driver's license, referred to as the Graduated Driver License (GDL) law (Missouri Department of Revenue, 2014b). Findings from this study suggest that the GDL law might be re-evaluated in light of the interaction between age, other variables that increase injury severity outcomes, and the elevated frequency of crash occurrence for younger drivers (Table 4.2). For instance, when a young driver is driving in a speed limit zone of 35mph or 40mph during dark, unlit conditions, a greater chance of a fatal and injury outcome exists than when driving during other lighting conditions. Upon evaluating the effectiveness of GDL programs before and after implementation, Ulmer et al. (2000) and the Office of Governor's Highway Safety Representative (2001) found significant reductions in severe crashes during night restricted hours. Moreover, according to the Insurance Institute for Highway Safety, Highway Loss Data Institute (2015) GDL Crash Reduction Calculator, increasing Missouri GDL night time restriction from 1:00am to 8:00pm could result in a 5% reduction in total claims and a 12% reduction in fatal crashes. This suggests that this age group might have restricted privileges for driving after dusk, and implies that this restriction be implemented throughout all three stages of the GDL program in order to reduce the risk of severe crashes. Finally, the importance of the young age of the driver on the prediction of crash severity prominently occurs in single occupant crashes. Insurance Institute for Highway Safety, Highway Loss Data Institute (2015) suggests that when teenage passengers are prohibited in vehicles operated by a teenage drivers, such as in Alaska, California, Colorado, Connecticut, D.C., Georgia, Indiana, Maine, Maryland, Massachusetts, Nevada, Oregon, Utah, Vermont, Washington, West Virginia, fatal crash rates for 15 to 17-year-old drivers are 21% lower than when two or more passengers are allowed. This suggests that throughout the stages of the GDL program that drivers should be accompanied in the front, passenger seat by a licensed driver who is at least 21 years old.

This study also identifies and recognizes important findings concerning older drivers and possible policy revisions even in light of their low frequency of crash per driver year as in Table 4.2. For example, in single occupant crashes, mature drivers (55 years of age or older) have an increased chance of a severe outcome when driving physically impaired than when driving unimpaired. According to Braitman et al. (2014), when passengers are present the risk of fatal crash is 43% lower for drivers 65 to 74-years-old and 38% lower for drivers at least 75 years-old. These findings suggest that consideration might be given to restricting drivers in this age group with physical impairments from driving alone, since the presence of other passengers could aid in assessing the physical state and capabilities of the aged driver.

Alcohol

Driver alcohol use is one of the most significant predictors of crash injury severity. Currently under Missouri law, drivers who are found guilty of driving while intoxicated (DWI) may be subject to paying a fine, having his/her license revoked, or being imprisoned as illustrated in Figures 6.1 and 6.2 (Missouri Department of Revenue, 2014a). Moreover, if someone is injured or killed as a result of driving under the influence of alcohol, the driver may "spend 2 to 7 years in jail, pay a $5,000 fine, and/or lose your driver license for 5 years" (Missouri Department of Revenue, 2014a, p.77). Because of the large increase in the probabilities of injury and fatal outcomes when driving under the influence of alcohol, these laws may not be stringent enough in the prevention of drinking and driving given the clear large increase in the likelihood of severe outcomes. Additionally, Missouri law currently requires any person guilty of a second alcohol intoxication-related traffic offense to install an ignition interlock device on all vehicles operated by the offender before reinstating driving privileges (Missouri Department of Transportation, 2013). Since drivers with a BAC above the legal limit that are involved in fatal crashes are six times more likely to have a prior DWI conviction (Department of Transportation (US), 2014) to deter multiple offenses from occurring all DWI first-time offenders could be required the use of ignition interlocks.

Figure 6.3: Administrative Actions for DWI (Source: Missouri Department of Revenue, 2014a, p. 78)

Administrative Action	Driver License Suspension/ Revocation/Denial
License Suspension	**1st Offense** - 90 day suspension • You may be eligible for a 90-Day or 60-Day restricted driving privilege. ***2nd Offense** - 90 day suspension, for a 2nd offense that occurred outside a 5-year period • You may be eligible for a 90-Day or 60-Day restricted driving privilege.
License Revocation	***2nd Offense within a 5-year period** - 1-Year license revocation

Figure 6.4: Court Convicted Actions for DWI (Source: Missouri Department of Revenue, 2014a, p. 79)

Crime	Fines/Jail	Driver License Suspension, Revocation, or Denial
BAC Driving/ operating a vehicle with .08% Blood Alcohol Content or more and/or **DWI** Driving while intoxicated.	**1st Offense** - Spend up to 6 months in jail. Pay up to a $500 fine. **2nd Offense** - Spend up to 1 year in jail. Pay up to a $1000 fine. **3rd Offense** - Spend up to 4 years in jail. Pay up to a $5,000 fine. **4th Offense** - Spend up to 7 years in jail. Pay up to a $5,000 fine. **5th Offense** - Spend between 5 and 15 years in jail.	**1st Offense** - 90 day suspension • You may be eligible for a 90-Day or 60-Day restricted driving privilege. ***2nd Offense** - 1-year license revocation. ***2nd Offense *Within 5 Years*** - 5-year license denial. **NOTE:** Only a BAC with a conviction date of August 28, 2009 or after can be used toward a five-year denial. ***3rd Offense** - 10-year license denial. ***3rd and Subsequent Offenses** - 10-year license denial.

Additionally, research suggests that injuries and fatalities from impaired driving can be prevented through community-based approaches (DeJong and Hingson, 1998; Holder et al., 2000; Shults et al., 2009). The Missouri Department of Revenue encourages such approaches through reporting drunk drivers by calling 911 and providing law enforcement with the license plate number of the vehicle, a physical description of the car and driver, and the vehicle's location (Missouri Department of Revenue, 2014a). However, in order to reduce the number of DWI drivers on Missouri roadways, this study recommends that this process be simplified and that a hotline and/or web-notification mechanism be considered (with possible rewards) for reporting DWIs.

Finally, to further reduce DWIs, Missouri law enforcement agencies implement sobriety checkpoints at temporary, random locations (Reynolds, 1989). Research indicates that high-profile enforcement efforts, specifically frequent sobriety checkpoints, are effective in reducing alcohol-related fatal crashes (Elder et al., 2002), and recent studies found such checkpoints reduce the number of fatal outcomes by 20% (Shults et al., 2001). As earlier described, a strong interaction is found between high speed limits, alcohol intoxication, and crash severity. As a result, this study recommends that future DWI checkpoints might be located at on-ramps to high speed highways and interstates to reduce the amount of intoxicated drivers driving at high speeds.

Chapter 7 – Conclusions

7.1 Conclusions

To expand the methodological frontier and advance the future of crash severity research, this study compares and combines different methodological techniques to uncover more intricate relationships amongst explanatory variables and provide better information to enhance transportation safety efforts. To do so, the following research questions are answered.

Q_1: What insights do the multinomial logit, ordinal probit, decision tree, artificial neural network, and model ensembles each reveal in the data?

The multinomial logit, ordinal probit, decision tree, ANN, and model ensembles each reveal important findings as described in Chapter 5 and summarized as follows:

Multinomial Logit

For the multinomial model estimated on the training set, the overall goodness of fit test with 948,679 observations yields a χ^2 = 130,650.385 with 112 degrees of freedom and a p-value of 0.000. The classification accuracy rate equals 72.0% for both the training set and the testing set, and the AUC scores are significantly greater than 0.5 indicating significant discriminatory power. The three most important predictors of crash severity are speed – exceeds limit, total number of occupants involved, and improper backing.

Ordinal Probit

The Brant test of parallel lines for the estimated ordinal probit model produces a chi-square of 6,544.677 with 59 degrees of freedom, which is significant at a level of less than 0.000; therefore, the fundamental proportional odds assumption underlying the ordered probit model is rejected. Rejecting the proportional odds assumption can lead to inconsistent model estimation (Eluru et al. 2008), and this approach is not carried forward.

Decision Tree

Both CART and CHAID trees are estimated and compared by evaluating the classification accuracy and the AUC values for each model. The CHAID algorithm provides greater classification accuracy and AUC values than does the CART algorithm; therefore, the CHAID approach is carried forward. The classification accuracy rate for the CHAID equals 73.06% for the training set and 73.06% for the testing set; and, the AUC estimates indicate significant discriminatory power. The top three most important predicators of crash severity are the total number of occupants, speed limit, and speed – exceeds limit.

ANN

The MLP ANN uses partitioned data to create an input layer, hidden layers, and output layers to explain relationships between variables. The final training model includes 948,679 observations, has 1 hidden layer, 11 neurons, and a classification accuracy of 72.84% for the training set and 72.89% for the testing set. AUC scores are significantly greater than 0.5, indicating above-chance discriminatory power. The top three most important predicators of crash severity are total number of occupants, speed – exceeds limit, and speed limit.

Model Ensembles

The study uses the final multinomial logit, CHAID decision tree, and ANN models to score the model ensemble using three common combinatory rules: Majority Voting, Weighted-Majority Voting, and Max Rule. The accuracy and discriminatory power of each model ensemble is assessed by examining the confidence matrices, the ROC curves, and the AUC values of each ensemble.

- All ensemble approaches have similar classification accuracy for the training set and for the testing set.
- The Weighted-Majority Voting Ensemble approach results in the highest AUC values for both fatal versus nonfatal outcomes and injury versus non-injury outcomes.
- The AUC scores for the Weighted-Majority Voting Ensemble and Max Rule are both significantly greater than 0.5, which indicates above-chance discriminatory power.
- The relatively low AUC values suggest that the Majority Voting Ensemble model does not have good discriminatory power; and, when the distribution of outcomes is as highly skewed as it is here, Majority Voting is not a useful ensembling method.
- The ROC curves for the Weighted-Majority Voting Ensemble and Max Rule Ensemble for the prediction of fatal versus non-fatal outcomes are everywhere

above or equal to all the individual model ROC curves, signifying that these ensemble models predict fatal versus non-fatal outcomes better than or equal to the individual modeling approaches.

- The ROC curves for the Weighted-Majority Voting Ensemble and Max Rule Ensemble for the prediction of non-injury versus injury outcomes are everywhere above the individual models' ROC curves, with the exception of the CHAID decision tree. This suggests that the ensemble models better predict non-injury versus injury outcomes than the individual modeling approaches, with the exception of the CHAID model.

Q_2: What is the relative accuracy of each model in comparison with the accuracy of the model ensembles?

Table 7.1 provides the relative accuracy of each model and model ensembles. As presented, the CHAID decision tree renders the greatest classification accuracy for both the training and testing sets compared to each individual model and model ensemble approach.

Table 7.1: Individual Model and Model Ensemble Classification Accuracy

Model Approach	Classification Accuracy Training Set	Classification Accuracy Testing Set
Multinomial Logit	72.00%	72.00%
CHAID Decision Tree	73.06%	73.00%
ANN	72.84%	72.89%
Majority Voting Ensemble	73.02%	72.99%
Weighted-Majoring Voting Ensemble	73.02%	72.99%
Max Rule Ensemble	72.84%	72.83%

Q_3: When adjacent severity outcomes are grouped, what is the relative discriminatory power of each model compared to the discriminatory power of the model ensembles?

The study compares AUC values for each of the individual models and the three model ensemble techniques to determine if there is a significant difference between the models' abilities to predict (1) a fatal outcome relative to property damage and injury only outcomes and to predict (2) a property damage only outcome relative to fatal and injury outcomes. Results suggest that there is a statistically significant difference between the AUC values of the CHAID model and the Multinomial Logit model and the CHAID model and the ANN model for both fatal versus non-fatal outcomes and injury versus non-injury.

Additionally, the study compares model ensemble approaches with statistically significant AUC values, Weighted-Majority Voting and Max Rule, to determine if there are significant differences between the two ensembles' prediction capabilities. Results indicate that there is not a significant difference between the AUC values of the Weighted-Majority Voting Ensemble and Max Rule Ensemble for fatal versus non-fatal outcomes, while there is a significant difference in AUC values for injury versus non-injury outcomes.

Finally, the study compares the CHAID AUC values with the Weighted-Majority Voting Ensemble AUC values, and results suggest that there is not a significant difference between the AUC values of the CHAID model and the Weighted-Majority Voting Ensemble for fatal versus non-fatal outcomes, yet there is a statistically significant difference between the AUC values for injury versus non-injury outcomes with the CHAID model providing better discriminatory power.

Q_4: What findings are derived from the model with the greatest accuracy and/or discriminatory power and do these findings support prior research?

The CHAID decision tree model is found to have the greatest accuracy and discriminatory power relative to a main effects multinomial logit model, ANN model, and each of the three model ensembles; and, the findings derived from the CHAID model are both consistent with and differ from findings of prior research. For example, the CHAID model indicates that as the total number of occupants involved in a crash increases, so does the probability that a fatal outcome will occur, which is consistent with prior research findings that crash injury severity probabilities increase as the number of vehicle passengers increase. CHAID results are also consistent with previous research findings that higher speed limits and the presence of alcohol significantly increase the risk of severe injury outcomes. Additionally, findings are consistent with prior research claims that age is a significant factor in predicting injury severity, yet this study does not find age to have as great an importance for crash severity outcomes as prior research.

The CHAID model also suggests that certain environmental conditions can increase likely crash severity in certain situations, and in yet other circumstances decrease likely crash severity. Finally, model results suggest that road conditions do not have high predictor importance, which differs from prior findings that road conditions have a great influence on crash severity.

Q_5: Do the findings support current Missouri public policy or point to needed revisions?

Among the individual model approaches examined, the CHAID decision tree is clearly best at predicting crash injury severity, and the interaction effects of variables identified by the CHAID model are important when analyzing Missouri crash severity data. For example, it is readily discovered that driving while under the influence of alcohol, driving at speeds that exceed the limit, failing to yield, driving on the wrong side of the road, violating a stop sign or signal, and driving while physically impaired lead to a significant number of fatalities each year in Missouri. Yet, the effect of these factors on the probability of a severe outcome is dependent upon other variables, including the number of vehicle occupants involved in the crash, the speed limit, actual driving speed, lighting conditions, and driver's age. As a result, this study indicates that policy makers should consider the interaction of driver related contributory circumstances and other conditions when formulating future legislation intended to reduce the number of fatal outcomes and save lives of Missouri highway drivers and passengers.

As presented in Chapter 6 section 6.2.2, findings support current Missouri public policy, still needed revisions are evident. Therefore, the following specific policy recommendations are identified and their likely effectiveness discussed:

1. To deter multiple offences from occurring, penalties could be modified to require the use of ignition interlocks by all first-time convicted DWI offenders.
2. DWI checkpoints could be located at on-ramps to highways and interstates to reduce the amount of intoxicated drivers driving at high speeds.
3. To prevent/deter drivers from entering high speed limit zones (highways and interstates) on the wrong-side of the road and going the wrong way, barriers, such as larger or illuminated "wrong-way" and "do not enter" signs could be considered.
4. To reduce crash fatalities, actions that deter/reduce driving at speeds that exceed limit during dark conditions (such as increased patrol) could be implemented.
5. To reduce the probability of a severe outcome, young drivers could have restricted privileges for driving after dusk throughout the GDL program.
6. To reduce the probability of a severe outcome, young drivers could be accompanied in the front, passenger seat by a licensed driver who is at least 21 years old throughout the GDL program.
7. To reduce the probability of fatalities, it is recommended that mature drivers with physical impairments be required to drive with a licensed driver of at least 21 years old.

7.2 Limitations and Future Research

Limitations of this research exist and may be resolved through future research endeavors. First, this study considers data compiled from the entire state of Missouri and the general findings may not be appropriate in specific differentiated locations throughout the state. Future research may address this limitation by partitioning data into smaller regions of Missouri (urban, rural, suburban, county, zip code, and other meaningful partitions) and by examining regional factors and their effect on injury severity in order to contribute to localized legislation.

Second, this study considers only Missouri data. Future research may apply the same methodological approach to additional state crash datasets to assess policy implications for various locations.

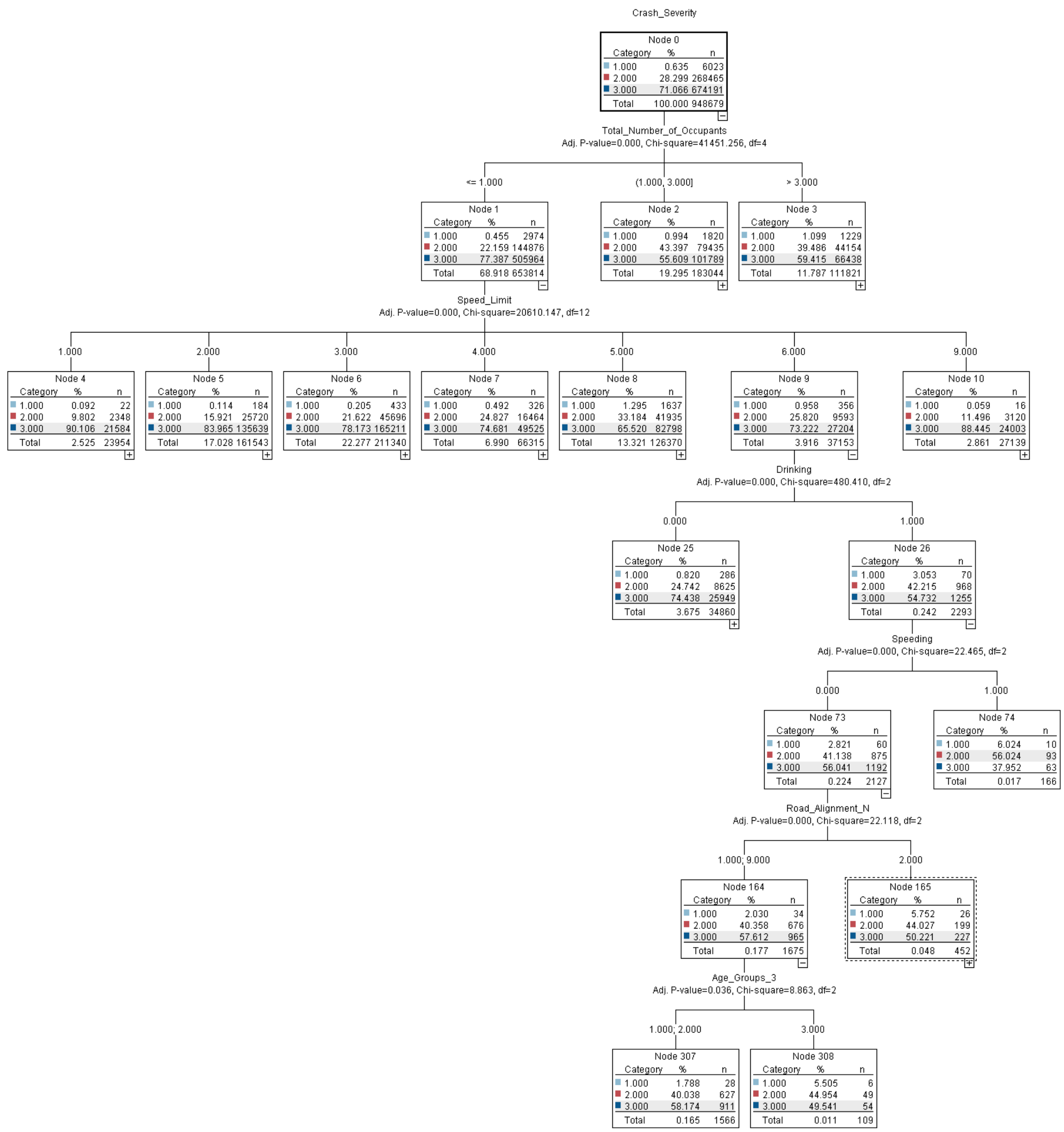
Third, additional or alternate variables may be considered in future research to broaden the research to other factors that may contribute differentially to crash severity. These include variables such as seasonality, peak driving times, highway class, rural versus urban location, crash type, and vehicle action.

Fourth, this study does not differentiate between types of motor vehicles (e.g. large truck, personal passenger, commercial). Future studies may partition data based on vehicle type to examine if explanatory variables and policy implications differ by vehicle type. Additionally, future research may apply the methodological techniques presented here to other modes of transportation and assess safety measures, risk, and disruptions beyond roadways.

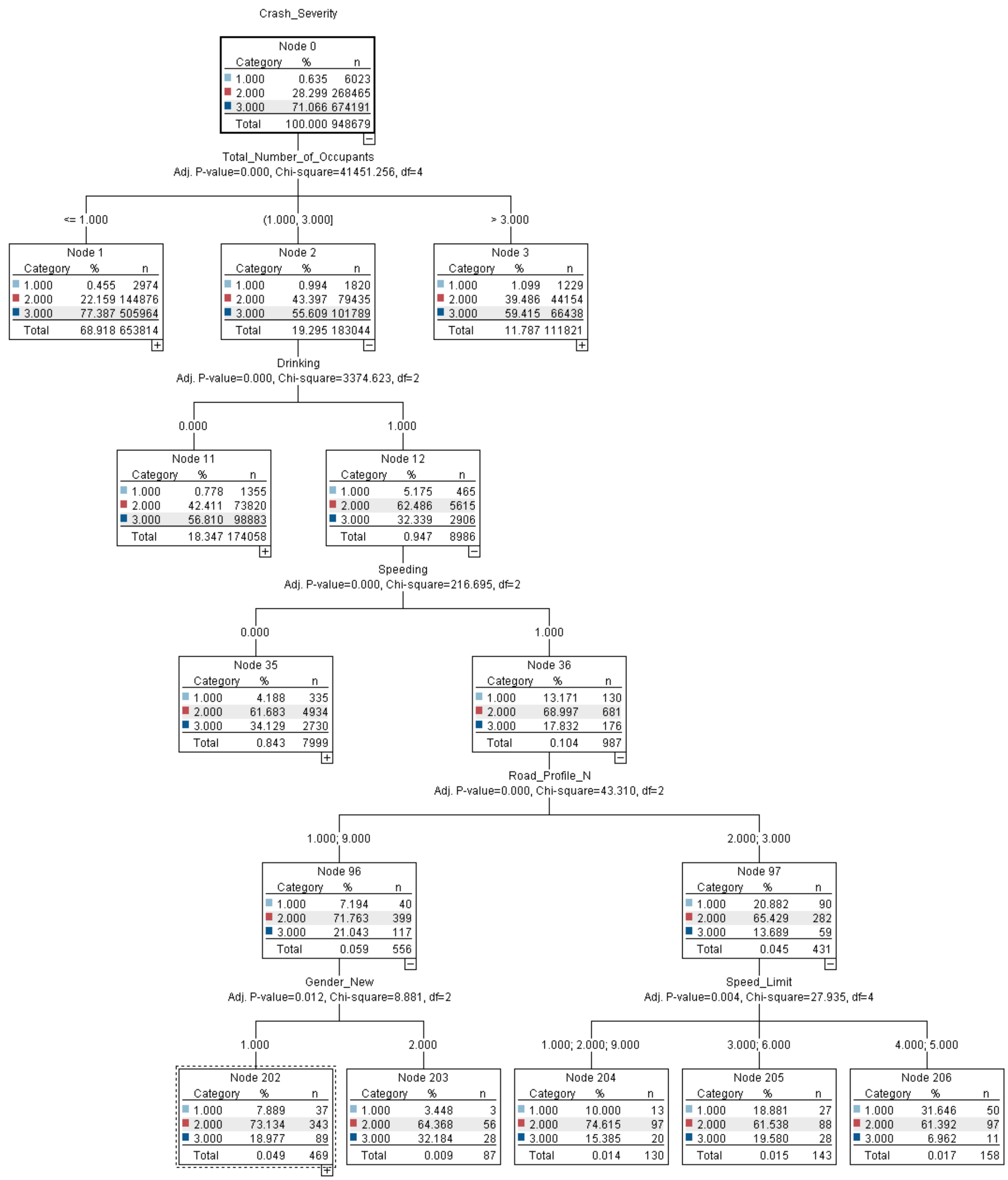
Lastly, this study limits itself to the comparison of four individual modeling techniques and three ensemble scoring methods. Future studies may introduce additional methodological approaches for comparison and model ensembling.

Appendices

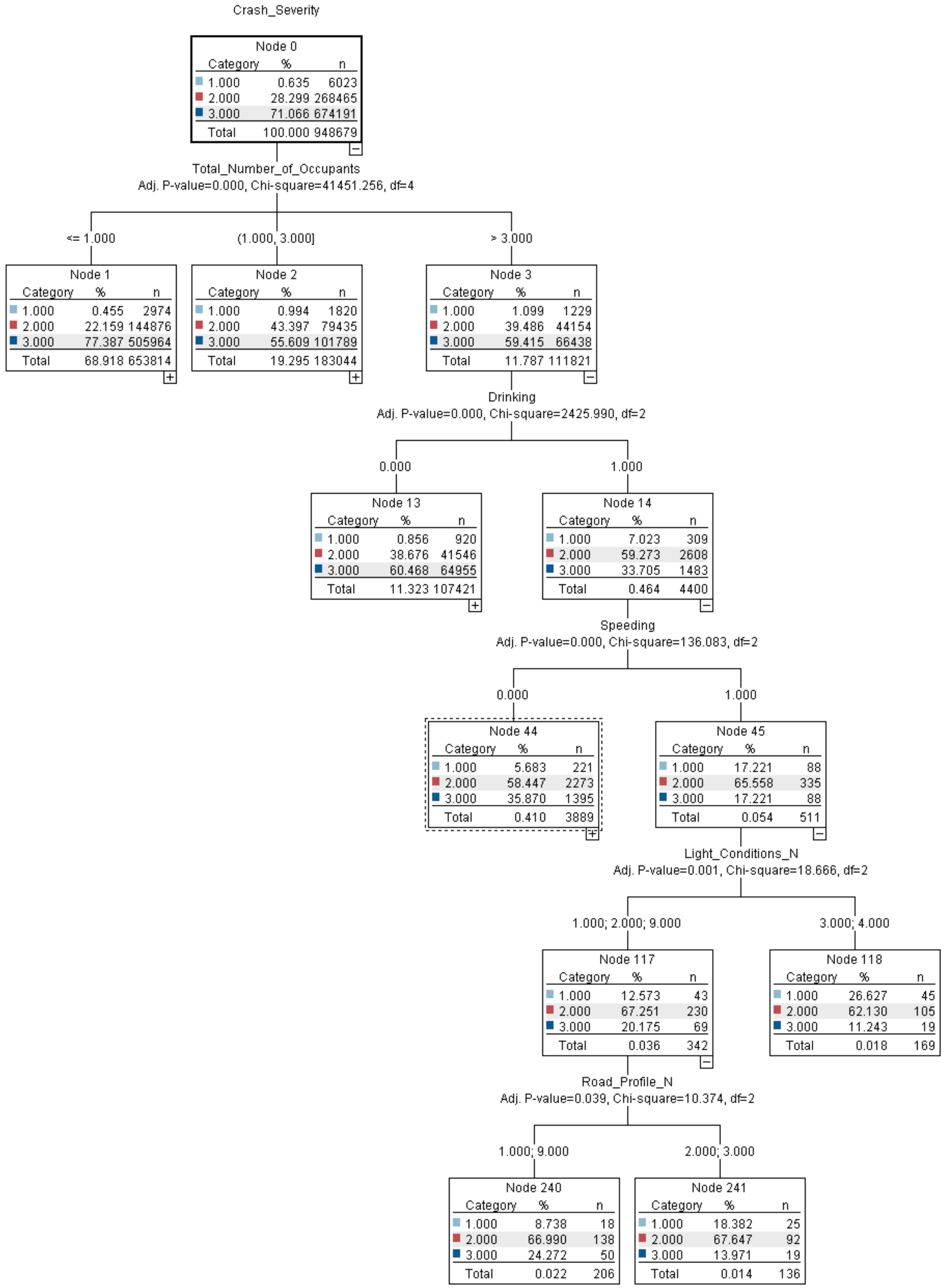
Appendix 1: Partial CHAID Tree - Single Occupant



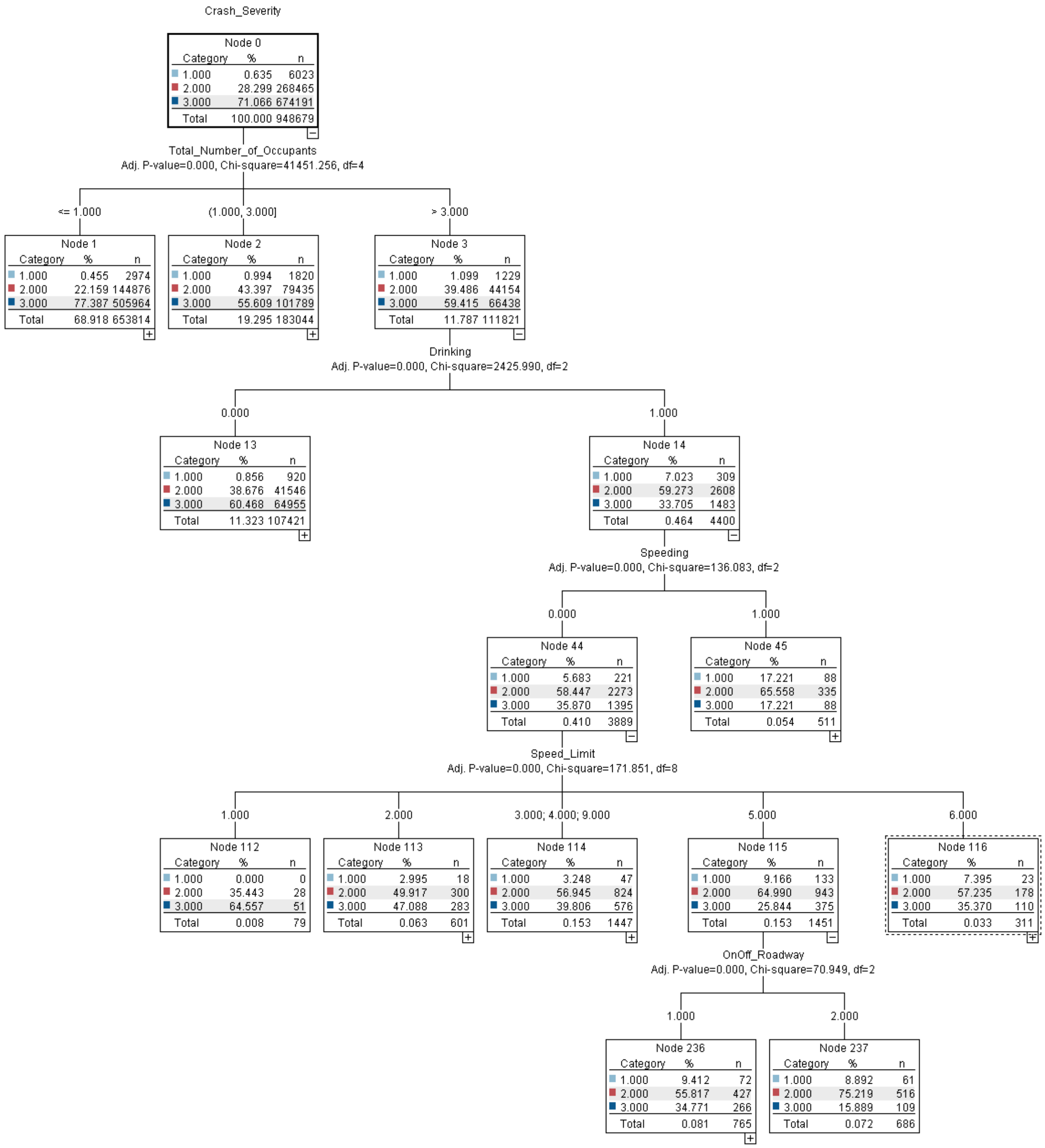
Appendix 2: Partial CHAID Tree – Two or Three Occupants



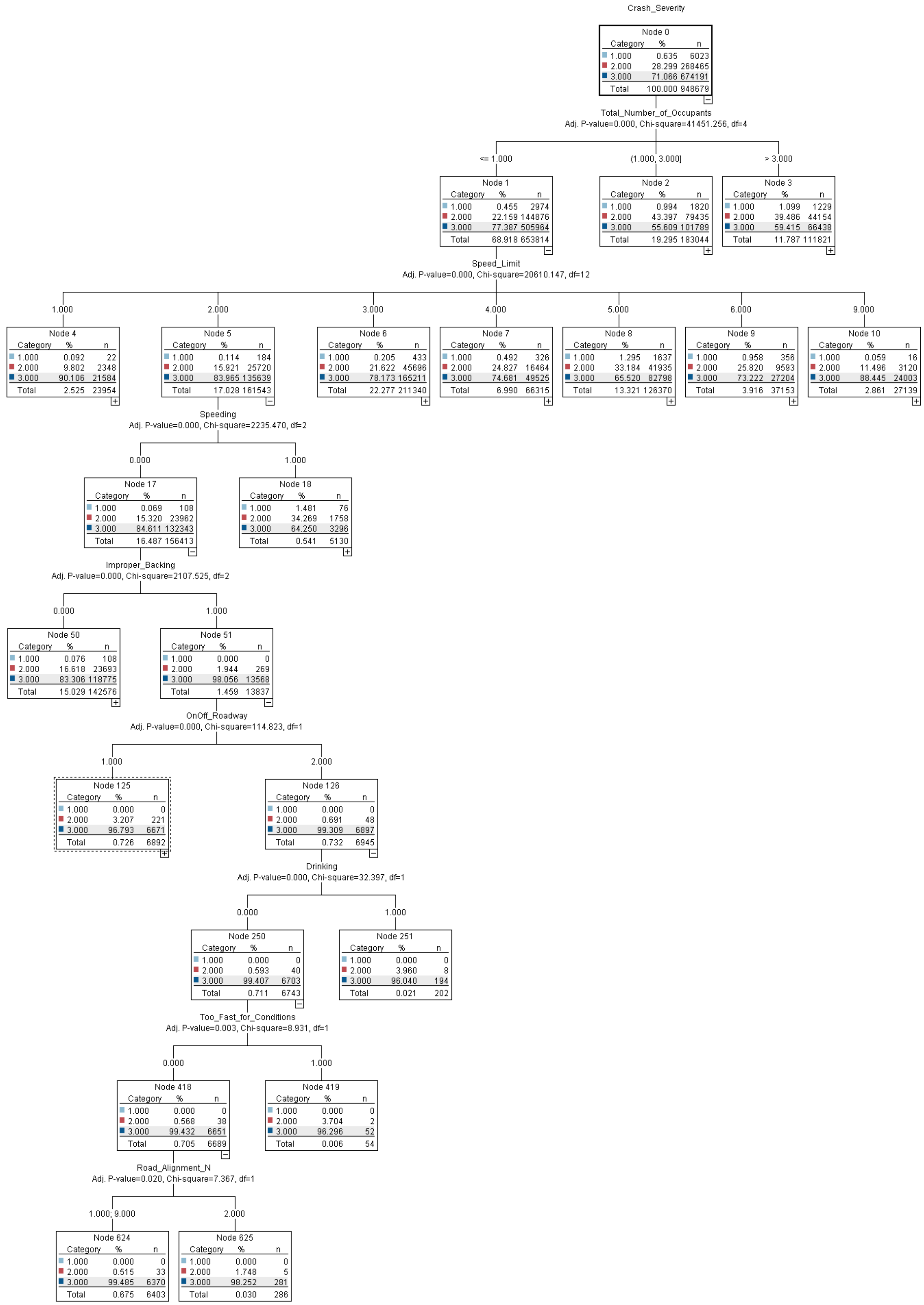
Appendix 3: Partial CHAID Tree – More than Three Occupants



Appendix 4: CHAID Branch with Greatest Probability of a Severe Outcome



Appendix 5: CHAID Branch with Least Probability of a Severe Outcome



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