Improving Accuracy of KABCO Injury Severity Assessment by Law Enforcement Officers

By

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ABSTRACT

Injury severity as assessed by law enforcement officers is one of the metrics used when allotting safety funds by transportation agencies. The Crash Outcome Data Evaluation System (CODES) is a database that contains injury severity assessments by law enforcement officers and the actual health outcomes as measured by medical practitioners. Crashes from 2008 through 2012 were analyzed to determine reasons for discrepancies between law enforcement officer's assessment of injury severity and that of a medical practitioner. Comparing the two assessments of injury severity shows law enforcement officers only rate serious injury severity "A" (Incapacitating Injuries) accurately for 33% of crash victims. Overall accuracy of injury severity is only 51% for all crash victims. Crashes where injury severity was inaccurately assessed were analyzed. Factors such as alcohol, gender, vehicle type, and lighting conditions contributed to law enforcement officer's inaccurate injury severity assessment. It was also found law enforcement officers have difficulty assessing injuries to almost every body region.

Crash victims with accurate injury severity assessments were also analyzed. Injuries and other crash data noted by a law enforcement officer in the crash report was collected to build a logistic regression model and classification trees to estimate injury severity. For both logistic regression and classification trees injury severity estimation improved from law enforcement officers current accuracy, particularly for "Incapacitating" (injury severity "A") and "Non-Incapacitating" (injury severity "B") injuries. Logistic regression was found to be the best method to improve injury severity. Injury severity "A" estimation increased to 77% from the 33% accuracy of law enforcement officers currently. Injury severity "B" estimation increased to 51% from 18% currently. Overall, accuracy was improved from 51% to 70%.

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EXECUTIVE SUMMARY

Injury severity as assessed by law enforcement officers, in particular "Incapacitating Injuries" (KABCO severity "A") is one of the basis for estimating crash cost, and in turn allocation of safety funds. The Crash Outcome Data Evaluation System (CODES) was used to analyze both a law enforcement officer's assessment of injury severity (KABCO) and the assessment of injury severity by medical practitioners (MAIS). Past research focused solely on work zones in Wisconsin (Coburn et al., 2012) found that law enforcement officers overestimated “Incapacitating Injuries” in 66% of injury severity assessments. This research analyzed probabilistically linked crashes in the CODES database from 2008 through 2012.

From analyzing all linked crashes in Wisconsin for the five analysis period, law enforcement officers were found to overestimate injury severity in 66.5% of crash victims, similar to past work zone research. Analyses to determine reasons for this overestimation, as well as reasons for underestimation were undertaken. Additionally, accurately assessed crashes were analyzed to create models to improve injury severity estimation. Overall, the goal of this research is to analyze injury severity practices by law enforcement officers to provide guidance learned from inaccurately assessed injury severity crashes. Additionally, the goal is to provide assistance in the form of models for more accurate injury severity assessment.

Studying crash victims with a discrepancy between a law enforcement officer's assessment of injury severity and the actual health outcomes found several reasons for inaccuracies. All body regions assessed by law enforcement officers in inaccurate injury severity crashes were found to be significantly different when compared to the total population's proportion of injured body regions, with the exception of lower extremities for underestimated crashes. Other factors such as the presence of alcohol, the gender of a crash victim, and vehicle type were found to be statistically significant in overestimated crashes. Similarly, for underestimated crashes alcohol, gender, vehicle type, and lighting conditions were found to be statistically significant. Law enforcement officers most frequently missed body regions at the scene of a crash were the spine, thorax, and abdomen or pelvic region. This may be due to the occult, or not immediately evident, nature of injuries to these body regions. The most frequent types of injuries were bone injuries, lacerations, abrasions, and contusions for overestimated and underestimated crashes.

Injury descriptions from crashes with accurately assessed injury severity were used to create models to estimate injury severity. Additionally, variables noted by law enforcement officers on crash reports such as crash type, seat belt use, vehicle type, and whether the victim was speeding were added as possible covariates. Current law enforcement officer accuracy for “A” and “B” injury severity assessments are only 33% and 18%, respectively. Logistic regression was used to fit a model to the predictor variables found in the crash reports. Using logistic regression, estimation of “A” and “B” injury severity rose to 77% and 51%, respectively. Overall, accuracy was 70%, compared to the current accuracy of 51%.

Classification trees were also constructed using the Generalized, Unbiased Interaction Detection and Estimation (GUIDE) algorithm. Two classification trees were constructed using GUIDE: one model with misclassification costs, and one without. Misclassification costs allow the user to define penalties to the algorithm for incorrect estimations. This creates a more conservative model with higher estimation accuracy. The classification tree constructed without misclassification costs raised injury severity estimation of “A” and “B” to 67% and 62%, respectively. Overall, accuracy was raised to 70%. The classification tree with misclassification costs was constructed using National Safety Council crash costs to calculate misclassification costs. This model raised “A” and “B” injury severity estimation to 70% and 80%, respectively. Overall, this model raised injury severity estimation to 69%. The logistic regression model was deemed best at estimating injury severity due to the high estimation accuracy of injury severity “A”, and the high overall estimation accuracy.

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CHAPTER 1. INTRODUCTION

The injury severity as rated by law enforcement officers at the scene of a crash is an important metric of highway safety. Injury severity, along with crash frequency can help determine where problems are located in the highway system. Additionally, injury severity determined by law enforcement officers is typically used for estimating cost-benefit ratios that determine the allocation of safety funds by transportation agencies. The funds are allocated to projects located at hot spots that have been deemed unsafe due to the frequency or severity of crashes that occur at that location. Since injury severity is so important in the allotment of funds to projects it is important to ensure accurate injury severity assessment by law enforcement officers at the scene of a crash.

At the scene of a crash a law enforcement officer makes an injury severity assessment of every person involved in the crash, both drivers and passengers. Past research that focused solely on work zones in Wisconsin determined that there was a discrepancy between a law enforcement officer’s assessment of injury severity and the actual health outcomes as rated by medical practitioners (*1*). This discrepancy can bias the crash cost, which in turn leads to cost-benefit analyses that inaccurately determine hot spots. By inaccurately locating spots that are not in need of improvement or failing to identify locations that are actually dangerous, limited transportation funds are not being used to their fullest potential. The inaccurate injury severity ratings can also impact safety assessments of projects by either understating their true impact, or overestimating the safety impact of the improvements. Accurate injury severity rating leads to a greater understanding of the social and financial burden of motor vehicle crashes in Wisconsin.

1.1 Background

In 2012, the most recent transportation bill, The Moving Ahead for Progress in the 21st Century Act (MAP-21), was signed into law. This new law required not only fatalities, but also serious injuries to be used for analyzing highway safety (*2*). In Wisconsin, one of the prioritized recommendations from the 2010 Traffic Record Assessment and one of the high priority issues in the 2011-2013 Wisconsin Strategic Highway Safety Plan (SHSP) was to improve the Statewide Injury Surveillance System (SWISS) (*3*). The added emphasis on serious injuries requires that injury severity assessments made by law enforcement officers at the scene of a crash are as accurate as possible.

An application of SWISS, the Crash Outcome Data Evaluation System (CODES) uses probabilistic linkage to create a database that provides both law enforcement data and hospital data from crash victims. The CODES database allows for a way to analysis not only law enforcement injury severity assessments, but also health outcomes as assessed by medical practitioners, driver behavior, safety equipment, vehicle factors, and crash configurations involved in a motor vehicle crash (*4*). Within the CODES database injury severity is presented in two formats: one from law enforcement officers and the other is the actual health outcome as assessed by medical practitioners at a hospital. Law enforcement officers use the KABCO scale to rate injury severity. KABCO rates injury severity on a decreasing scale, where “K” is a fatality, “A” is an incapacitating injury, “B” is a non-incapacitating injury, and “C” is a possible injury. Injury severity rated as “O” is property-damage-only, or in other words the crash victim did not sustain any injuries in the crash. In the CODES database, the actual health outcomes as rated by a medical practitioner are rated on the MAIS scale. MAIS is a threat-to-life scale that rates each crash victim’s injury severity on a scale from 1 to 6, where 1 is a minor injury, 2 is a moderate injury, 3 is a serious injury, 4 is a severe injury, 5 is a critical injury, and 6 is a maximum injury. A rating of 6, or maximum injury, on the MAIS scale is defined as an injury that is currently untreatable and results in the crash victim's death. In other words, a rating of 6 on the MAIS scale is analogous to a “K” severity rating on the KABCO scale.

1.2 Problem Statement

New federal and state guidelines requiring the use of serious injuries as a metric of highway safety means law enforcement assessment of injury severity needs to be as accurate as possible. Past research in Wisconsin work zones has determined that 66% of injuries deemed serious, or “incapacitating injuries” were actual only minor or moderate injuries (*1*). While this discrepancy between law enforcement officers assessed injury severity and actual health outcomes exists in work zones, it is important to understand the discrepancy in all crashes in Wisconsin. Improving the accuracy of injury severity assessment is important to understand the true safety of highways throughout Wisconsin. Therefore, research is needed to understand reasons for discrepancies between law enforcement officers assessment of injury severity and actual health outcomes. In addition, research is needed to help improve injury severity assessment, when possible.

1.3 Research Objectives

The objectives of this thesis research were as follows:

- Examine characteristics of crash victims where a discrepancy between law enforcement officer’s assessment of injury severity and the actual health outcome exists.

- Analyze crash victims whose injury severity was accurately assessed by law enforcement officers.
- Develop and compare models to estimate a crash victim's injury severity using information from crash victims with accurate injury severity assessments.

The aforementioned investigations of a crash victim's injury severity were analyzed using the KABCO and MAIS scales.

1.4 Research Scope

Crash data was analyzed to determine current injury severity rating practices by law enforcement officers at the scene of a crash. Crash data collected in the state of Wisconsin from January 1st, 2008 through December 31st, 2012 was analyzed. The most recent CODES dataset available was for the year 2012. The four preceding years were analyzed for a total of five years in the analysis period. All crashes that were probabilistically linked and included in the CODES database were examined. These data were used to determine when law enforcement officers rated injury severity correctly, and when they inaccurately assessed injury severity. Crash reports for crashes where injury severity was correctly and incorrectly assessed were examined. All crash reports were retrieved from the WisTransPortal data hub (*5*).

1.5 Thesis Organization

The research topic and overall thesis are broken down into six main chapters. The introduction is presented in Chapter One, which includes the motivation for the research and the issues to be addressed. Chapter Two presents a comprehensive literature review of injury severity scales and how they are used, as well as research comparing injury severity assessed using KABCO with actual health outcomes of the MAIS scale. Chapter Three lays out the study design, including the research tasks and data collection and processing methods. Chapter Four presents the analysis of crash victims with inaccurately (both overestimated and underestimated) assessed injury severity. Chapter Five presents the analysis of crash victims with accurately assessed injury severity, including models to estimate injury severity based on accurately assessed injury severity. Finally, conclusions based upon the analyses in Chapters Four and Five are drawn in Chapter Six.

CHAPTER 2. LITERATURE REVIEW

2.1 KABCO Injury Severity Scale

The KABCO method of rating injury severity was developed by the National Safety Council (NSC) in the Manual on Classification of Motor Vehicle Traffic Accidents in 1966 (*6*). The original KABCO scale was developed to allow police officers at the scene of a crash to estimate the level of injury severity suffered by crash victims. The original scale had five categories designated fatal (K), serious (A), moderate (B), minor (C), and no injury or property damage only (O). This scale defines injury as bodily harm to a person due to a crash, excluding the "effects of disease such as stroke, heart attack, diabetic coma, [and] epileptic seizure."

The guidelines in the Manual on Classification of Motor Vehicle Traffic Accidents are used for officers in the field, typically without medical training beyond first aid to make a quick, accurate assessment of the severity of injuries sustained by victims in a crash. In an effort to standardize and assist officers in determining the level of injury severity, the KABCO scale was revised in 2007 (*7*). "A" crashes were changed to "incapacitating injuries", "B" crashes were changed to "non-incapacitating injuries", and "C" crashes were changed to "possible injury crashes". In addition to the changes in naming the crash severity guidance was provided to help determine the severity.

The NSC defines an incapacitating injury as "any injury, other than a fatal injury, which prevents the injured person from walking, driving or normally continuing the activities the person was capable of performing before the injury occurred." Examples provided by the NSC of incapacitating injuries include:

- Severe lacerations,

- Broken or distorted limbs,
- Skull or chest injuries,
- Abdominal injuries,
- Unconsciousness at or when taken from the accident scene,
- And the inability to leave the accident scene without assistance.

However, an incapacitating injury would not include momentary unconsciousness. Similarly, a non-incapacitating injury was defined as “any injury, other than a fatal injury or an incapacitating injury, which is evident to observers at the scene of the accident in which the injury occurred.” Examples include:

- Lumps on the head,
- Abrasions,
- Bruises,
- Or minor lacerations.

However, non-incapacitating injuries would exclude such injuries as limping because the injury cannot be seen.

Possible injuries are “any injury reported or claimed which is not a fatal injury, incapacitating injury or non-incapacitating evident injury.” This injury severity level would include the following injury types:

- Momentary unconsciousness,
- Claims of injury that are not evident or observed,
- And limping, complaints of pain, nausea, and hysteria.

Injury severity decisions are made by an officer based on conditions observed at the scene of the crash. An exception to this rule is if the crash involves a fatal injury. If a fatal injury occurs due to a crash the original injury severity is updated to reflect the fatality. Typically, 30 days is used as the period of time after a crash where the injury severity field can be updated to reflect a fatal accident. The 30-day threshold is typically used because 98.0 percent of all crashes resulting in a fatality occur within 30 days of the motor vehicle crash (*7*).

Despite the guidelines developed by the NSC, differences still occurred at state and local levels for injury severity reporting guidelines. In an effort to rectify this disparity between reporting, another guideline was used to standardize the KABCO injury severity scale. The Model Minimum Uniform Crash Criteria (MMUCC) Guideline developed a new set of definitions for the KABCO scale in order to standardize reporting (*8*). The first edition of the MMUCC was developed in 1998, and was most recently updated in 2012.

The latest update to the MMUCC again changed the definitions of the injury severities in the KABCO acronym. The levels of “A” and “B” were again changed. For the updated version of the KABCO scale, “A” crashes reflected a “suspected serious injury”. The types of injury examples included in the MMUCC match the NSC examples, with the addition of paralysis and significant burns. The definition of a “B” crash was revised to be a “suspected minor injury”. Examples provided by the MMUCC of these crash types remained the same as the NSC examples. The definition of “C” severity injuries was not changed, however additional guidance was given. Specifically, the MMUCC added that “possible injuries are those which are reported by the person or are indicated by his/her behavior, but no wounds or injuries are readily evident.”

As part of NCHRP Project 20-24, a study was conducted to determine state Department of Transportation performance in reporting and evaluating serious injuries (*9*). As part of this study a survey was conducted that was disseminated to all states and territories in the fall of 2012. In total, the survey received 50 responses from 36 states and one territory. Primarily, responses came from Traffic Records Coordinators in State Highway Safety Offices (SHSO) or highway safety program managers in state DOTs. Responses also came from representatives in state departments of public health, state departments of public safety, state police, academia, and safety consultants.

Of the 37 states and territories who responded, 36 states and territories currently measure and report serious injuries as part of their safety improvement plan, with Florida being the only exception. Most states used the terms “incapacitating” or “disabling” to define a serious injury, with definitions similar to those in the Manual on Classification of Motor Vehicle Traffic Accidents (ANSI D.16). Of the 37 states, 18 use language similar to the ANSI D.16 definition. In Wisconsin, injury severity descriptions follow the ANSI D.16 definitions, according to the Wisconsin Law Enforcement Officer’s Instruction Manual (*10*).

2.2 MAIS Injury Severity Scale

In addition to the KABCO injury severity scale, several other scales can be used to measure the severity of a traffic crash. The predominant scale used by the medical community for the assessment of the injury severity of traffic crashes is the Abbreviated Injury Scale (AIS). The AIS scale was developed by the Association for the Advancement of Automotive Medicine (AAAM) in 1969, with the first scale published in 1971 (*11*). Since the creation of the AIS scale there have been several updates and revisions, most recently in 2011.

The AIS scale is a trauma scale that determines the severity of an injury based on a 6-point scale, which increase in severity from 1 to 6. The six levels include 1 which is a “minor” injury, 2 which is a “moderate” injury, 3 is a “serious” injury, 4 is a “severe” injury, 5 is a “critical” injury, and 6 is a “maximum” injury or an injury that is currently untreatable (similar to a “K” fatal crash on the KABCO severity scale). Additionally, a MAIS level 9 can be assigned if not enough information is available to make a determination about the severity of a crash victim’s injury. The AIS score is determined for every body region. In total there are 9 body regions that include:

- Head,
- Face,
- Neck,
- Thorax,
- Abdomen,
- Spine,
- Upper extremity,
- Lower extremity,
- And unspecified regions.

From the AIS scores several other useful injury severity scores can be developed. One injury severity scale derived from AIS is the Injury Severity Score (ISS). This system takes the sum of the squares of the AIS scores for the top three injured regions. The ISS ranges from zero and has a maximum value of 75. Typically, a score of 16 is taken to be a severe injury (*12*).

Another scale commonly used is the Maximum Abbreviated Injury Scale (MAIS). This scale simply assigns the crash victim the most severe AIS score from all body regions. The MAIS score is typically used in transportation due to the similarities between the MAIS score and the KABCO scale. However, the scales have a major difference in that the MAIS score is determined based on threat to life of the crash victim, while the KABCO scale is not. Despite the differences in the scales, MAIS scores are generally considered to be more accurate at determining injury severity because they are determined by trained medical professionals. Typically, a MAIS value of 3+ is assumed to be a serious injury (*13)*.

2.3 Safety Research Comparing KABCO and MAIS

Popkin et al. (1991) was one of the first to test the accuracy of the KABCO scale (*14*). The research was conducted in North Carolina and utilized several phases to understand the true nature of the injury severity accuracy problem. Phase one determined the factors officers used to determine the injury severity using the KABCO scale. State Patrol Officers were given a supplemental form to fill out, in addition to the normal crash report form they would fill out at the scene of a crash. In total, 45 supplemental forms were completed by the officers, approximately ten forms for each crash level along with one fatality. From the supplemental forms, Popkin et al. found that at 73 percent of the crashes the crash victims remained at the scene. This was higher for “C” or “O” crashes, with more than 80 percent remaining at the scene. For crashes rated “A” and “B” only 67 percent and 55 percent remained at the scene, respectively. This would make determining the true injury severity of a crash victim more difficult for the officer since they primarily determine injury severity from the scene of the crash.

Additionally, Popkin et al. determined that only 14 percent of all severity ratings were based on any information other than the officer's judgment, even when the officer was required to go to the Emergency Department to finish conducting the crash report. Injury severity was determined by the appearance of the victim at the scene of the crash, or based on information provided by the victim. For "C" and "O" crashes the severity was primarily determined via conversation with the victim.

The next phase of the Popkin et al. study was to determine if there was a bias in North Carolina when law enforcement officers reported injury severity using the KABCO scale. For this phase crash reports from 1985 to 1989 were examined, approximately 1.5 million crash reports in total. The results found that law enforcement officers were more likely to rate males as uninjured than female crash victims. This result was found to be significant level $p < 0.01$. Additionally, younger victims (aged 16 and less) and older victims (60 and older) were rated by law enforcement officers with a higher injury severity than those victims who were in the middle age range. However, the research could not determine if this was due to a bias in injury severity reporting or if the two extreme age groups actually had more significant injuries.

The final phase conducted a comparison of police and physician judgments of injury severity. For this phase physicians were asked to rate crash victims in hospitals using the KABCO rating system. These ratings were then compared to the KABCO rating police officers in the field determined for the crash victims. Physicians were unaware of the rating the police officers had reported for the victims. The results found that law enforcement officers tended to over report injury severity when the victim appeared seriously injured due to a superficial wound, such as large amounts of bleeding. Police also tended to over report injuries when an at-risk group was present, such as pregnant women. Another reason for over reporting from law enforcement officers was if the victim had an altered state of mind, such as due to alcohol intoxication. Finally, police tended to determine an injury severity was more severe if there was an injury that was "readily reversible" such as a minor concussion, that would improve between the time of the crash and the evaluation by a medical professional.

The results found the police officers under reported the injury severity of persons with occult injuries, or injuries that would not be easy to determine at the scene of the crash, such as hemorrhages or non-displaced fractures. Motor vehicle crashes that appeared to have little vehicle damage also caused an under reporting of injury severity by law enforcement officers at the scene of a crash. Additionally, socio-economic factors, such as language barriers, could affect the police officers rating of injury severity.

In total, 51 percent of crashes had a discrepancy between the law enforcement officers and the physician's injury severity ratings. Of the 51 percent, 12 percent had a discrepancy of two or more levels on the injury severity scale. The greatest agreement occurred at the extremes of the KABCO scale. In other words, if there was a fatality or a crash where no injury occurred there was little discrepancy. When a discrepancy did occur, the discrepancy tended to be a police officer over reporting the severity of the injury. The least agreement between the police officers and physicians occurred in the "B" category. This category was often rated as "C" or "O" when a physician examined the victim. Motorcycle crash victims and pregnant women frequently had their injury severity over reported. This was assumed to be caution on the part of the law enforcement officer.

Farmer (2003) examined the reliability of law enforcement officer reported information in determining injury severity (*15*). Particularly he was interested in using posted speed as a surrogate for change in velocity, and discrepancies in the KABCO scale compared to MAIS. Farmer used the NASS/CDS database to look at all crashes from 1996 to 2000 that involved a towed vehicle. Slightly more than half the AIS measurements for the crash victims were taken from medical records, while the rest were based on interviews with those in the crash. This may present a bias in the AIS scores reported; however, the AIS scores determined via interview were thought to be accurate since they had taken place after the crash and medical treatment.

Farmer found that all crash victims coded by law enforcement officers as fatalities were also coded in the NASS/CDS database as killed. However, a small number of victims who were died were not coded as fatalities by law enforcement officers. This could be due to a death happening after the 30 day reporting period, or the law enforcement officer never followed up with the crash victim in the hospital. Additionally, 46 percent of drivers coded by officers as having incapacitating injuries had minor injuries on the MAIS scale (MAIS 1), and an additional three percent had no injuries at all.

Farmer found that law enforcement officers over estimated injuries of crash victims as incapacitating more during the daytime than during the nighttime. This was thought to be due to officers trying to clear the scene of the crash as quickly as possible during the daytime due to higher traffic volumes on roadways, and higher workloads for the police officers. Certain crash types also lead to higher over reporting of incapacitating crashes. Specifically, rear-end crashes, angle crashes, and same side sideswipe crashes lead to higher over reporting. Female crash victims were significantly more likely to have their injury severity overestimated than males. Similarly drivers aged 16 through 64 were more likely to have their injury severity overestimated than drivers aged 65+. This was thought to be due to elderly drivers being more likely to be injured in general than their younger counterparts. Finally, Farmer found that misclassification of injury severity also varies by region. This misclassification by region was assumed to be due to differences in state classification systems.

Compton (2005) examined the NASS/CDS database for crashes occurring between 1994 and 2003 (*6*). This research focused only on injured persons, and did not include the uninjured or the fatally wounded. Compton's results found that significant bleeding from injuries led to police officers overestimating injury severity. Discrepancy was also found from occult injuries that would not have been evident to the officer at the scene of the crash. Overall, Compton found that police officers did a good job determining injury severity for crash victims. Specifically, Compton found that 65 percent of incapacitating injuries were labeled as AIS 2+, and the errors resulted from over estimating superficial injuries and underestimating occult injuries.

Flannagan et al. (2012) conducted an assessment of the discrepancy between the KABCO scale and the MAIS scale (*16*). For this research a data set from the National Automotive Sampling System and the Crashworthiness Data System (NASS/CDS) was used. Crashes were examined from 2000 to 2010, examining both MAIS and KABCO scores for each crash. If a crash had a MAIS score of 3 or higher the crash was coded as a serious injury. From the research the KABCO scale had the ability to predict injury mortality to a significance level of $p = 0.0119$.

Flannagan et al. determined the KABCO rating was strongly associated with serious injury. Specifically, if a crash victim had a worse rating on the KABCO scale, they were more likely to be seriously injured. There was also shown to be a correlation between using “KA” and MAIS 3+ for serious injuries. However, when “KA” is used as the definition for serious injury the KABCO scale overestimates serious injury by approximately three times. By adding hospitalization information along with the “KA” rating the results improve to only 21 percent overestimation. Flannagan et al. suggest using hospitalization information to improve the accuracy of the KABCO rating. Additionally, further research was suggested to determine if the overestimation rates of “KA” are observed across state lines. Finally, Flannagan et al. was recommended that the National Trauma Data Bank (NTDB) be used to correct and improve the KABCO estimate.

2.4 Past Research Using Logistic Regression

Logistic regression has been used in the past to model injury severity using data from the scene of a crash as predictors. Dissanayake and Lu (2002) studied traffic crashes in Florida to estimate the injury severity of young drivers in fixed object crashes (*17*). Their results found that factors such as alcohol or drugs, the crash resulting in ejection, the point of impact with the vehicle, and the vehicle’s speed prior to collision impacted the probability of a more severe crash. Kong and Yang (2010) used logistic regression to model the probability of serious injuries using AIS for pedestrian collisions in China (*18*). Age and impact speed were predictor variables used to model injury severity. The results found that modest increases in speed result in a much higher probability of the collision resulting in fatality for the pedestrian. Kononen et al. (2011) used multivariate logistic regression to determine the probability of a crash resulting in a serious injury as measured by ISS score (*19*). In their model, speed differential, seat belt use, and crash direction were significant factors in estimating serious injuries. To date, no research has used injuries suffered by crash victims to estimate injury severity.

2.5 Past Research Using Classification Trees

A classification tree is a machine learning algorithm used for prediction. The tree is created by recursively partitioning data to yield the maximum reduction in the variability of the response. One of the benefits of a classification tree is the easily understood graphical nature of the decision tree. Qin and Han (2008) compared classification trees using two different methods: classification and regression trees (CART) and Generalized, Unbiased Interaction Detection and Estimation (GUIDE) (*20).* Their results found that variable selection bias of some classification tree algorithms can be overcome by using the GUIDE algorithm. In addition, they concluded CART should be used with caution when the model has many variables with differing values.

In 2009, Scheetz et al. used a classification tree was used to estimate moderate and severe injuries using vehicular variables and crash dynamics (*21*). Using the CART algorithm for developing a regression tree produced a highly sensitive model with specific crash scene information that was created to help assist paramedics at the crash scene give proper care to crash victims. In 2013, research in Wisconsin was conducted to develop estimation models for fatal and injury crashes on rural horizontal curves on undivided roads (*22).* The regression tree analysis provided a simple model that showed an increase in crashes on curves with radius less than 2,500 foot and traffic volume greater than approximately 1,300 vehicles per day.

CHAPTER 3. STUDY DESIGN

3.1 Research Tasks

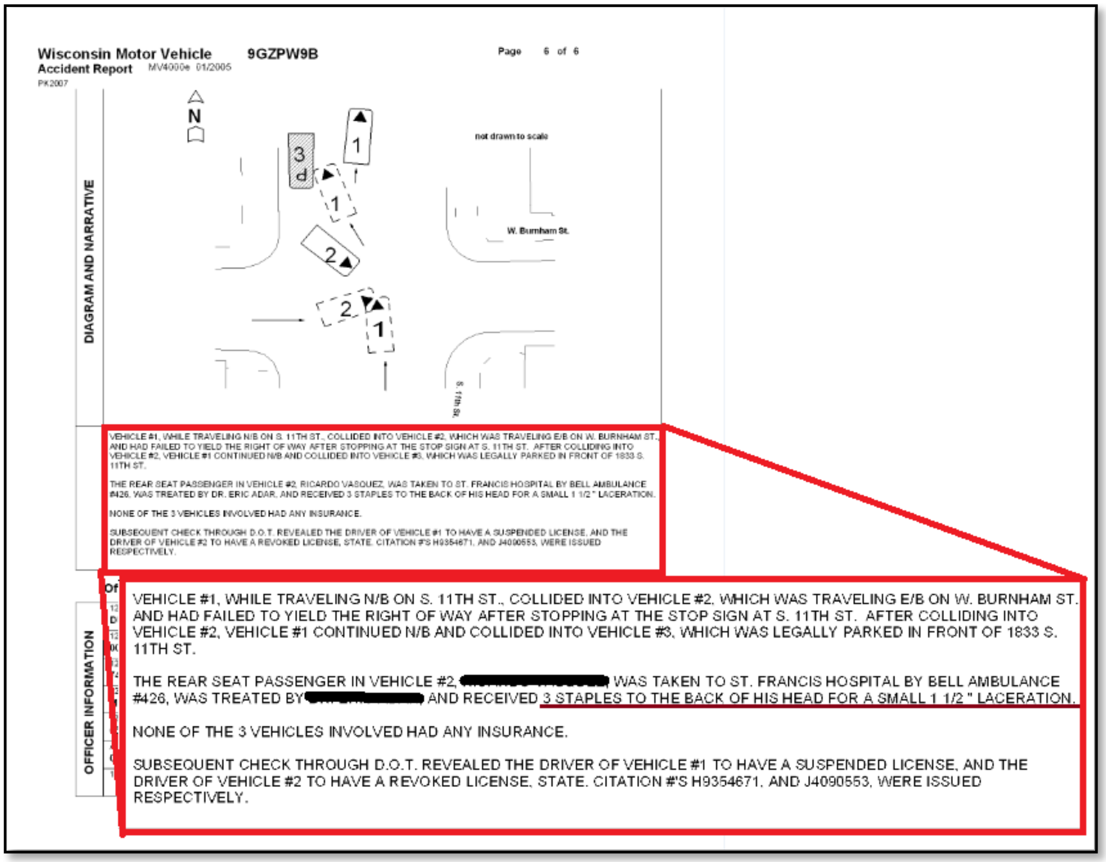
After the research objectives were identified, a list of tasks was created in order to guide the research process. The first task involved reviewing the literature to determine injury severity rating practices of both law enforcement officers and medical practitioners. Additionally, the literature was reviewed to determine the state-of-the practice in regards to comparisons between the two injury severity assessment methods. Finally, the literature was reviewed to determine different modelling techniques used to analyze transportation data. The data collection and processing is outlined in detail in Section 3.2. Once the raw data was analyzed and sorted, analyses were conducted on crashes with inaccurate injury severity assessment (Chapter 4). The analyses included a high-level view of the data to show body regions and injuries described by law enforcement officers in the crash report narrative. After a high-level view of the data was completed statistical analyses were conducted. Analyses were also conducted on crashes with accurate injury severity assessment (Chapter 5). A high-level view of the data was conducted to determine body regions and injuries described by law enforcement officers in the crash report narrative for crash victims with accurately assessed injury severity. Additionally, other factors noted by law enforcement officers in crash reports were also analyzed. Models were then created and compared to determine the best method to estimate injury severity.

3.2 Data Collection and Processing

3.2.1 CODES Data Collection

Crash data for all of Wisconsin from 2008 through 2012 were analyzed. 2012 was the most recent year available using the CODES dataset. To obtain five years for the analysis 2012, and the four preceding years were analyzed. Only crashes in the CODES database that had probabilistically linked medical and law enforcement crash data were analyzed in this project. In total, there were 120,534 linked crashes over the five year period analyzed. From these crashes the following information was obtained: the law enforcement officer injury severity rating (KABCO), the injury severity as assessed by medical practitioners (MAIS), the body regions injured as determined by medical practitioners using the AIS body regions. Additionally, the gender of the crash victim, lighting conditions and weather conditions at the scene of the crash, whether alcohol was present, vehicle type (motorcycle or moped, bicycles, pedestrians, or other motor vehicles), crash type, and the safety equipment used (seatbelt, helmet, child seat) were examined.

The MV4000 crash report forms for overestimated, underestimated and accurately assessed crash victims were analyzed to understand circumstances that led law enforcement officers to overestimate or underestimate the injury severity of a crash victim. This was done by analyzing the narratives that law enforcement officers recorded to describe the crash details. Although law enforcement officers are not required to report any information regarding injuries a crash victim incurs beyond the injury severity, they occasionally report on the injuries of victims in the narrative of the crash report. Figure 1 shows an example of a crash report narrative with an injury described within. The injury description is underlined in red.



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VEHICLE #1, WHILE TRAVELING N/B ON S. 11TH ST., COLLIDED INTO VEHICLE #2, WHICH WAS TRAVELING E/B ON W. BURNHAM ST., AND HAD FAILED TO YIELD THE RIGHT OF WAY AFTER STOPPING AT THE STOP SIGN AT S. 11TH ST. AFTER COLLIDING INTO VEHICLE #2, VEHICLE #1 CONTINUED N/B AND COLLIDED INTO VEHICLE #3, WHICH WAS LEGALLY PARKED IN FRONT OF 1833 S. 11TH ST.

THE REAR SEAT PASSENGER IN VEHICLE #2, RICARDO VASQUEZ, WAS TAKEN TO ST. FRANCIS HOSPITAL BY BELL AMBULANCE #426, WAS TREATED BY DR. ERIC ADAR, AND RECEIVED 3 STAPLES TO THE BACK OF HIS HEAD FOR A SMALL 1 1/2 " LACERATION.

NONE OF THE 3 VEHICLES INVOLVED HAD ANY INSURANCE.

SUBSEQUENT CHECK THROUGH D.O.T. REVEALED THE DRIVER OF VEHICLE #1 TO HAVE A SUSPENDED LICENSE, AND THE DRIVER OF VEHICLE #2 TO HAVE A REVOKED LICENSE. STATE. CITATION #'S H9354671, AND J4090553, WERE ISSUED RESPECTIVELY.

VEHICLE #1, WHILE TRAVELING N/B ON S. 11TH ST., COLLIDED INTO VEHICLE #2, WHICH WAS TRAVELING E/B ON W. BURNHAM ST. AND HAD FAILED TO YIELD THE RIGHT OF WAY AFTER STOPPING AT THE STOP SIGN AT S. 11TH ST. AFTER COLLIDING INTO VEHICLE #2, VEHICLE #1 CONTINUED N/B AND COLLIDED INTO VEHICLE #3, WHICH WAS LEGALLY PARKED IN FRONT OF 1833 S. 11TH ST.

THE REAR SEAT PASSENGER IN VEHICLE #2, [redacted] WAS TAKEN TO ST. FRANCIS HOSPITAL BY BELL AMBULANCE #426, WAS TREATED BY [redacted] AND RECEIVED 3 STAPLES TO THE BACK OF HIS HEAD FOR A SMALL 1 1/2 " LACERATION.

NONE OF THE 3 VEHICLES INVOLVED HAD ANY INSURANCE.

SUBSEQUENT CHECK THROUGH D.O.T. REVEALED THE DRIVER OF VEHICLE #1 TO HAVE A SUSPENDED LICENSE, AND THE DRIVER OF VEHICLE #2 TO HAVE A REVOKED LICENSE. STATE. CITATION #'S H9354671, AND J4090553, WERE ISSUED RESPECTIVELY.

Figure 1 MV4000 Crash Report Narrative Example

3.2.2 Overestimated and Underestimated Injury Severity Crash Victims

Crash victims with an inaccurate injury severity assessment as rated by law enforcement officers were broken into two categories: crash victims with overestimated injury severity, and crash victims with underestimated injury severity. A crash victim was deemed to have an injury severity that was "overestimated" if the law enforcement officer rated the injury as an "A" on the KABCO scale, but the actual health outcome as assessed by a medical practitioner on the MAIS scale was below 3. Conversely, a crash victim was deemed to have an "underestimated" injury severity if a law enforcement officer assessed the injury severity to be "B", "C", or "O" on the KABCO scale but the actual health outcome assessed by a medical practitioner on the MAIS scale was greater than 3.

The proportion of overestimation and underestimation compared to all crashes can also be calculated. Equation (1) was used to calculate the percent of crashes overestimated in the analysis period. Similarly, underestimation as a percentage of all crashes was calculated used Equation (2).

$$\%\,Overestimation = \frac{\sum(\text{"A-1" + "A-2" Crashes})}{\sum(All\ \text{"A"+"B"+"C"+"O" Crashes})} \tag{1}$$

$$\%\,Underestimation = \frac{\sum(All\ Underestimated\ Crashes)}{\sum(All\ \text{"A"+"B"+"C"+"O" Crashes})} \tag{2}$$

The Pearson chi-squared test (Equation 3) was used to determine the statistical difference between each body region's ground truth proportion and the corresponding proportion of the overestimated or underestimated case. Additionally, the chi-squared test was used to determine if there was a statistically significant difference between factors such as alcohol, gender, vehicle type, weather, and lighting conditions for overestimated and underestimated crashes. Expected values were calculated using the proportion from the ground truth (all linked crashes during the five years) data for each of the five years analyzed. These expected were compared to the observed proportions for overestimated and underestimated crashes.

$$\mathrm{X}^2 = \sum_{i=1}^{n}\sum_{j=1}^{n}\frac{(O_{ij}-E_{ij})^2}{E_{ij}} \tag{3}$$

3.2.3 Crash Victims with Accurate Injury Severity Assessment

Crash victims with an accurate KABCO injury severity assessment from law enforcement officers were also analyzed. Each KABCO severity rating was matched with the correct corresponding MAIS score to determine which crash victims had an injury severity assessment by law enforcement officers that matched the actual health outcomes as rated by medical practitioners. For this analysis crash victims with KABCO severity ratings “A”, “B”, and “C” were analyzed. Crash victims with KABCO severity ratings “K” and “O” were excluded due to law enforcement officers accurately assessing a crash victim’s injury severity for these categories. Additionally, these categories provide little insight into specific injuries that determine how law enforcement officers rate injury severity.

Accuracy was found for each individual injury severity “A”, “B”, and “C” by comparing the proportion of correct assessment to the total number of crashes for that injury severity. The overall accuracy can be calculated using Equation (4).

$$Overall\ Accuracy\ (\%) = \frac{\#\ of\ correctly\ assessed\ \text{"A" + "B" + "C" crash victims}}{\#\ of\ total\ crashes} \tag{4}$$

To estimate the injury severity of a crash victim all injury descriptions noted by a law enforcement officer at the scene of the crash, as well as the additional factors were tested. The full dataset was divided into two sets: one to create the models, and one to validate the models. To create the model, 80% of the full dataset were used. For each injury severity, 80% of the crashes were used for model creation. Conversely, 20% of each injury severity was used for validation purposes. Injury severity was estimated using two methods: multinomial logistic regression (Chapter 5.2) and classification trees (5.3). These two methods were then compared to determine the strengths and weaknesses of each method at estimating injury severity. The datasets used were constant for each model created.

3.2.3.1 Multinomial Logistic Regression

Multinomial logistic regression was used for estimating the severity of an injury based on the crashes examined. For multinomial logistic regression, the log odds for response j is calculated using Equation (5) (*23*).

$$\log\left(\frac{\pi_j}{\pi_J}\right) = \alpha_j + \beta_j x, \quad j = 1, \ldots, J-1 \tag{5}$$

For this research J is equal to 3, "A", "B", and "C", where 3 or injury severity "C" is the baseline constraint. Two equations are created to calculate the log odds of "A" over "C" and "B" over "C". The probability of each injury severity can be calculated based on the fact that $\sum_j \pi_j=1$. From this fact, the probabilities for each injury severity "A", "B", and "C" can be calculated using Equations (6), (7), and (8).

$$\widehat{\pi_A} = \frac{1}{1+e^{\alpha_A+\beta_A x}+e^{\alpha_B+\beta_B x}} \tag{6}$$

$$\widehat{\pi_B} = \frac{e^{\alpha_B+\beta_B x}}{1+e^{\alpha_B+\beta_B x}+e^{\alpha_B+\beta_B x}} \tag{7}$$

$$\widehat{\pi_C} = \frac{1}{1+e^{\alpha_A+\beta_A x}+e^{\alpha_B+\beta_B x}} \tag{8}$$

In total, there were 38 variables included in the original model. 34 of these were injury descriptions law enforcement officers included in the crash report narratives. Four of the variables were other factors that law enforcement officers noted in the crash report. The variable crash type had 7 levels for each of the different crash types reported (angle, rear end, no collision, sideswipe same, sideswipe opposite, no collision, and unknown). The variable vehicle type had three levels (pedestrian and bicycle, motorcycle, and car and truck). All other variables were binary, where 1 is a success, or "yes", and 0 is a failure, or "no".

First, highly correlated variables were removed from the model. This was done by examining a correlation matrix and removing variables that were highly correlated to many variables. Once the highly correlated variables were removed, Akaike's Information Criteria (AIC), shown in Equation (9), was used along with backward stepwise regression to reduce the model from the full preliminary model to the final model. AIC is a measure of goodness-of-fit, describing the balance between a models accuracy and complexity. Generally, a model including more parameters will have a better fit; however the model becomes increasingly more complex with each additional parameter.

$$AIC = -2 * loglikelihood + 2 * (\# \ of \ parameters) \tag{9}$$

The model was fit with all injury and crash variables, and then the AIC was applied to arrive at the final model used to estimate injury severity. To arrive at the best model, the full model with all variables was assessed. Variables were then removed at each step, based on which provided the largest decrease in the AIC. This was repeated until adding or removing a variable no longer decreases the AIC. It is suggested that there should be 10 outcomes for the least likely response variable (*24*). In this case there are 300 “C” injury severity responses, so the maximum number of predictors should not exceed 30.

3.2.3.2 GUIDE Classification Tree

Classification trees were another method used to estimate injury severity given the injury descriptions and other factors found in the crash report. Classification trees were chosen as one model because the result is easy to visualize, which would be easier for law enforcement officers in the field to use. To estimate injury severity each of the 34 injuries, as well as crash cause factors denoted by law enforcement officers, and crash type were added to help estimate injury severity. If the crash report narrative indicated a specific crash victim had any given injury category, it was marked as "Yes" for that injury, otherwise the injury description was flagged as "No". This was done for every injury for every crash victim analyzed.

Classification trees can be constructed using many different algorithms, but the GUIDE algorithm, as developed by Loh (*25*), was used in this research. GUIDE was chosen to construct the classification tree because the algorithm provides unbiased splits, allows tree pruning using cross validation to select the appropriately sized tree, and the ability for the user to define misclassification costs (*26*).

To construct the classification tree using GUIDE the whole data set, S, is placed at the root node (*26, 27*). A chi-squared test for independence is performed with each independent variable, X and the dependent variable, Y with the data at each node. From the chi-squared tests, the variable X' with the smallest p-value is chosen as a splitter node. The split set {X' ∈ S} that minimizes the weighted sum of variance is determined. This is calculated using the Gini criterion (*20, 28*). First, the impurity function, S, must be calculated for each node t for j number of classes of categorical dependent variables, using Equation (10).

$$S = \Sigma p^2(j|t) \tag{10}$$

From the impurity function, the Gini index can be calculated using Equation (11).

$$i(t) = 1 - S \tag{11}$$

To determine where to split the node a goodness of split must be determined. The goodness of split is defined as the decrease in impurity and can be calculated using Equation (12).

$$\Delta i(s,t) = i(t) - p_L[i(t_L)] - p_R[i(t_R)] \tag{12}$$

Where:

s = a split,
p_L = proportion of cases at node t that go to left child node, t_L,
p_R = proportion of cases at node t that go to right child node, t_R,
$i(t_L)$ = impurity of left child node, and
$i(t_R)$ = impurity of right child node.

The best split, s*, is obtained by maximizing the decrease in impurity and can be calculated using Equation (13).

$$\Delta i(s^*,t) = max_{s\in S}\Delta i(s,t) \tag{13}$$

These steps are repeated for each node until no X variables are statistically significant, or the node sizes are too small to continue splitting the tree.

Once the tree is constructed it is pruned using V-fold cross classification, where the dataset is divided into V approximately equal parts. One part is left out and the GUIDE algorithm is applied to the remaining V-1 parts to construct a tree. This is repeated V times, for each of the V parts. The mean estimation deviance of each tree is found by applying the left out part to each tree. A cross-validation estimate is constructed by averaging the V estimates for the tree using all the data. In this research 10-fold cross validation was used to prune the tree.

All data from the model set was used to create a classification tree. Two classification trees were created using the above algorithm. The first classification tree uses no misclassification costs when constructing the tree. This means the penalty for incorrectly assessing an “A” type crash as “B” is the same as the penalty for incorrectly assessing the crash as injury severity “C”.

GUIDE allows a user to input misclassification costs, which will penalize wrong estimations by the classification tree. The costs used for this research were based on the National Safety Council (NSC) crash costs, shown in Table 1 (*29*).

Table 1 National Safety Council Crash Costs

Crash Type	**Unit Cost (2011 $)**
Incapacitating Injury (A)	$221,059.44
Non-Incapacitating Injury (B)	$56,404.62
Possible Injury (C)	$26,824.00

The crash costs from the NSC were then used to create the custom misclassification costs used for this research. Misclassification costs were calculated using Equation (14). The final misclassification costs for each estimated and observed injury severity level are shown in Table 2.

$$Misclassification\ Cost = \frac{Cost\ of\ Higher\ Severity\ Crash}{Cost\ of\ Lower\ Severity\ Crash} x100 \tag{14}$$

Table 2 Misclassification Costs Based on NSC Crash Costs

	Observed		
Estimated	A	B	C
A	100	392	824
B	392	100	210
C	824	210	100

Using the NSC crash costs for misclassification costs penalizes the tree heavily for estimating injury severity “A” when the observed severity was “C”, and vice versa. Using the misclassification costs will make the model more conservative, and ideally improve the accuracy of the injury severity estimation.

CHAPTER 4. ANALYSIS OF INACCURATELY ASSESSED INJURY SEVERITY CRASH VICTIMS

4.1 Over- and Under-Estimated Injuries Assessed by Law Enforcement Officers

The CODES data was examined to determine the extent of overestimation and underestimation. Table 3 shows the total overestimated (green) and underestimated (red) crashes that occurred during the five year period analyzed.

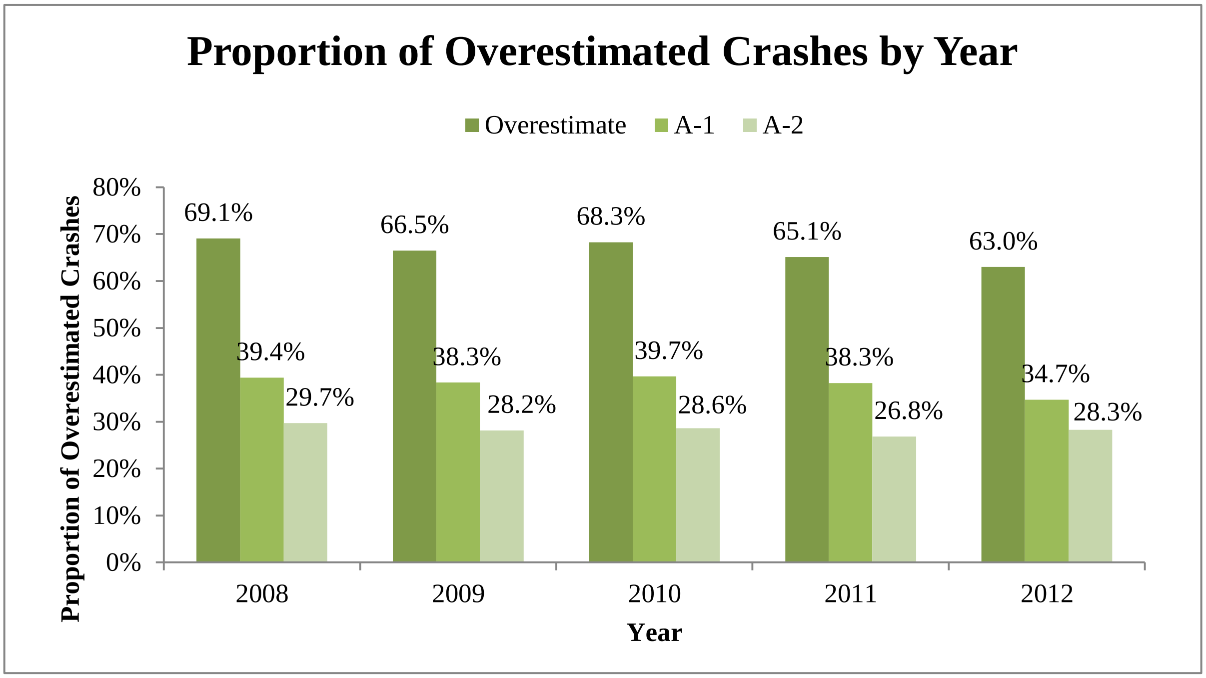
Table 3 Over- and Under- Estimated Crashes using KABCO and MAIS Comparison

	KABCO SCORE				
MAIS Score	**O**	**C**	**B**	**A**	**K**
1 (Minor)	13914 (92.2%)	40893 (88.7%)	32554 (76.1%)	5993 (38.2%)	0 (0%)
2 (Moderate)	1104 (7.3%)	4405 (9.6%)	7654 (17.9%)	4459 (28.4%)	0 (0%)
3 (Serious)	41 (<1%)	507 (1.1%)	1770 (4.1%)	3044 (19.4%)	0 (0%)
4 (Severe)	25 (<1%)	263 (<1%)	807 (1.9%)	1905 (12.1%)	0 (0%)
5 (Critical)	4 (<1%)	12 (<1%)	40 (<1%)	296 (1.9%)	0 (0%)
6 (Maximum/Fatal)	1 (<1%)	3 (<1%)	2 (<1%)	14 (<1%)	824 (100%)
Total	15089	46083	42827	15711	824

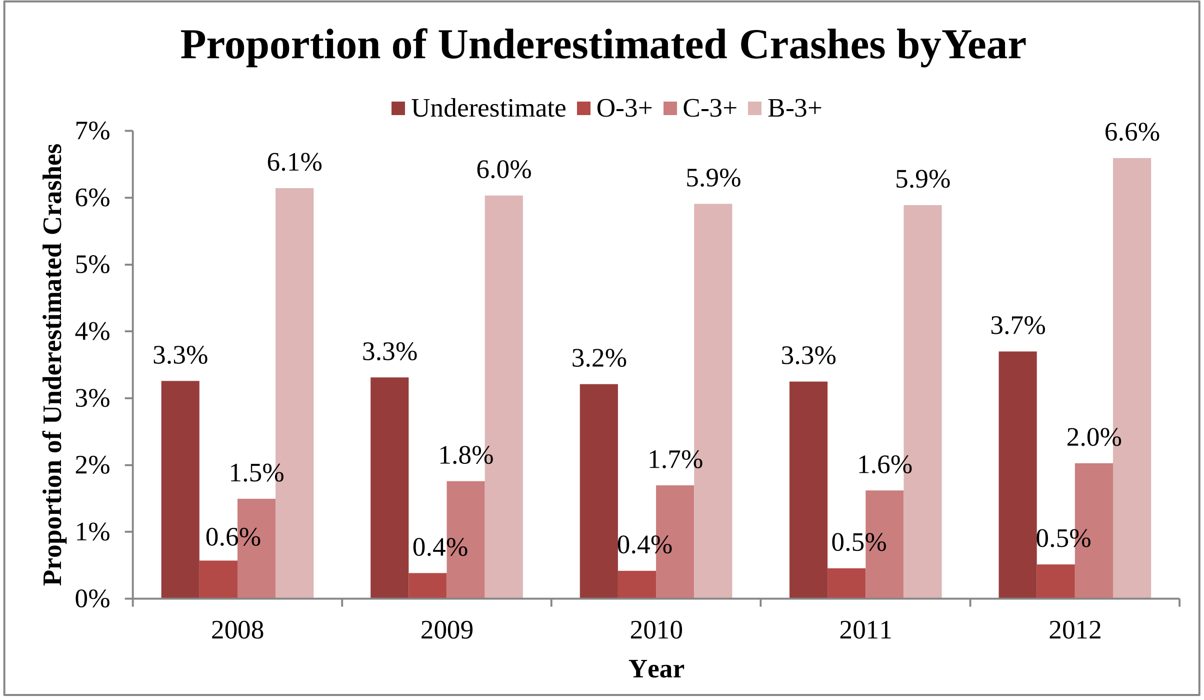
🟥 Overestimated Crashes
🟩 Underestimated Crashes

Table 3 shows law enforcement officers overestimated injury severity for 66.6% (38.2% A-1 plus 28.4% A-2) of crash victims when compared to the actual health outcomes assessed by medical practitioners on the MAIS scale. This result is nearly identical to past research in Wisconsin that analyzed crashes at work zones between 2001 and 2007. This research found approximately two-thirds of "A" crash victims sustained only "minor" or "moderate" injuries (MAIS 1 or 2) (*1*). Similarly, using data from the National Automotive Sampling System (NASS) Crash Worthiness Data System (CDS) from 1996 to 2000, Farmer found injury severity was overestimated in 70% of crash victims (*16*). Compton found law enforcement officers overestimated injury severity for 66.4% of crash victims using NASS CDS from 1994 to 2003 (*6*). Tarko et al. found that law enforcement officers in Indiana overestimated injury severity for 65.8% of crash victims (*30*). These results suggest that not only is overestimation consistent throughout Wisconsin over time, but overestimation is also relatively consistent throughout the United States over time.

The proportions of overestimated "A" crashes, compared to all "A" crashes were examined to determine if the trend of overestimated proportions were consistent for each year. Figure 2a shows the proportion of overestimated "A" crashes in different years between 2008 and 2012. Included in Figure 2a is the proportion "A" crashes that are overestimated. Additionally, the figure shows KABCO "A" with MAIS 1 (A-1), and MAIS 2 (A-2), separately. Similarly, Figure 2b shows the proportion of underestimated crashes for each year between 2008 and 2012. The total level of underestimation is shown, as well as the level of underestimation for KABCO severity "B" (B-3+), "C" (C-3+), and "O" (O-3+) with a MAIS score greater than 3.



(a) Proportion of Overestimated "A" Crashes by Year



(b) Proportion of Underestimated Crashes by Year

Figure 2 (a) Over - and (b) Under- Estimated Crashes per Year

Overestimation was at a high of 69.1% of all "A" crashes in 2008, and then overestimation decreased to a low of 63.0% of all "A" crashes in 2012. However, overall overestimation remained at approximately two-thirds of the "A" crashes during the five years analyzed. Underestimation varied from a high of 3.7% of all "B", "C", and "O" crashes in 2012 to a low of 3.2% in 2010. The proportion of underestimation remained at approximately 3 percent of non-serious crashes during the five years analyzed.

Overestimation totals 66% of all crashes with injury severity "A". When considering the rate of overestimation out of all crashes analyzed law enforcement officers overestimated the injury severity of crash victims in 8.7% of all crashes. Injury severity was deemed underestimated if the law enforcement officer assessed the injury severity to be "B", "C", or "O" on the KABCO scale but the actual health outcome as rated by a medical practitioner on the MAIS scale was greater than 3.

Law enforcement officers underestimated the injury severity of crash victims in 2.9% of all cases. Overall, the total rate of overestimation and underestimation of all the linked crashes analyzed was 11.6%. In nearly 9 out of 10 crash victims the injury severity as assessed by law enforcement officers (KABCO) was accurately assessed to match the actual health outcomes as assessed by medical practitioners (MAIS). Of the crash victims where a law enforcement officer inaccurately assessed injury severity, 75% were overestimated. This suggests the overestimation of injury severity by law enforcement officers is a more serious problem than underestimation.

Table 4 shows a summary of the numbers of crash reports with any mention of an injury occurring in the crash report narrative. In addition, the table shows crash reports with references to medical transport or care, body regions injured in the crash, or if the crash report narrative mentions specific injury descriptions or symptoms the crash victim sustained. Examples of injury descriptions and symptoms would include concussions, loss of consciousness, fractured bones, and lacerations. All overestimated and underestimated crashes with crash reports available were examined for this analysis.

Table 4 Overestimated and Underestimated Crash Report Analysis

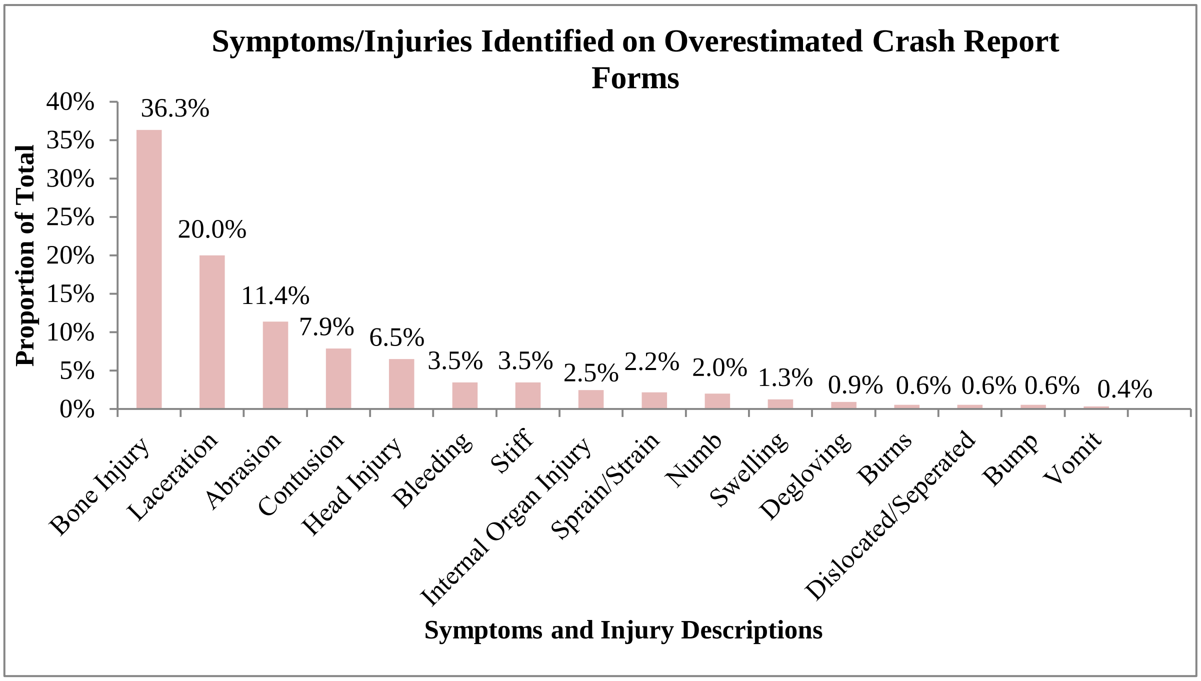
Injury Severity KABCO	MAIS	Crash Reports Examined	Injury Reference	Medical Transport/Care Reference	Symptom/Injury Description Reference	Body Region Reference
A	**1**	5061	1267 (25.0%)	977 (19.3%)	216 (4.3%)	550 (10.9%)
A	**2**	3994	1116 (27.9%)	823 (20.6 %)	370 (9.3%)	578 (14.5%)
Overestimate Total		**9055**	**2383 (26.3%)**	**1800 (19.9%)**	**586 (6.5%)**	**1128 (12.5%)**
B	**3+**	2427	779 (32.1%)	639 (26.3%)	244 (10.1%)	368 (15.2%)
C	**3+**	717	266 (37.1%)	213 (29.7%)	74 (10.3%)	170 (23.7%)
O	**3+**	65	7 (10.8%)	5 (7.7%)	3 (4.6%)	2 (3.1%)
Underestimate Total		**3209**	**1052 (32.8%)**	**857 (26.7%)**	**321 (10.0%)**	**540 (16.8%)**

Approximately one quarter (26.3%) of all crash victims with overestimated injury severity had some reference to an injury within the crash report. For crash victims with underestimated injury severity roughly one third (32.8%) had a reference to an injury in the crash report narrative. This included any reference to medical transport, injury or symptom descriptions, or a specific body region referenced. Of the crash reports that referenced an injury, roughly 20% and 25% of crashes with overestimated and underestimated injury severity, respectively, included a reference to medical transport or care. This included any reference of transport to a hospital, or hospital care for a crash victim.

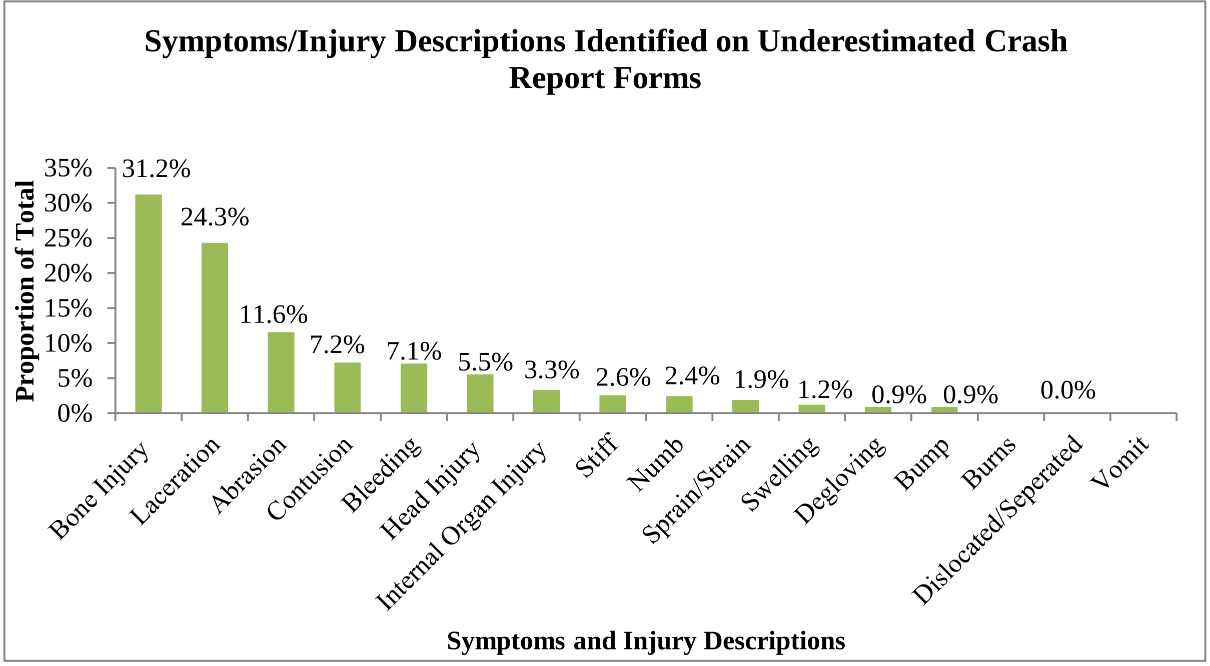
Crashes with overestimated and underestimated injury severity referenced specific injury descriptions or symptoms in 6.5% and 10% of crash reports, respectively. Crash victims with underestimated injury severity may have injuries referenced at a higher rate than overestimated injuries due to the law enforcement officer thinking the injury is more severe than it actually is, and therefore listing the injury. Specific body regions that were injured, or suspected of injury, were referenced in 12.5% and 16.8% of crash victims with overestimated and underestimated injury severity, respectively. Crash victims with overestimated and underestimated injury severity in which the law enforcement officer made reference to specific injury descriptions or symptoms, or body regions are discussed in detail in the following sections.

4.1.1 Analysis of Injury Descriptions and Symptoms from Crash Reports

For crash reports where the crash victim's injury severity was overestimated 586 (6.5%) made reference to a specific injury description or symptom in the crash report narrative. Each unique reference from each crash report was recorded. Figure 2 shows the proportion of injury descriptions and symptoms referenced for crash victims whose injury severity was overestimated by law enforcement officers. For crash victims with underestimated injury severity there were 321 crash reports (10.0%) that made reference to a specific injury description or symptom resulting from the crash. Figure 3b shows the injury description and symptom proportions for underestimated crash reports.



(a) Proportion of Injury Descriptions or Symptoms for Overestimated Crashes



(b) Proportion of Injury Descriptions or Symptoms for Underestimated Crashes

Figure 3 (a) Overestimated and (b) Underestimated Injury Descriptions and Symptoms as Identified by Law Enforcement Officers

Figure 3 shows the proportion of injury descriptions and symptoms found in crash report narratives in order of descending frequency. For the sake of clarity some injury descriptions and symptoms were combined into one category. All head injuries were combined in this analysis. The head injuries included were loss of consciousness, headaches, concussions, or dizziness resulting from the crash. Bone injuries were also combined for this analysis. The bone injuries referenced in the crash reports included fractures, breaks, crushes, and cracks. Finally, internal organ injuries were combined. The internal organ injuries found in the crash report narratives included collapsed and punctured lungs, torn spleens, and ruptured organs. For both overestimated and underestimated injury severity cases the most common injury descriptions and symptoms noted by law enforcement officers in the crash report narrative were bone injuries, lacerations (cuts), abrasions (scrapes), and contusions (bruises). This finding is not surprising as these would be some of the most common injuries found at the scene of the crash, and are more common injuries in general. The findings of the injury description and symptom analysis for overestimated and underestimated injury severity are described fully below.

Overestimated Injury Severity

From the 586 crash reports to include injury descriptions or symptoms in the crash report narrative there were 1,090 unique references to injury descriptions or symptoms. Law enforcement officers noted 16 different injury descriptions or symptoms in the crash report narratives of crash victims with overestimated injury severity. Bone injuries were the most frequently referenced injury description, accounting for 36.3% of all references. Of the bone injuries, there were 254 mentions of broken bones, which alone accounted for 23.3% of all overestimated crashes with an injury description or symptom description included in the crash report narrative. Collectively, the four most frequently referenced injury descriptions and symptom references accounted for 75.6% of all references, or 824 unique references.

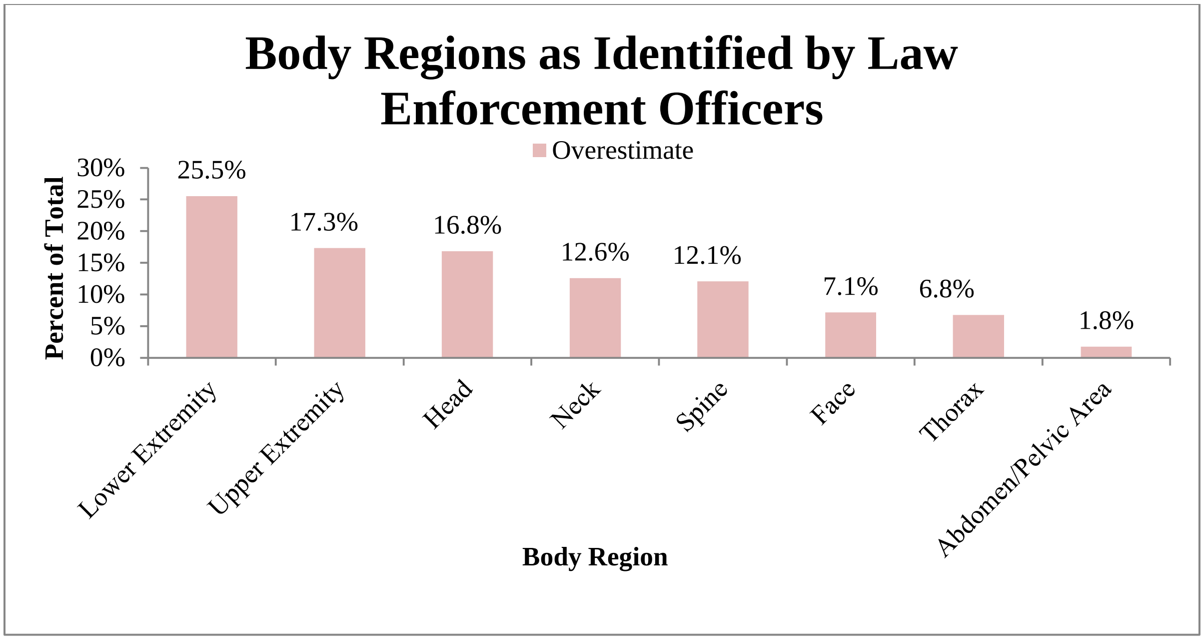
External injuries were referenced 506 times, accounting for 46.4% of overestimated crashes with an injury reference.

Underestimated Injury Severity

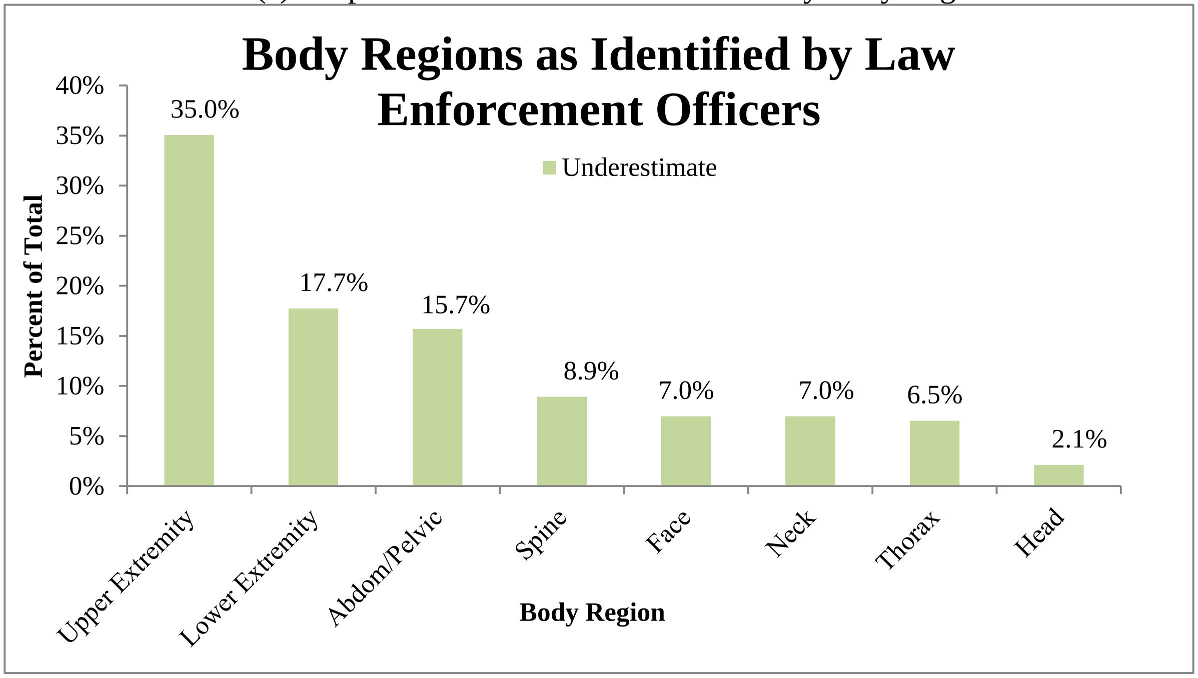
From the 321 crash reports that included injury descriptions or symptoms in the crash report narrative there were 580 unique references to injury descriptions or symptoms. Law enforcement officers noted 13 different injury descriptions or symptoms in the crash report narratives of crash victims with underestimated injury severity. Again, bone injuries were the most frequently referenced injury description, accounting for 31.2% of all references. Of the bone injuries, breaks were again the most frequent, accounting for 107 references, or 18.5% of all underestimated crashes with an injury description or symptom included in the crash report narrative. The top four injury descriptions and symptoms accounted for 74.3% of all references, or 431 unique references. External injuries accounted for 308 of the 580 injury references, or 53.1%.

4.1.2 Analysis of Injured Body Regions from Police Crash Reports

In many cases the law enforcement officer referenced a specific body part that was injured, or was suspected to be injured, in the crash report narrative. Of the crash reports where injury severity was overestimated, 1,128 crash reports (12.5%) contained a reference to an injured body part. Similarly, for crash reports where the injury severity of a crash victim was underestimated, 540 crash reports (16.8%) contained a reference to an injured body part. For this analysis the injured body parts noted by the law enforcement officer in the crash report narrative were aggregated into their corresponding AIS body region. This allowed for clarity in this analysis and also allows for a comparison with injured body regions as assessed by medical practitioners in the following section. The AIS category of “burn/other” was excluded from this analysis due to the inability to discern an “other” AIS body region from a crash report narrative in which the law enforcement officer did not list an injured body region. Figure 4a and Figure 4b show the proportion of body regions noted by law enforcement officers in the crash report narratives for overestimated and underestimated crashes, respectively.



(a) Proportion of Overestimated Crashes by Body Region



(b) Proportion of Underestimated Crashes by Body Region

Figure 4 (a) Overestimated and (b) Underestimated Injured Body Regions as Identified by Law Enforcement Officers

The frequency of body regions referenced is shown in order of descending frequency. The distribution of body region proportions was not consistent between crashes with overestimated and underestimated. However, the AIS body regions of face (approximately

7%) and thorax (approximately 6.5%) had similar proportions in both overestimated and underestimated crash reports. Additionally, the AIS body regions of upper and lower extremities were the two most frequently referenced by law enforcement officers for both crashes with overestimated injury severity and crashes with underestimated injury severity.

Overestimated Injury Severity

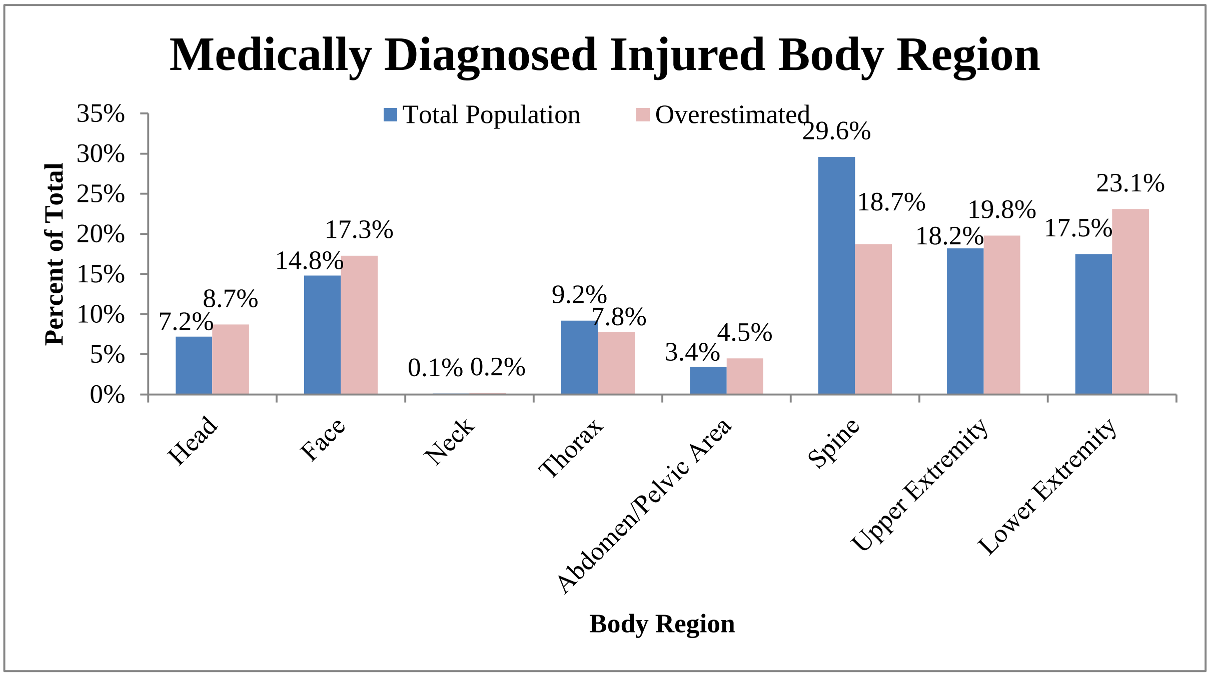
For cases in which the law enforcement officer overestimated injury severity there were 1,128 crash reports referencing 2,322 unique injuries to body parts. The body regions listed by the law enforcement officers most frequently were lower and upper extremities, accounting for 25.5% and 17.3% of injured body region references in the crash report narratives, respectively. Head injuries were the next most frequent, accounting for 391 references, or 16.8% of the total. The high frequency of references to extremities and to the head may be due to the superficial nature of most injuries to these regions. The two body regions with the lowest proportion of body regions referenced were the thorax, and the abdomen or pelvic region. These two body regions accounted for only 8.5% of all body regions injured. The low recognition of injuries to these body regions may be due to their occult nature. Additionally, injuries to these body regions tend to be severe, leading to officers assessing a crash victim's injury severity higher than the injury actually is.

Underestimated Injury Severity

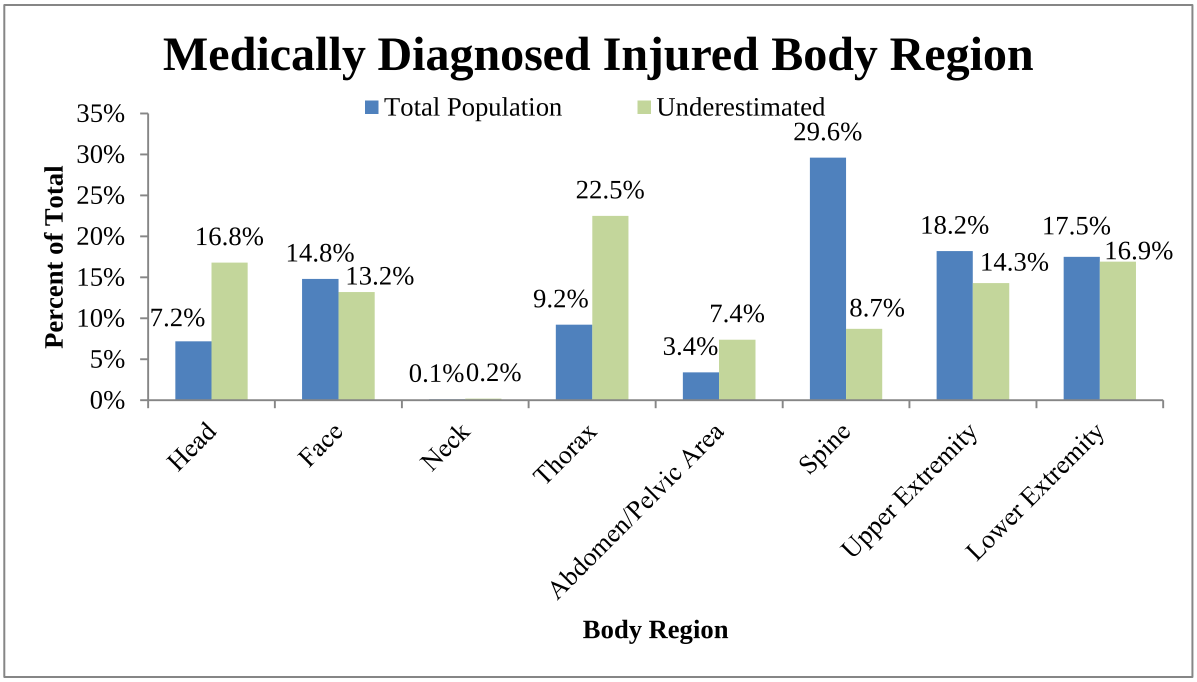
For cases in which the law enforcement officers underestimated injury severity there were 540 crash reports referencing 1,133 unique injuries to body parts. Again, upper and lower extremities were the body regions most frequently referenced for underestimated crashes. These two regions combined accounted for 52.8% of all references, or 598 injured body region references. The abdomen or pelvic region was the third most frequently referenced body region for underestimated crashes, accounting for 178 of the crashes, or 15.7% of the total. The abdomen body region may be more highly referenced because injuries to this region are generally occult, which makes accurately estimating their injury severity difficult.

4.1.3 Analysis of Medically Determined Injured Body Regions

The health outcome data from the CODES dataset was analyzed to determine the body regions actually injured, as identified by medical practitioners. The ground truth distribution of proportions of injured body regions was determined from the whole CODES dataset of all 164,761 crashes as a benchmark. The ground truth distributions are shown in blue on the left side in Figure 5a and Figure 5b. The ground truth proportions of injured body regions were then compared to the corresponding proportions in cases where injury severity was overestimated and underestimated. Figure 5a compares the ground truth proportion of medically diagnosed injured body regions to the proportion of medically diagnosed injured body regions for cases where injury severity was overestimated. Similarly, Figure 5b compares the ground truth proportion of medically diagnosed injured body regions to the proportion of medically diagnosed injured body regions for cases where injury severity was underestimated.



(a) Proportion of Overestimated Crashes by Body Region



(b) Proportion of Underestimated Crashes by Body Region

Figure 5 (a) Overestimated and (b) Underestimated Medically Diagnosed Injured Body Regions

Every body region was tested for both overestimated and underestimated cases, except the neck body region. This is due to the low sample sizes of the neck body region.

The results of the chi-squared test performed for each body region are summarized in Table 5.

Table 5 Statistical Significance of Medically Diagnosed Body Regions

	Overestimate			**Underestimate**		
Body Region	**X^2 (df = 4)**	**P-Value**	**Significant?**	**X^2 (df = 4)**	**P-Value**	**Significant?**
Head	56.081	<0.001	Yes	1059.579	<0.001	Yes
Face	65.447	<0.001	Yes	17.465	0.002	Yes
Neck	Sample Size Too Small			Sample Size Too Small		
Thorax	32.145	<0.001	Yes	1601.674	<0.001	Yes
Abdomen/Pelvic Area	60.284	<0.001	Yes	382.212	<0.001	Yes
Spine	653.606	<0.001	Yes	1210.826	<0.001	Yes
Upper Extremity	24.826	<0.001	Yes	70.167	<0.001	Yes
Lower Extremity	291.233	<0.001	Yes	6.922	0.140	No

Overestimated Injury Severity

The results for the chi-squared test comparing overestimated injury severity to the ground truth proportions are shown in the left column of Table 5. The results of the chi-squared goodness-of-fit test show that proportions of all overestimated body regions were significantly different from the ground truth proportions, except the neck body region. The neck body region had a sample size too small to test for significance. The proportions of head, face, abdomen and pelvic area, upper extremity, and lower extremity body region injuries were all significantly higher than the ground truth proportions for each respective body region. The thorax and spine had significantly lower proportions than their respective ground truth proportions for each body regions. The low proportion of overestimated thorax and spine injuries may be due to injuries to these body regions being occult in nature. Additionally, these body regions tend to have more severe injuries in general.

Underestimated Injury Severity

The results for the chi-squared test comparing underestimated injury severity to the ground truth proportions are shown in the right column of Table 5. All underestimated body region proportions were found to significantly differ from the ground truth body region proportions, with the exception of the neck and lower extremity body regions. Again the neck body region sample size was too small to be tested for significance. The lower extremity body region was the only body region not to be found significant (p = 0.140). The head, thorax, and the abdomen and pelvic area body regions had proportions that were found to be significantly higher than the ground truth proportions of body regions. The face, spine, and upper extremity proportion of body regions for crash victims with underestimated injury severity was found to be significantly lower than the ground truth body region proportions.

4.1.4 Analysis of Missed Injuries by Law Enforcement Officers

Using the injured body regions determined by law enforcement officers in the crash report narrative a comparison was made to the actual injury outcome determined by medical practitioners. Data from crash reports where a crash victim's injury severity was underestimated was compared to a medical practitioner's determination of injured body regions to determine which body regions law enforcement officers are most frequently missing. Cases with underestimated injury severity were used for this analysis because a law enforcement officer may be underestimating the severity of a crash victim's injuries due to missing an injury sustained by the crash victim. Similarly, the law enforcement officer may not deem an injury serious enough to note in a crash report when a crash victim's injury severity is underestimated. Figure 6 shows the percentages of missed injuries by body regions when comparing injuries noted by law enforcement officers in crash reports and medical practitioners. The body regions head and face were combined due to the ambiguity of a law enforcement officer's description of these body regions in the crash reports.

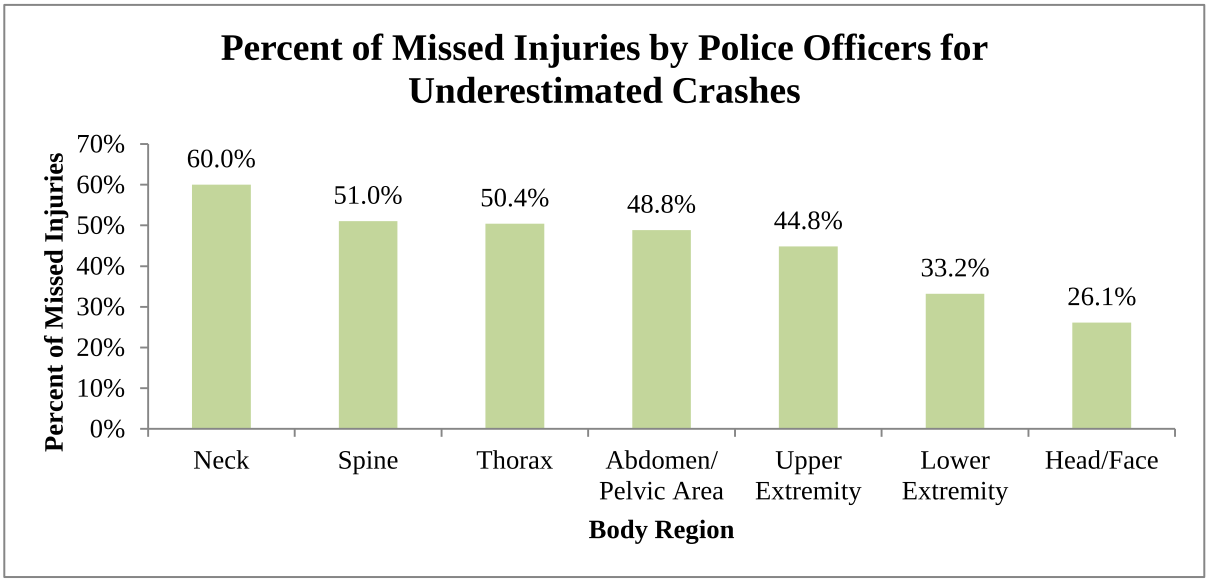


Figure 6 Missed Injuries by Law Enforcement Officers by Body Region for Underestimated Crashes

The neck body region had the highest frequency of missed injuries by law enforcement officers. The neck region was not reported in 60% of crash reports where a medical practitioner noted a neck injury. However, the neck body region only had five injuries for underestimated cases noted by medical practitioners during the analysis period. Spine and thorax injuries were the next most frequently missed body regions. Law enforcement officers missed, or did not report, 51.0% and 50.4% of spine and thorax injuries, respectively. The four most frequently missed body regions involved body regions where injuries tend to be occult in nature. Conversely, body regions where most injuries tend to be superficial in nature were least likely to be missed by a law enforcement officer in the crash report narrative. The upper extremity, lower extremity, and the head and face body regions were the least frequently missed. The head and face body regions were the least likely to be missed, with law enforcement officers failing to report these injuries on slightly over a quarter of crash report narratives.

4.2 Factors Impacting Overestimation and Underestimation of Injury Severity

In addition to examining the overestimated and underestimated crash reports other factors were examined to determine their impact on a law enforcement officer's assessment of injury severity, if any. The CODES data from 2008 to 2012 was analyzed to determine the impact of factors not directly related to the injury itself. The factors examined included alcohol impairment, gender, vehicle type (bicycle/pedestrian, motorcycle/moped), daylight, and adverse weather conditions. These factors were chosen because they may make an injury or crash scene appear more or less severe to a law enforcement officer. The overestimated and underestimated proportions of these factors was compared to the total CODES dataset to determine differences in reporting for overestimated and underestimated cases. The chi-squared test in Equation (4) was used to determine if these differences were statistically significant. The expected values were calculated for each year of the study period by finding the proportion of each factor for all overestimated and underestimated crashes. The observed values were found using proportion of each factor using overestimated and underestimated populations for the analysis period (2008 through 2012). The results of the chi-square analyses can be seen in Table 6.

Table 6 Statistical Significance of Factors Influencing Injury Severity Assessment

	Overestimate			**Underestimate**		
Factor	**X^2 (df = 4)**	**P-Value**	**Significant?**	**X^2 (df = 4)**	**P-Value**	**Significant?**
Alcohol	187.994	<0.001	Yes	326.589	<0.001	Yes
Gender	55.961	<0.001	Yes	174.863	<0.001	Yes
Adverse Weather	2.350	0.672	No	4.463	0.347	No
Light Condition	2.256	0.689	No	30.126	<0.001	Yes
Motorcycle/Moped	194.990	<0.001	Yes	114.604	<0.001	Yes
Pedestrian/Bicycle	1261.122	<0.001	Yes	934.956	<0.001	Yes

Overestimated Injury Severity

The results from the chi-squared analysis of factors for the overestimated cases are shown in the left hand column of Table 6. The results show that the presence of alcohol, gender, and vehicle type (motorcycle/moped, pedestrian/bicycle) leads to a statistical difference between the factors in overestimated cases and the overall proportion using the whole dataset. Adverse weather and light conditions at the scene of the crash were not found to impact overestimation by law enforcement officers at the scene of the crash.

Underestimated Injury Severity

The results for the chi-squared analysis of factors for underestimated cases are shown in the right hand column of Table 6. All factors except adverse weather were found to influence a law enforcement officer's assessment of injury severity in cases where injury severity was underestimated.

5. ANALYSIS OF ACCURATELY ASSESSED INJURY SEVERITY CRASH VICTIMS

5.1 Accurately Assessed Injuries by Law Enforcement Officers

Table 7 shows the frequency of crash victims with accurate injury severity assessment for each KABCO category. A crash victim was deemed to have an accurate injury severity assessment as rated by a law enforcement officer for injury severity “A” if the MAIS score was greater than 3 (shown in green in Table 7). For KABCO severity “B”, a MAIS score of 2 was correct (shown in red in Table 7). For KABCO severity “C” a MAIS score of 1 was correct (shown in blue in Table 7).

Table 7 Accurate Injury Severity Rating Using KABCO and MAIS Comparison

	KABCO SCORE				
MAIS Score	**O**	**C**	**B**	**A**	**K33**
1 (Minor)	13914 (92.2%)	40893 (88.7%)	32554 (76.1%)	5993 (38.2%)	0 (0%)
2 (Moderate)	1104 (7.3%)	4405 (9.6%)	7654 (17.9%)	4459 (28.4%)	0 (0%)
3 (Serious)	41 (<1%)	507 (1.1%)	1770 (4.1%)	3044 (19.4%)	0 (0%)
4 (Severe)	25 (<1%)	263 (<1%)	807 (1.9%)	1905 (12.1%)	0 (0%)
5 (Critical)	4 (<1%)	12 (<1%)	40 (<1%)	296 (1.9%)	0 (0%)
6 (Maximum/Fatal)	1 (<1%)	3 (<1%)	2 (<1%)	14 (<1%)	824 (100%)
Total	15089	46083	42827	15711	824

🟩	Accurate “A” Severity Crashes
🟥	Accurate “B” Severity Crashes
🟦	Accurate “C” Severity Crashes

Table 7 shows law enforcement officers rated crash victims with injury severity “A” accurately for only 33% of crash victims. For injury severity “B” the percentage of accurate injury severity assessment was only 18%. Crash victims with injury severity “C” were correctly assessed 89% of the time.

Overall, injury severity was accurately assessed for 51% of crash victims, or only slightly better than random chance. While the assessment of injury severity “C” is high, the low percentages of correct responses for more serious injury severities “A” and “B” is a serious issue because these severities impact the allotment of funds via cost-benefit analyses more than injury severity "C" does. Table 8 summarizes the existing accuracy of law enforcement officer's assessment of injury severity.

Table 8 Existing Severity Assessment Accuracy

Injury Severity	Assessment Accuracy
A	33%
B	18%
C	89%
Total	**51%**

The proportion of correctly assessed injury severity was plotted per year of the analysis period to determine if a law enforcement officer's assessment of injury severity was changing from 2008 through 2012. The proportion of correct injury severity assessments for injury severities "A", "B", and "C" crashes are shown in Figure 7. The figure shows the proportion of correctly assessed injury severities "A" (green), "B" (red), and "C" (blue) out of the total number of crash victims with an injury severity assessment of "A", "B", or "C", whether correctly assessed or not.

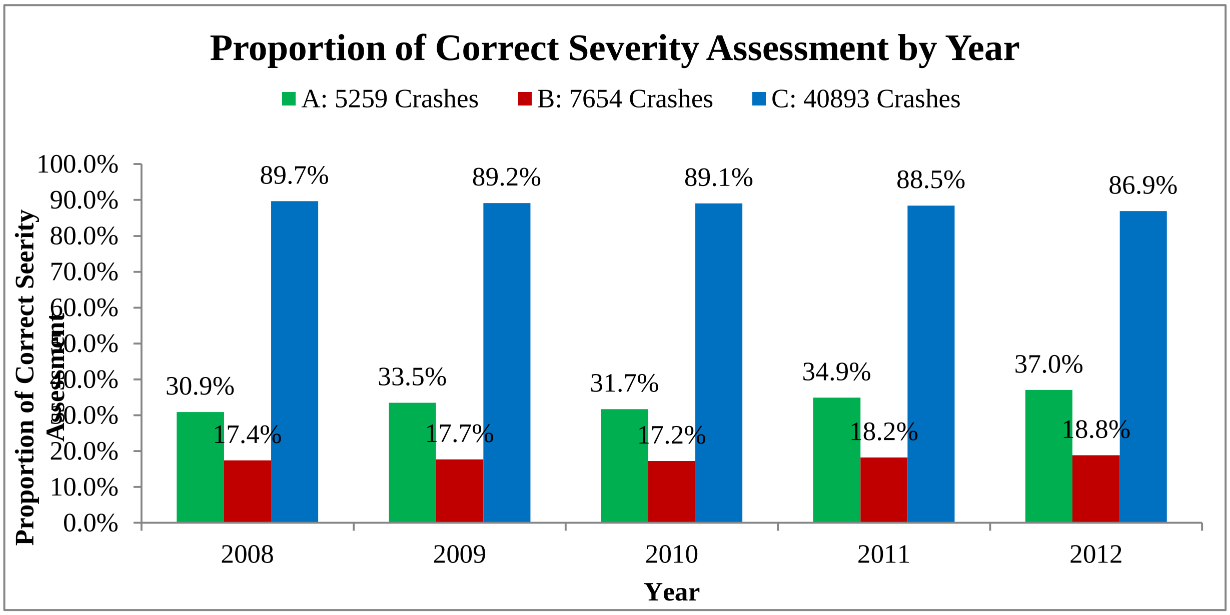


Figure 7 Correct Injury Severity Assessment by Year

The proportions of correctly assessed injury severities are relatively stable across the five years analyzed. Crash victims with an injury severity “A” were correctly assessed at a low of 30.9% in 2008 and rose to a high of 37.0% in 2012. Injury severity “B” had a low of 17.2% in 2010 and a high of 18.8% in 2012. The proportion of correctly assessed injury severity “C” had a high of 89.7% in 2008 and decreased to a low of 86.9% in 2012. When comparing the proportions of correctly assessed injuries Figure 7 shows law enforcement officers had the most difficulty assessing injury severity “B”, followed by injury severity “A”. Law enforcement officers assessed injury severity “C” at a much higher level of accuracy than the more serious injury severities “A” and “B”. While the proportions of correctly assessed injury severity fluctuated slightly over time the proportions remained similar throughout the five years analyzed.

Crash victims with correctly assessed injury severity by a law enforcement officer were examined closer. The crash reports for each correctly assessed crash victim were analyzed and information regarding injuries from the crash narrative was extracted. The correctly assessed injury conditions for each injury severity provide information about what injuries law enforcement officers using to assess injury severity. In total, 13,989 crash reports with accurate injury severity assessment were analyzed. Table 9 lists the number of accurately assessed crash reports examined for each injury severity. For "Incapacitating Injuries", all "A" crashes with a MAIS score greater than 3 were examined. "Non-Incapacitating Injuries" corresponded to a KABCO severity of "B" and a MAIS score of 2. "Possible Injuries" referred to a KABCO rating of "C" and a MAIS score of 1.

Table 9 Accurately Assed Injury Severity Crash Report Summary

Injury Severity		**Crash Reports**	**Symptom/Injury Description**
KABCO	**MAIS**	**Examined**	**Reference**
A	3	2728	268 (9.8%)
A	4	1758	173 (9.8%)
A	5	276	27 (9.8%)
A	6	13	1 (7.7%)
Ground Truth "A" Incapacitating Injury Total		**4775**	469 (9.8%)
Ground Truth "B" Non-Incapacitating Injury Total		**3500**	344 (9.8%)
Ground Truth "C" Possible Injury Total examined		**5714**	300 (5.3%)

In total, 1,113 crash reports included an injury description in the crash report narrative. Crash reports with an accurate assessment of "Incapacitating Injuries" had an injury description or symptom referenced in 9.8% (469 crash reports) of crash report narratives. Similarly, for "Non-Incapacitating Injuries", injury descriptions or symptoms were referenced in 9.8% (344 crash reports) of crash report narratives. For "Possible Injuries" injury descriptions were only referenced in 5.3% (300 crash reports) of crash report narratives. The lower percentage of injuries listed in "C" type injury severities may be due to the law enforcement officer not deeming the less severe injury conditions as important as the more severe injury types, leading to a lower reporting of these injuries in the crash report narrative.

5.1.1 Analysis of Injury Descriptions in the Ground Truth Crash Report Narratives

Crash reports where the law enforcement officer made an accurate assessment of injury severity were examined for any injury descriptions or symptoms (i.e., broken bones, lacerations, etc.) mentioned in the narrative. Additionally, the body region where the injury was recorded as well, if mentioned by the law enforcement officer in the narrative. If no body region was referenced with an injury, the body region was classified as "general". In total, there were 34 different injuries that occurred across the 8 different body regions. Table 10 lists all unique injuries found in the crash report narratives from crash victims with an accurate injury severity assessment. Included as well are the frequency of the specific injury for each injury severity level, "A", "B", and "C". If a crash victim suffered multiple injuries, each was counted in the correct category. Some injuries were combined if they had similar characteristics and if the distribution of injury severity was similar among the injuries.

Table 10 Frequency of Injury Descriptions from Accurate Crash Report Narratives

Body Region and Injury	A	B	C	Total
Head Swell/Brain Bleed	44	2	2	**48**
Head Broken/Fractured	26	2	0	**28**
Head Abrasion	7	8	5	**20**
Head Bump	0	5	9	**14**
Head Contusion	8	10	3	**21**
Head Laceration/Avulsion	38	28	14	**80**
Concussion	9	15	3	**27**
Neck Abrasion/Laceration/Sprain/Strain/Swell/Contusion	5	3	5	**13**
Face Contusion/Swelling	14	17	12	**43**
Face Bump/Loss of Teeth	0	3	7	**10**
Face Laceration	35	47	42	**124**
Face Fracture	22	9	2	**33**
Face Abrasion	21	16	7	**44**
Spine Broken/Fractured	32	3	0	**35**
Spine Strain	0	3	24	**27**
Thorax Broken/Fractured	67	15	0	**82**
Thorax and Abdomen Contusion/Strain/Laceration/Abrasion	8	14	9	**31**
Internal Organ Damage	60	5	0	**65**
Upper Extremity Sprain/Strain/Contusion/Swelling/Bump/Numb	7	10	19	**36**
Upper Extremity Dislocation/Separation/Break/Sever/Fracture	66	73	8	**147**
Upper Extremity Laceration/Avulsion	30	32	21	**83**
Upper Extremity Abrasion	23	29	19	**71**
Lower Extremity Swelling/Bumps/Sprain/Contusion/Numb	11	23	22	**56**
Lower Extremity Break/Fracture/Dislocation/Sever	206	51	5	**262**
Toe and Foot Break/Fracture	5	6	1	**12**
Lower Extremity Laceration/Avulsion	18	16	14	**48**
Lower Extremity Abrasion	16	25	18	**59**
Bumps/Bruises/Sprain/Swelling/Muscle Spasm/Whiplash	14	10	35	**59**
Broken Bones/Fractures	7	0	0	**7**
Lacerations	11	14	8	**33**
Bleeding	36	18	17	**71**
Abrasions	18	22	7	**47**
Headache/Dizzy/Nausea	1	6	41	**48**
Unconscious	70	13	9	**92**
Total	**935**	**553**	**388**	**1,876**

In total, for the 34 injury descriptions and symptoms found in the crash report narratives, there were 1,876 total references to the injuries. Most of these (935) references were from "Incapacitating Injury" crashes. "Non-Incapacitating Injuries" accounted for 553 references, and "Possible Injuries" accounted for 388 references. These injury descriptions will be used to help create models to estimate injury severity at the scene of a crash.

Examining Table 10 shows that law enforcement officers referenced specific injuries more frequently for some injury severities than others. Injuries such as head swelling and brain bleeds, unconsciousness, internal organ damage, spine breaks and fractures, and lower extremity breaks and fractures are primarily "A" type injuries. Similarly, concussions appear to be related to "B" type injuries. Injury descriptions for "C" type injuries include headaches, dizziness and nausea, bumps and contusions, and spine strains.

The data was also shown graphically by injury severity to determine which types of injuries were most common for each injury severity. The injury descriptions and symptoms noted by law enforcement officers in crash report narratives for each injury severity level are shown in Figure 8,Figure 9, Figure 10.

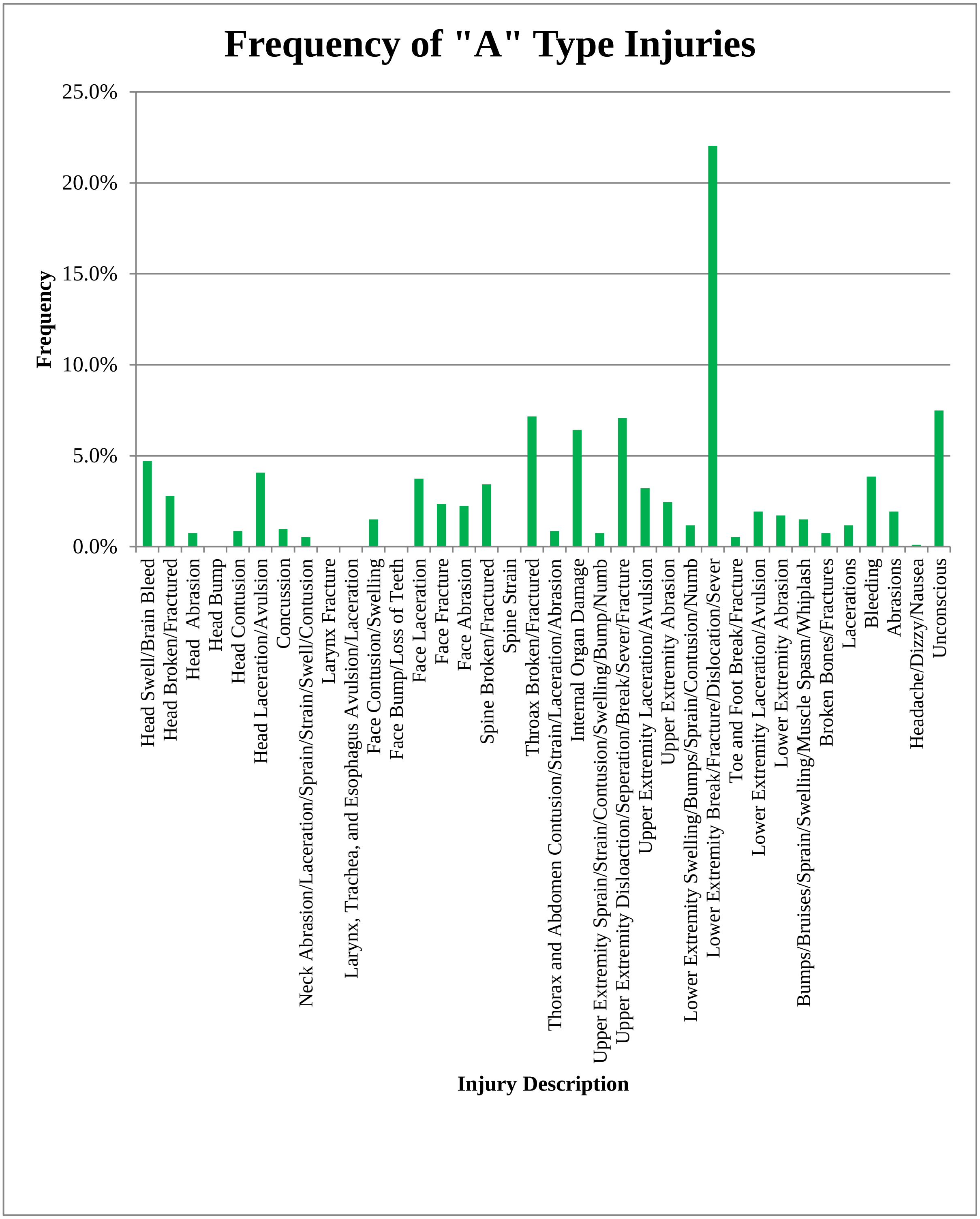


Figure 8 Frequency of Injury Descriptions for Incapacitating Injuries

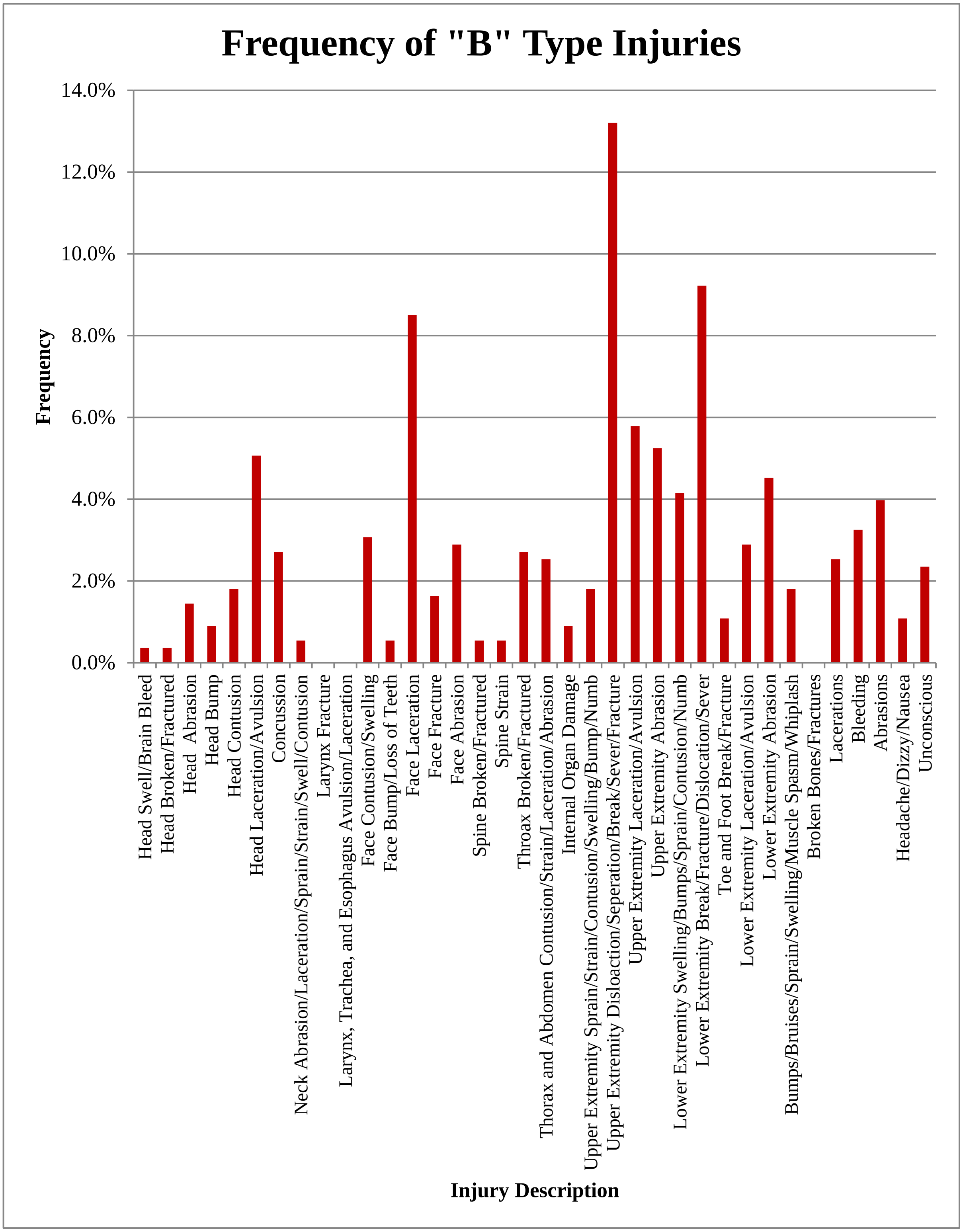


Figure 9 Frequency of Injury Descriptions for Non-Incapacitating Injuries

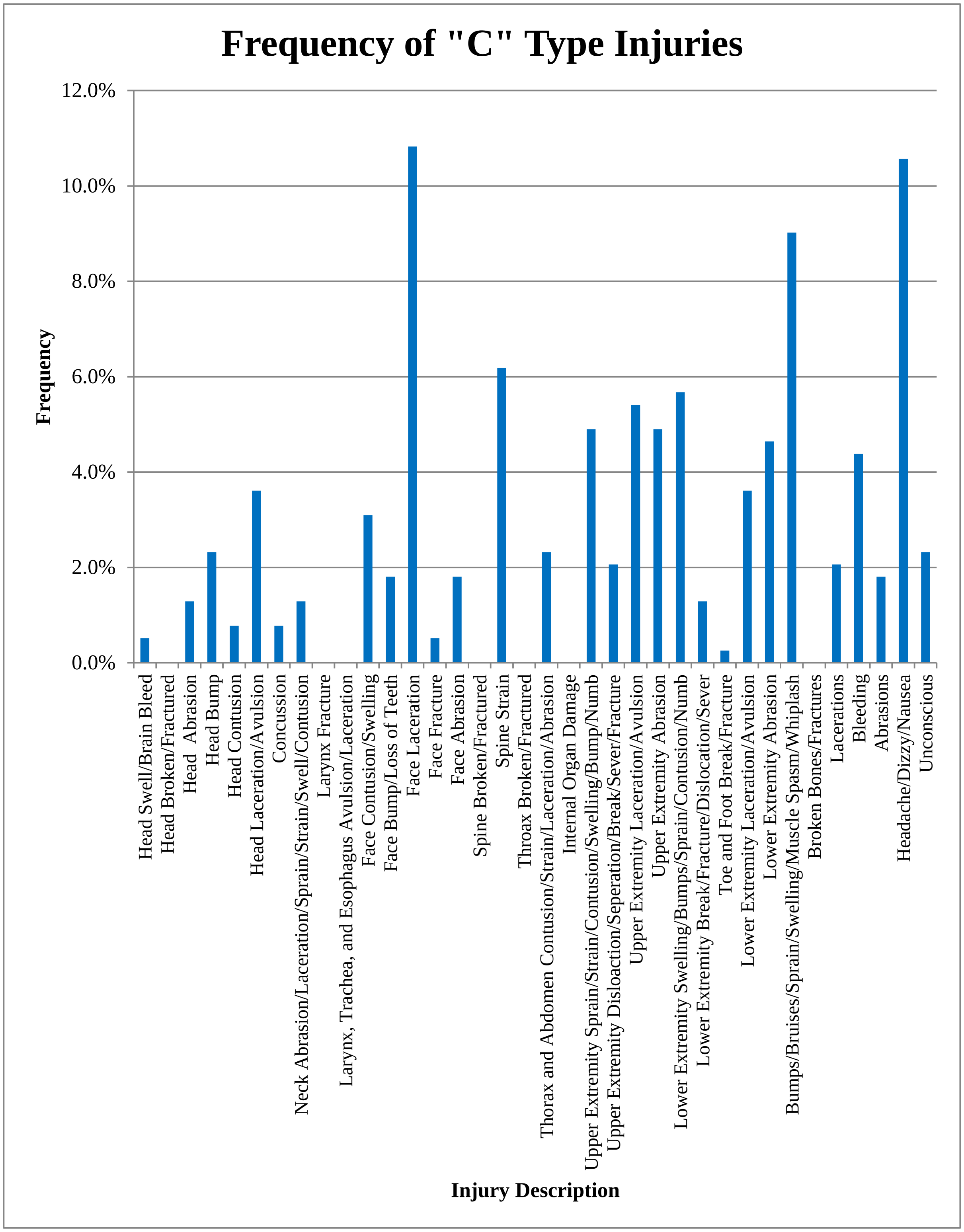


Figure 10 Frequency of Injury Descriptions for Possible Injuries

From examining the frequency of injuries for "Incapacitating Injuries", shown in Figure 8, lower extremity breaks and fractures can be seen to be the most frequent injury referenced for injury severity "A". Additional "A" type injuries included internal organ damage, or if the crash victim was found to be unconscious at the scene of the crash. Figure 9 shows the most common type of "Non-Incapacitating Injury" to be upper extremity breaks and fractures. Additionally, common "B" type injuries included cuts to the head and face region. From Figure 10 the most common type of "Possible Injury" was face lacerations. Additionally, for "C" injuries law enforcement officers noted headaches, feelings of dizziness or the crash victim feeling nauseous. Other common "C" type injuries included bumps and bruises, abrasions, and sprains.

5.1.2 Analysis of Additional Variables

In addition to injuries noted in the crash report narrative, other information noted by law enforcement officers on crash reports was included in the analysis. This information included the crash type, if safety equipment (seatbelt, child seat, etc.) was used, if the vehicle was speeding, and vehicle type (motorcycle, pedestrians and bicycles, and cars and trucks). These variables were included to increase the injury severity estimation accuracy.

The proportion of crashes by crash type for each injury severity is shown in Table 11. Safety equipment use by injury severity is shown in Table 12. The proportion of crashes by vehicle type for each injury severity is shown in Table 13.

Table 11 Crash Type by Injury Severity

	Crash Type						
Injury Severity	**No Collision**	**Angle**	**Head On**	**Sideswipe Same**	**Sideswipe Opp.**	**Rear End**	**Unknown**
A	61.1%	23.5%	5.6%	3.2%	0.6%	5.2%	0.6%
B	57.8%	23.0%	3.2%	4.9%	0.6%	9.0%	1.5%
C	27.3%	40.0%	1.3%	6.3%	1.0%	21.3%	2.7%

Table 12 Safety Equipment by Injury Severity

	Safety Equipment Use	
Injury Severity	**Safety Equipment**	**No Safety Equip**
A	74.9%	25.1%
B	82.8%	17.2%
C	89.7%	10.3%

Table 13 Vehicle Type by Injury Severity

	Vehicle Type		
Injury Severity	**Bike/Pedestrian**	**Motorcycle**	**Car**
A	28.1%	24.4%	47.5%
B	25.0%	21.5%	53.5%
C	7.7%	4.7%	87.7%

From Table 11, the most frequent type of crash for injury severities "A" and "B" is "No Collision". This includes vehicles colliding with fixed objects, as well as with bicycles and pedestrians. Angle crashes are the next most frequent. For injury severity "C", angle crashes are the most frequent, accounting for 40% of crashes. For injury severity "C", rear ends account for 21.3% of crashes, or twice as frequent as rear end crashes for injury severities "A" and "B". Unknown crashes are crashes where the law enforcement officer could not determine the crash type at the scene of the crash. This may be due to the vehicles being removed before the officer arrived at the scene, or the crash type being unfamiliar. These crashes accounted for 0.6% (3 crashes), 1.5% (5 crashes), and 2.7% (8 crashes) of "A", "B", and "C" crashes respectively. If the crash type was not able to be determined by the law enforcement officer when completing the crash report form, the crash was not included in the modelling.

From Table 12, seatbelt use appears correlated to injury severity. As injury severity increases, the proportion of crash victims who did not use safety equipment during the crash increases. When the injury severity is "C", only 10.3% of crash victims use no safety equipment. When injury severity is "A", the percentage of crash victims not using safety equipment is 25.1%. The proportion may be so high for injury severity "A" partially because it includes crash victims who were pedestrians.

Table 13 shows the proportion of vehicle type by injury severity. When a crash includes a bicycle, pedestrian, or motorcycle the crash is more likely to be more severe. For crash victims on bicycle, pedestrian, or motorcycle most were injury severity "A". For injury severity "A", 28.1% of crash victims were bicyclists or pedestrians, and 24.4% of crash victims were motorcyclists. Conversely, for injury severity "C" only 7.7% of crash victims were pedestrians or bicyclists, and only 4.7% of crash victims were motorcyclists. This is due to the crash victims being more vulnerable when they are not in a car or truck.

5.2 Injury Severity Estimation Using Multinomial Logistic Regression

The first method used to estimate injury severity was multinomial logistic regression. Multinomial logistic regression was used because the response, injury severity, can take three values: the probability of injury severity "A", the probability of injury severity "B", and the probability of injury severity "C". For the multinomial logistic regression model there were two equations created to solve for the probability of each injury severity, given specific injuries as the predictors. In multinomial logistic regression, the two equations use a baseline probability. For these equations, the baseline was the probability of injury severity "C".

The list of variables removed from the full model including all 38 variables, shown in Table 14.

Table 14 Variable Selection and AIC

# Removed	Variable Removed
-	Full Model (38 variables)
1	Lower Extremity Swelling
2	Lower Extremity Laceration
3	Neck Abrasion/ Contusion
4	Face Fracture
5	Concussion
6	Face Abrasion
7	Lower Extremity Abrasion
8	Thorax and Abdomen Contusion
9	Head Bump
10	Speeding
11	Head Abrasion
12	Face Contusion
13	Headache, Dizzy, Nausea

In total, 13 variables were removed due to confounding, or due to the AIC equation selecting their removal for a better model. After removing the 13 variables shown in Table 14, the final AIC was 725.5, reduced from an AIC of 852.7 for the full model including all terms. If the model only included the intercept term, the AIC would be 1,714.5. Once the optimized model using AIC has been determined there are 25 terms left in the final model. The final list of predictors and the corresponding variable name, along with their significance and coefficients are shown in Table 15.

Table 15 Final Model Coefficients

			Coefficients	
Predictors	Variable Name	Statistical Significance	Model I	Model J
Intercept			-1.097	-0.724
Unconscious	x_1	<0.001	22.170	0.866
Bleeding	x_2	<0.001	19.867	-0.328
Upper Extrem. Abrasion	x_3	<0.001	1.168	-2.713
Upper Extrem. Dislocation/ Seperation/ Break/ Sever/ Fracture	x_4	<0.001	1.435	2.331
Internal Organ Damage	x_5	<0.001	2.378	3.230
Face Laceration	x_6	<0.001	0.683	-1.370
Vehicle Type	x_7	<0.001		
Bike/Ped	I($x_{7,}$ BikePed)		-0.699	-0.709
Car	I($x_{7,}$ Car)		-1.981	-1.902
Head Swell/ Brain Bleed	x_8	<0.001	3.852	0.044
Thorax Broken/ Fractured	x_9	<0.001	19.934	16.303
Upper Extrem. Sprain/Strain/ Contusion/ Swelling/ Bump/ Numb	x_{10}	<0.001	-1.779	0.758
Lower Extrem. Break/ Fracture/ Dislocation/ Sever	x_{11}	<0.001	4.667	3.176
Bumps/Bruises/Sprain/Swelling/ Muscle Spasm/Whiplash	x_{12}	<0.001	20.359	20.708
Abrasions	x_{13}	<0.001	19.912	-1.117
Broken Bones/ Fractures	x_{14}	0.001	21.222	-0.391
Spine Strain	x_{15}	0.001	-20.283	2.106
Spine Broken/ Fractured	x_{16}	0.001	2.008	1.327
Head Laceration/ Avulsion	x_{17}	0.002	1.435	1.060
Upper Extrem. Laceration/ Avulsion	x_{18}	0.002	1.520	-0.636
Toe and Foot Break/Fracture	x_{19}	0.007	20.204	21.095
Face Bump/ Loss of Teeth	x_{20}	0.007	-19.617	-20.638
Head Broken/ Fractured	x_{21}	0.009	2.317	1.620
No Safety Equipment	x_{22}	0.009	1.158	0.909
Lacerations	x_{23}	0.013	20.177	0.207
Crash Type	x_{24}	0.016		
Angle	I($x_{24,}$ Angle)		-0.048	0.500
Head On	I($x_{24,}$ Head On)		0.774	1.143
No Collision	I($x_{24,}$ No Coll)		0.925	1.413
Rear End	I($x_{24,}$ Angle)		-0.569	0.224
Side Swipe Opp.	I($x_{24,SSO}$)		-0.143	0.738
Head Contusion	x_{25}	0.047	1.053	2.328

For multinomial logistic regression there are two equations, one used to calculate log-odds of injury severity "A" over "C", and one used to calculate the log-odds of injury severity "B" over "C". The final logistic regression equations used are shown in Equations (10), and (11). Equation (10) corresponds to model I in Table 15, and Equation (11) corresponds to model J.

$$\log\left(\frac{\pi_A}{\pi_C}\right) = -1.097 + \sum_{i=1}^{25} \beta_i x_i \tag{10}$$

$$\log\left(\frac{\pi_B}{\pi_C}\right) = -0.724 + \sum_{j=1}^{25} \beta_j x_j \tag{11}$$

For the logistic regression models variable x_7, the variable for vehicle type has 3 levels: motorcycle, bicycle and pedestrian, and car. Two of the three levels have their own indicator variable, while motorcycle is the default. In other words, when the vehicle type is motorcycle the two indicator variables for x_7 will be zero, and the intercept will be the effect from bicycle/motorcycle on the log-odds. Similarly, for x_{24}, the variable for crash type has 6 levels, where same side sideswipe is the baseline.

In general, a positive value for the β coefficients corresponds to an increase in the log-odds, and a negative β value corresponds to a decrease in the log-odds. The greater the absolute value of the coefficient, the greater the increase or decrease in odds. When a β coefficient has a large positive value, the odds of a crash victim having injury severity "B" or "C" are much higher than a crash victim having injury severity "A". Conversely, when a β coefficient has a large negative value, the odds of a crash victim having injury severity "A" are much higher injury severity "B" or "C".

Using the models in equations (10) and (11) the probabilities of injury severities "A", "B", and "C" can be calculated using Equations (6), (7), and (8). The injury severity with the highest probability was chosen as the final estimated injury severity. The estimated injury severity for each crash was compared with the actual injury severity outcome, shown in Table 16.

Table 16 Accuracy of Logistic Regression Injury Severity Estimation

	Observed			
Estimated	A	B	C	**Accuracy**
A	72	13	2	**77.4%**
B	11	35	10	**50.7%**
C	10	21	48	**80.0%**
Total	**93**	**69**	**60**	**69.8%**

The logistic regression model does quite well at estimation injury severity when compared to the current rate of law enforcement officer assessment. The logistic regression model estimates injury severity “A” accurately in 81.7% of crashes, compared to a law enforcement officer’s current rate of 33% accuracy. Additionally, the model only estimates injury severity “C” when the actual injury severity is “A” in approximately 9% of crash victims. Injury severity “B” is improved to 61%, compared to current law enforcement officer assessment of only 18%. For injury severity “C”, the model estimation is accurate in 80% of crash victims, as opposed to 89% for law enforcement officers currently. However, if this model was used as guidance at the scene of the crash, a law enforcement officer’s assessment of injury severity “C” is not likely to drop. Overall, accuracy improved from 51% to approximately 75%, and would likely be higher in the field considering law enforcement officer’s proficiency at assessing injury severity “C”.

5.3 Injury Severity Estimation Using Classification Trees

5.3.1 Classification Tree Construction

All 34 injury description variables and the additional 4 variables tested were added to the model. The final injury severity estimation at each terminal node is based off the injury severity level with the highest probability at that node. The classification tree created without using misclassification costs is shown in Figure 11. In the classification tree, each splitter node is colored white. Above each node is the splitting variable criteria. If the injury, or crash condition was noted by the law enforcement officer in the crash the branch to the left was followed; this branch is denoted with a “Yes” box. If the injury or crash condition was not present, the branch to the right is followed; this branch is denoted with a “No” box. Each colored circle corresponds to an injury estimation. The injury severity estimated is present inside each circle, as well as color coordinated, where green corresponds to injury severity “A”, red corresponds to injury severity “B”, and blue corresponds to injury severity “C”. Beside each terminal node estimating injury severity is the frequency of injuries of each severity found at that node. The top row is the number of “A” crashes, followed by “B” crashes, and finally “C” crashes.

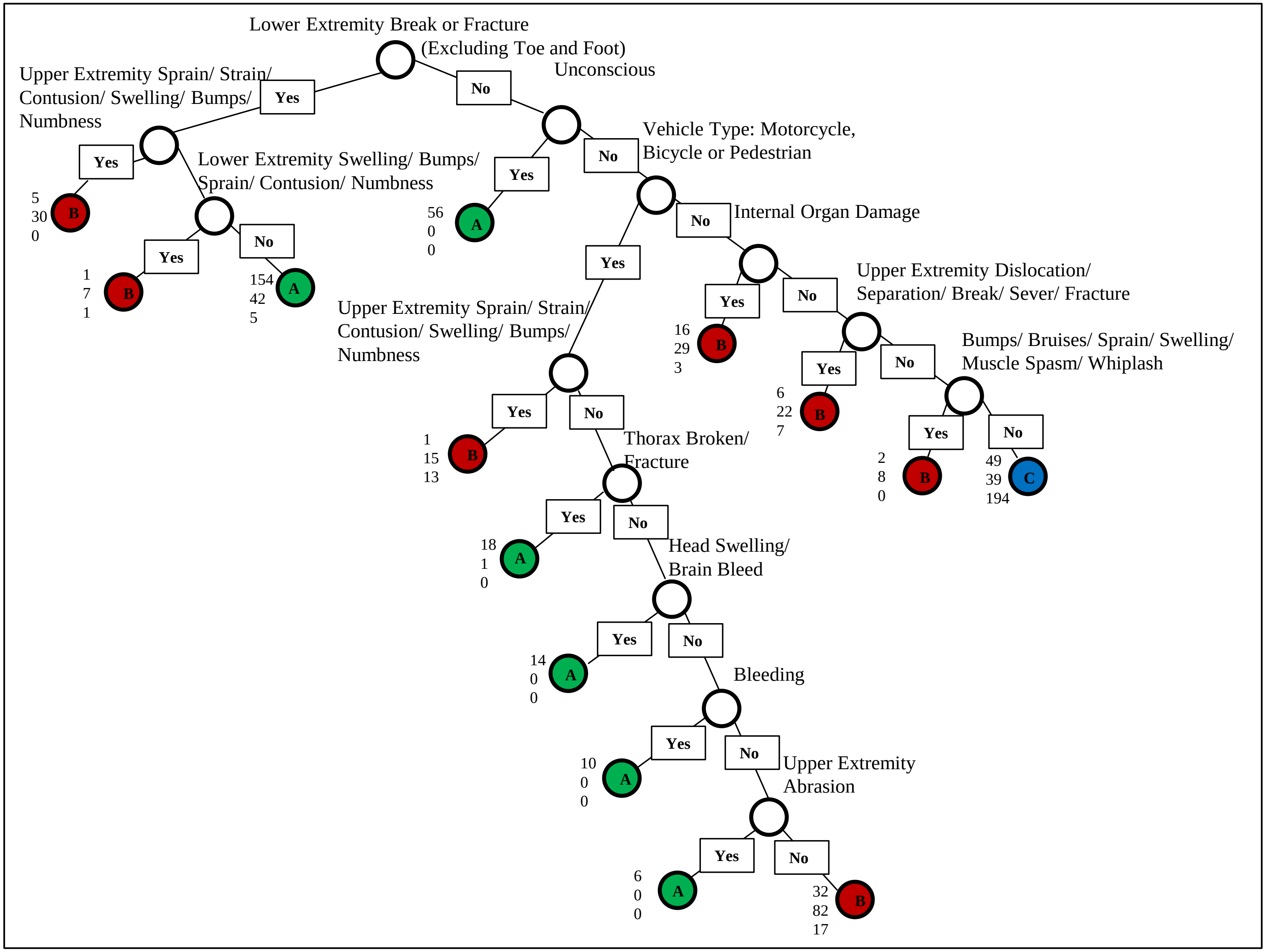


Figure 11 Classification Tree without Misclassification Costs

The classification tree created without using misclassification costs has 14 terminal nodes to estimate injury severity. Of the 14 nodes, 6 estimate injury severity “A”, 7 estimate injury severity “B”, and only 1 node estimates injury severity “C”. The node that estimates injury severity “C” is the final node of the tree, if all other injury and crash conditions have a “No” response the classification tree estimates the rest will be injury severity “C” due to 69% of the rest of the crashes being injury severity “C”.

The sample of the dataset for validation was then used to check the accuracy of the classification tree. The results for the classification tree created without misclassification costs are shown are Table 17.

Table 17 Accuracy of Classification Tree without Misclassification Costs Injury Severity Estimation

	Observed			
Estimated	A	B	C	**Accuracy**
A	62	8	1	**66.7%**
B	13	43	9	**62.3%**
C	18	18	50	**83.3%**
Total	**93**	**69**	**60**	**69.8%**

The classification tree without misclassification costs estimates injury severity with an overall accuracy of 69.8%, compared with the current assessment rate of 51% accuracy from law enforcement officers in the field. Much of this improvement is due to the estimation of injury severity “A” and “B”, which increased from 33% and 18% to 66.7% and 62.3%, respectively. This improvement of “A” and “B” injury severity assessment is important because these injury severities have much higher crash costs and impact determination of “hot spots” far more than injury severity “C”. Injury severity “C” dropped slightly from the current assessment rate of 89% to 83.3%.

Classification Tree with Misclassification Costs

To try and further improve injury severity estimation, especially for injury severities “A” and “B”, another classification tree was created using misclassification costs. The classification tree constructed using NSC crash costs calculated in Table 2 is shown in Figure 12. All formatting for the classification tree remains the same as the previous tree.

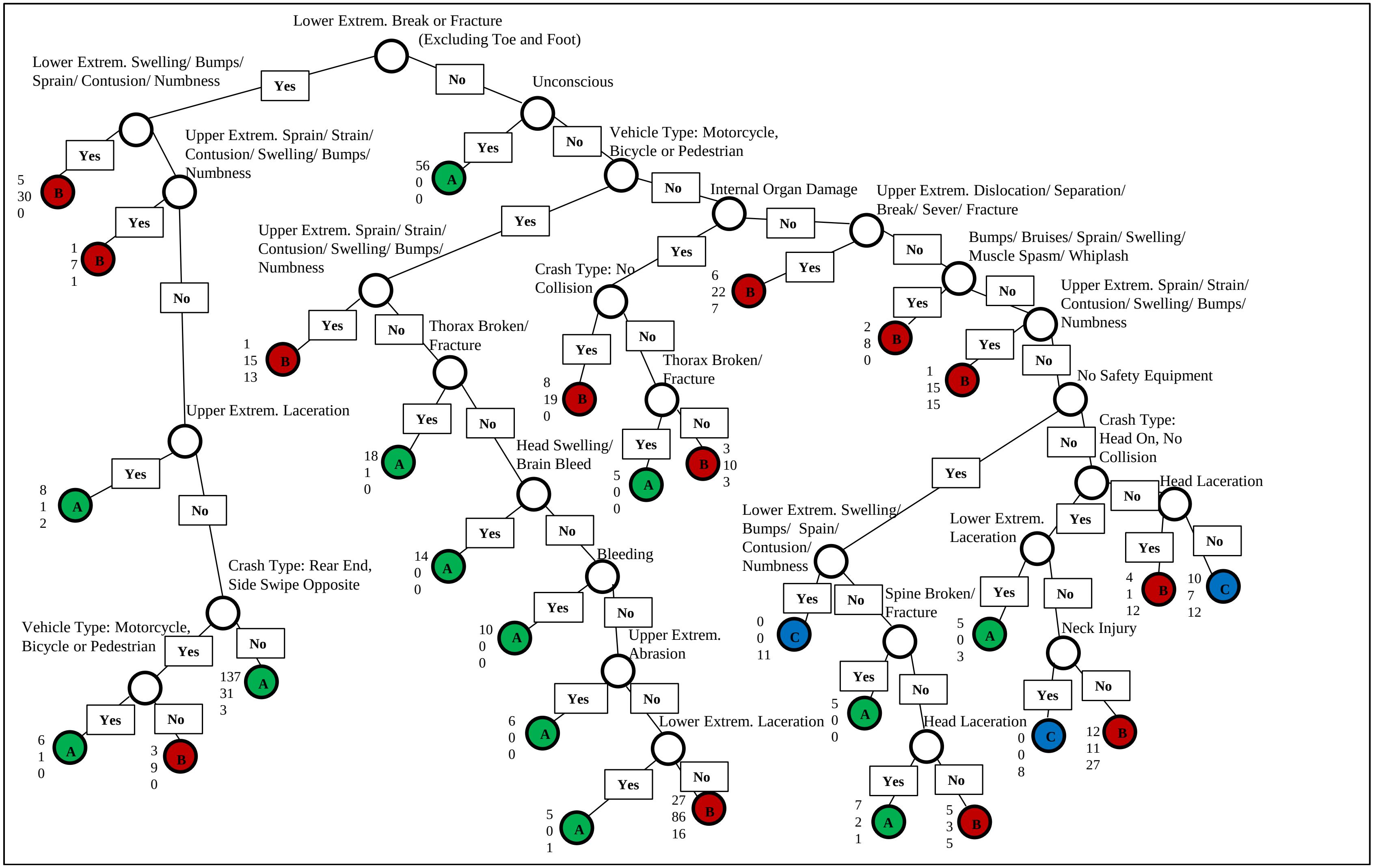


Figure 12 Classification Tree with National Safety Council Misclassification Costs

Using misclassification costs to construct the tree created a much more "full" tree than the tree using unit misclassification costs. The high penalty associated with misclassification has forced the tree to add branches to terminal nodes with large numbers of crashes, to further refine the estimation of injury severity. Another difference between the two classification trees is the method in which the injury severity for each terminal node is estimated. When misclassification costs are used to construct a tree, the tree often choses the middle level, injury severity "B", rather than simply assign the highest frequency injury severity level. This is due to the high penalty associated with an incorrect classification.

The classification tree constructed using NSC crash costs for misclassification costs has 29 terminal nodes to estimate injury severity. Of the 29 terminal nodes, 13 estimate injury severity "A", 13 estimate injury severity "B", and the remaining 3 estimate injury severity "C". Both classification trees primarily pick injury severities "A" and "B". This may be due to the injury types most commonly seen with injury severity "C" often occurring for higher severity crashes as well, confounding the estimation of injury severity "C".

Once the tree was constructed, the validation sample was used to check the accuracy of injury severity estimation. The results are shown in Table 18.

Table 18 Accuracy of Classification Tree with Misclassification Cost Injury Severity Estimation

	Observed			
Estimated	A	B	C	**Accuracy**
A	65	8	4	**69.9%**
B	21	55	24	**79.7%**
C	7	6	32	**53.3%**
Total	**93**	**69**	**60**	**68.5%**

Constructing the classification tree with misclassification costs improved the accuracy of "A" and "B" injury severity estimations at the cost of reducing the estimation of injury severity “C”, when compared to the classification tree without misclassification costs. From the previous classification tree injury severity “A” estimation increases from 66.7% to 69.9%, far above the current 33% accuracy law enforcement officers have when assessing injury severity at the scene of a crash. Injury severity “B” estimation increased from 62.3% to 79.7%, from the current 18% accuracy. Injury severity decreased when misclassification costs were used to construct the classification tree, from 83.3% to 53.3%. The overall accuracy decreased slightly with this classification tree from 69.8% to 68.5%.

5.4 Summary of Estimation Models

Both the logistic regression model and the classification trees constructed greatly improved injury severity estimation accuracy from the current rates from the scene of a crash. Injury severity estimation of more serious injury severities “A” and “B” improve greatly, regardless of which model is used. Table 19 compares the current injury severity assessment accuracy with the estimation accuracy of each model created.

Table 19 Comparison of Model Accuracies

	Injury Severity Assessment Accuracy			
KABCO Injury Severity	Existing Officer Accuracy	Logistic Regression Model	Classification Tree without Misclassification Costs	Classification Tree with Misclassification Costs
A	33%	82%	67%	70%
B	18%	61%	62%	80%
C	89%	80%	83%	53%
Overall (Total)	**51%**	**75%**	**70%**	**69%**

Both the logistic regression model and the classification trees raise injury severity estimation for more serious injury severities “A” and “B” substantially. Particularly for injury severity “A”, where the accuracy is at least doubled for every model created. Additionally, injury severity “B” is increased by at least three times compared to the existing accuracy of law enforcement officer’s injury severity assessment. Injury severity “C” estimation drops from the existing injury severity assessment accuracy for every model created. This is not thought to be a problem, as a law enforcement officer will likely estimate injury severity “C” with the same accuracy that they currently do, even if guidance is used to assist with injury severity assessment.

The logistic regression model accuracy for injury severity “A” suggests it would be a better model to use for injury severity estimation. While estimation of injury severity “B” is higher when using classification trees, the accuracy of estimation for injury severity “A” is more important, due to the high cost associated with "A" crashes and the recent focus on serious injury crashes. The classification tree does offer some benefits, such as misclassification costs, which lower the number of incorrectly assessed crashes from “A” to “C”, and vice versa. Additionally, the classification tree has the benefit of being easily understood visually.

6. Conclusions and Future Research

6.1 Conclusions

Due to changes in recent legislation, a much higher emphasis has been placed on using serious injuries as a metric for highway safety. This change means the accuracy of injury severity, particularly incapacitating injuries (injury severity “A”), is of upmost importance. The CODES dataset revealed that only 33% of “A” crashes, and only 18% of “B” crashes, are accurately assessed. Overall, law enforcement officers assess injury severity accurately for only 51.4% of crash victims. Injury severity assessment accuracy can be improved by examining crashes where injury severity was overestimated, underestimated, and accurately assessed to create guidance for law enforcement officers at the scene of the crash.

From examining overestimated and underestimated crashes, analyses showed that law enforcement officers missed an injury in a crash victim approximately 50% of the time. Factors such as the presence of alcohol, the gender of a crash victim, lighting conditions at the scene of a crash, and the type of vehicle impacted an officer’s assessment of injury severity for overestimated and underestimated cases. When examining the body regions injured as assessed by a medical practitioner, the proportions of body regions injured differed significantly from the total sample for both underestimated and overestimated cases. The only exception was crash victims with underestimated injury severity who suffered from a lower extremity injury. The results from crash victims with inaccurately assessed injury severity show law enforcement officers have difficulty accurately assessing injuries to most body regions, can miss a large portion of injuries, and extraneous factors can impact their assessment of injury severity at the scene of the crash.

Accurately assessed injury severity crash victim’s crash reports were examined to gather information such as injury descriptions from the crash report narrative, if any, and other factors such as vehicle type, and crash cause as noted by a law enforcement officer. These factors were used to create and compare models to estimate injury severity. Both the logistic regression model and the classification trees improved estimation of injury severity greatly. Overall, both logistic regression and classification tree estimated injury severity at 70%. Logistic regression is better at estimating injury severity"A" than the model created using classification trees with and without misclassification costs. Logistic regression estimates injury severity "A" correctly 77% of the time, compared to 67% for the classification tree without misclassification costs, and 70% for the classification tree with misclassification costs. Injury severity "B" also increased from the current accurate assessment rate of 18% to 51% for the logistic regression model, 62% for the classification tree without misclassification costs and 80% for the classification tree with misclassification costs. Estimation of injury severity "C" decreases for each of the models created, but this reduction would likely not be seen in the field because officer's will likely estimate injury severity "C" with the same accuracy as before. Given the high overall estimation accuracy, and the high estimation of "A", logistic regression is the best model to estimate injury severity.

Based on all findings from overestimated, underestimated, and accurately assessed injury severity the following guidance can be provided to law enforcement officers to aid in injury severity assessment:

- Adoption of KABCO definitions provided in the 4th edition of the MMUCC will improve accuracy and standardize injury severity assessment. Additionally, the MMUCC provides examples of injuries for each injury severity. The definitions provided in the MMUCC definitions also align more closely with the AIS definitions for injuries.

- When alcohol is present at a crash, the crash victim is a female, the crash victim is a bicyclist, pedestrian, or motorcyclist the law enforcement officer needs to take caution when assessing injury severity. The assessment should be made solely on injuries found from assessing the crash victim, and all extraneous factors should be ignored.
- Crashes occurring at night require extra caution on the part of the law enforcement officer, as injuries suffered by a crash victim may be missed during low light conditions. Interviews with a crash victim, when possible, can ensure injuries are not missed. This can reduce number of occult injuries missed at the scene of a crash, and the number of superficial injuries overestimated.
- Medical professionals, such as paramedics at the scene of the crash, or medical professionals at a medical center can provide insight into the injuries and should be consulted about the crash victim’s condition, when possible.
- Using the logistic regression model created, along with a law enforcement officer’s judgment and experience can greatly improve the injury severity assessment of crash victims at the scene of the crash.

6.2 Future Research

Future research could build on the models created by analyzing more crash reports to find more injury descriptions listed in the crash report narratives. A more complete dataset may lead to more accurate and complete logistic regression models and classification trees. The addition of more covariates related to the crash may improve the accuracy. Misclassification costs could be incorporated into the logistic regression model to further improve the accuracy of the model.

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