METHODOLOGY FOR THE DEVELOPMENT AND VALIDATION OF INJURY PREDICTING ALGORITHMS

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ABSTRACT

Current Automatic Collision Notification Systems (ACN) utilize deltaV as a simple predictor of injury likelihood. When considered independently, this single variable provides a general indication of injury potential, yet it lacks specificity to adequately distinguish between injured and uninjured occupants in many cases. However, when additional crash attributes are considered in conjunction with deltav, the accuracy of injury predictions greatly improves. The following paper presents two crash models of varied complexity and compares their predictive ability with predictions based on deltaV alone.

Within this paper, regression models are presented which relate occupant, vehicle and impact characteristics to two different injury outcome variables. These are Maximum Abbreviated Injury Scale Level (MAIS) and occupant Injury Severity Score (ISS). The accuracy of proposed models are evaluated using National Automotive Sampling System/ Crashworthiness Data System (NASS/CDS) and Crash Injury Research and Engineering Network (CIREN) case data.

Cumulatively, the positive prediction rate of models identifying the likelihood of MAIS3 and higher injuries is 74.2%. Regression models which predict ISS on a continuous scale correctly identify injured occupants with a sensitivity of 86.1%. The predictive accuracy of each model presented is compared with deltaV alone to support the need for additional model variables for use in future ACN systems.

INTRODUCTION

The National Highway Traffic Safety Administration (NHTSA) has reported that 27 million vehicles were involved in over 17 million crash events on US roadways in 2000. During these events, an estimated 2 million occupants sustained injuries requiring medical care, but only 1 in 8 sustained injuries that were considered life threatening [1]. Although these 250,000 seriously injured occupants require the most urgent medical attention, they are not easily distinguished from the less severely injured using current rescue protocols. This inability to distinguish occupants at high risk for severe injury results in costly delays in treatment and poor allocation of medical resources.

A number of crash attributes have been recognized as important indicators of injury potential, yet the use of this information to improve rescue care has been limited to date. In the event of a motor vehicle crash, potentially injured occupants rely on passing motorists or accessible cellular technology to initiate a call for help. Once this call has been made, rescue services verbally gather location and crash severity data from callers in order to select and deploy rescue services to the crash site. A study by Evanco et. al. estimates a potential reduction of 3,069 rural fatalities if notification times within one minute of the crash are achieved [2]. Clark and Cushing estimate this potential fatality reduction to be 1,697 for the 1997 fatally injured population [3].

Upon arrival to the crash, first care providers rely on anatomical, physiological and mechanism criteria to distinguish occupants who require trauma center care from those who do not. In many cases, evidence of severe internal injury is difficult to discern in the field. A large number of crash involved occupants are improperly transported to non-trauma center care before the true severity of their injuries is recognized.

Conversely, many occupants are triaged to trauma centers based on “High Suspicion of Injury” criteria in the absence of definitive evidence of injury. In this case, first care providers may choose trauma center care based on their overall impression of an occupant’s condition even if they do not meet any established trauma criteria. This use of paramedic judgment greatly improves the chance that an occupant who has sustained non-obvious or occult injuries will receive necessary trauma center care. In many cases, this practice taxes rescue and in-hospital resources.

In Miami, Florida 60% of occupants triaged to the Ryder Trauma Center under "High Suspicion of Injury" criteria are discharged within 24 hours of hospital arrival [4]. This suggests that better methods to discern the seriously injured from uninjured in the field may help to reduce the unnecessary use of valuable medical resources.

In 1997, Malliaris et. al. propose the URGENCY algorithm to predict the risk of serious injury in the event of a motor vehicle crash [5]. The algorithm processed crash conditions using logistic regression models to predict the likelihood of AIS3 or higher injury for crash involved occupants. A single regression model was developed to predict injury risk for all crash modes based on characteristics known to be influential for injury outcome. This approach is effective in the characterization of the interaction between model variables; however, it assumes that variations in crash attributes are equally influential in all crash directions. The creation of distinct crash models by impact direction is necessary to enhance the predictive ability of predictive injury models.

The following paper supports further implementation and enhancement of Automatic Collision Notification technology to improve crash rescue care. Further development of the URGENCY algorithm is described and its predictive ability is documented through an analysis of real world crash cases. Four independent injury models by crash mode were developed. Each algorithm was created in two levels of complexity and tested for its accuracy. Model performance is also compared with the use of deltaV alone as an independent predictor of injury.

DATA SOURCES AND METHODS

For this study, National Automotive Sampling System / Crashworthiness Data System (NASS/CDS) crash data was used to develop models that predict the likelihood of severe injury. Early versions of the URGENCY algorithm are based on occupant level data from NASS/CDS 1988-1995 while more recent improvements are based on NASS/CDS 1995-1999 cases. Model testing and validation was performed using NASS/CDS 2000 and 2001 data as well as Crash Injury Research and Engineering Network (CIREN) case files.

Both NASS/CDS and CIREN databases provide cases where crash attributes and their corresponding injury outcomes are known for each crash involved occupant. NASS/CDS cases provide information regarding crashes across all injury severities at a national level while CIREN cases provide more detailed investigations of occupant injury mechanism for only the most severely injured crash population.

NASS/CDS 1995-1999 cases were processed such that accident, vehicle and occupant level data are linked for any crash involved occupant twelve years and older. The analysis was performed for all occupants in any seating position. For the purpose of model development during this stage, only maximum injury severity (MAIS) and overall occupant injury severity (ISS) were necessary for processing; therefore, injury level data was not linked.

Model variables were conditioned and categorized into continuous or dichotomous variables classes. Crash attributes, where multiple categories exist, were recoded as single binary variables. Table 1 below shows a subset of model variables used in each proposed model.

Table 1. Crash attributes Considered for Regression Models

Variable	Description
DELTAV	Tot. DeltaV- High Severity Event
BELT	3-Point Belt Usage
BDPLY	Airbag Deployment
MAXC1	Maximum Exterior Crush 1 (in.)
MAXC2	Maximum Exterior Crush 2 (in.)
NARROW	Narrow Object Collision
INTRUS	Intrusion Near Occupant (in.)
EJP	Partial Occupant Ejection
EJC	Complete Occupant Ejection
SQR_AGE	Occupant Age Squared
STRIM	Steering Rim Deformation
OCCHT	Occupant Height (in.)
OCCWT	Occupant Weight (lb.)
BMI	Body Mass Index
FEMALE	Occupant Gender
TRACK	Seat Track Position
MULTI	Multiple Significant Impacts
SEATPOS	Seating Position

CIREN investigations consider only crash involved occupants who are transported to one of nine Level I trauma centers participating in the study or those who are fatally injured during a crash. Case investigations focus on fewer cases per year with significant emphasis on analysis of crash causation and injury mechanism. Accordingly, CIREN case investigations provide very detailed information regarding only the most serious crash events. CIREN cases were used primarily for recognition of injury patterns and final model validation during this study.

CIREN crash variables were coded identically to the NASS/CDS variables shown in Table 1. This allows for direct application of NASS/CDS based parameters to CIREN populations during validation. Figure 1 shows a comparison of MAIS level per crash involved occupant for NASS/CDS 2000-2001 as well as CIREN census data. It may be easily recognized that the average severity of injured occupants within the CIREN census far exceeds that of the NASS/CDS dataset. The effect of this varied distribution on model behavior will be discussed later in this text.

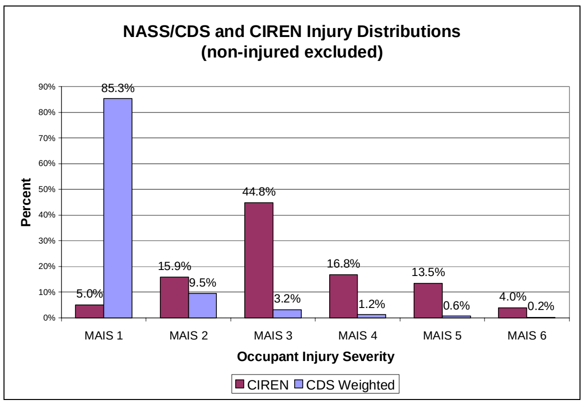

Figure 1. NASS/CDS and CIREN Injury Distribution

Regression Modelling

Simple linear regression and logistic regression techniques were used during this study to represent observable relationships between a population of independent parameters and dependant outcomes. Each approach uses the Method of Least Squares to generate a function describing the behavior of some outcome variable in terms of a series of input parameters. The primary difference between linear regression and logistic regression techniques lies in the form of the dependent outcome variable (i.e. injury measure).

Simple linear regression fits data points in order to predict outcomes which are unbounded or could have any value (positive or negative). This technique was used to linearly relate crash parameters to an ISS value on a continuous scale. Equation 1 presents a model containing two parameters (deltaV and age) as they relate to a predicted ISS value for a given crash configuration. During model fitting, values for the *intercept*, β_1 and β_2 are generated forming a linear function to best approximate ISS score based on observed crash characteristics.

Eq. 1: $$ISS = (Intercept) + \beta_1 * deltaV + \beta_2 * age$$

Alternatively, logistic regression models fit relationships to predict the probability that a selected event will occurred (yes or no response). This approach, using the Principle of Maximum Likelihood, yields a probability value on a scale which is bounded by 0 and 1 (i.e. probability of event occurrence between 0 and 100 percent). For this study, the hypothesis that a crash event will result in an MAIS3 or higher injury based on input parameters is tested. Equation 2 below defines the relationship between input parameters and the intermediate parameter *w*. When substituted into Equation 3, this parameter yields the maximum likelihood that an MAIS3+ injury will occur.

Eq. 2: $$w = (Intercept) + \beta_1 * deltaV + \beta_2 * age$$

Eq. 3: $$P(MAIS3+) = \frac{1}{(1+\exp(-w))}$$

The relationships shown above (Equations 1, 2 and 3) can be expanded to include additional crash descriptors that are known to be influential to injury risk. If a variable is significant to the modelled outcome, the addition of that parameter to the regression equation should enhance the predictive ability of the model. In some cases, however, additional model parameters do not lead to significant increases in model accuracy. Therefore, model parameters should be judiciously selected. During this study, variable selection was performed through an iterative analysis of model accuracy while parameters were added or removed from each. Details of this process have been previously reported [6].

INJURY PREDICTION BASED ON CRASH CHARACTERISTICS

In order to quantify the level of injury sustained by occupants involved in motor vehicle crashes, a consistent and meaningful measure of injury severity must first be selected. The scoring system must provide a clear indication of the most severe injury level sustained so that injured occupants may receive the most appropriate medical care in the post crash phase. At the same time, this scale must accurately reflect the total amount of crash energy to which an occupant was exposed during a crash event.

As shown in Figure 2, the risk of MAIS3+ injury (vertical markings) increases in a nonlinear fashion with respect to deltaV. When accurately calculated, deltaV provides a good indication of the kinetic energy of the vehicle/occupant system before impact. Dissipation of this energy and the degree to which an occupant is subjected to it directly relates to the level of trauma an occupant is likely to sustain.

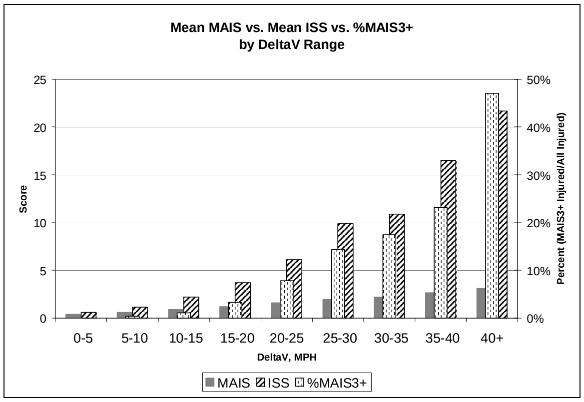

Figure 2. Injury Severity Distribution by DeltaV-Mean MAIS Value and ISS

MAIS

The Abbreviated Injury Scale (AIS) is a well established measure of trauma per injury sustained during a crash. It measures the physical disruption of tissue due to the ill effects of impact energy. An AIS score is assigned to each discernable injury across all body regions and provides an indication of the threat to life due to a specific injury. The highest AIS or Maximum AIS value (MAIS) has been used by many to represent the overall severity of injury sustained by an occupant. This measure indicates the extent of occupant injury and the corresponding level of required medical care; however, it does not adequately account for all injuries sustained across the entire body. If multiple occurrences of harmful occupant loading take place, reporting a single MAIS value does not adequately gauge the total trauma experienced by an occupant.

ISS

The Injury Severity Score (ISS), was proposed by Baker in 1974 to account for the effect of multiple injuries on mortality risk [7]. The group studied a population of motor vehicle crash victims and found that mortality increased disproportionately with AIS rating of the most severe grades. They proposed that the risk of mortality could be better correlated using a quadratic equation. The Injury Severity Score is calculated by summing the squared AIS values for three of the most severely injured body regions is shown in Equation 4 below.

Eq. 4:
$$ISS = [AIS_{\max}(region_1)]^2 + [AIS_{\max}(region_2)]^2 + [AIS_{\max}(region_3)]^2$$

Unlike the MAIS level, ISS provides an indication of the total loading or trauma sustained by the human body by including the three highest body regions and their severity in its calculation.

Figure 2 shows the mean value for MAIS and ISS for all crash modes as a function of deltaV. Superimposed on this plot is the percent of MAIS3+ injuries which are sustained within each deltaV range. The average MAIS score, indicated by the solid bars, increase linearly with respect to the deltaV range while the rate that MAIS3+ injuries occur increases in a non-linear fashion. ISS better follows the rate of serious injury (MAIS3+ injury risk) with respect to deltaV.

Similar behavior of the average ISS and the severe injury risk suggests that ISS may be a better measure of injury severity for models based on deltaV and crash energy. The ISS score also provides a graduated scale which accounts for injury severities that may extend beyond the single most severe injury (as suggested by MAIS). This hypothesis is evaluated below.

Within the following sections, logistic regression models indicating the likelihood of MAIS3+ injury and simple linear regression models predicting ISS score are presented for two levels of model complexity so that the relative accuracy of each approach may be understood.

DeltaV Threshold

Currently, ACN systems utilize a single deltaV value to initiate a rescue call in the event of a crash. In general, the threshold for ACN calls corresponds with the approximate deltaV value where airbag systems deploy. Based on an investigation of the univariate relationship between separate crash attributes and injury, deltaV provided the most meaningful estimate of occupant exposure to potentially harmful crash energy compared to other variables [6]. For this reason, its use as an indicator of injury risk in the absence of other crash information is useful. Used independently, a single cutoff deltaV can be selected where all occupants involved in crashes exceeding the chosen value would be considered potentially injured by ACN systems. Conversely, a call for help may not be initiated below this threshold value.

When NASS/CDS crash events are classified as serious or non-serious based on a single deltaV value, a series of correct and incorrect classification rates result. As the deltaV threshold level is varied, the ratio of correct to incorrect injury classifications also changes.

The accuracy of each selected deltaV threshold was judged based on the percentage of correct indications of a high risk of injury within a given population. This value is known as model sensitivity. The accuracy of this model can be further characterized by its ability to correctly predict when an injury has not occurred. This characteristic is known as model specificity. For a given population of data, Table 2 indicates the four possible classifications of an event based on observed vs. predicted injury values.

Table 2. Classification Table for Evaluation of Model Accuracy

		Predicted	
		Uninjured	Injured
Observed	Uninjured	n_{11}	n_{12}
	Injured	n_{21}	n_{22}

Eq. 5: $$Sensitivity = \frac{n_{22}}{n_{21} + n_{22}}$$

Eq. 6: $$Specificity = \frac{n_{11}}{n_{11} + n_{12}}$$

Model sensitivity, as shown in Equation 5, is defined as the number of correctly identified injured occupants divided by the complete population of those injured. A sensitivity of 75% would indicate that three quarters of all those injured were correctly identified. While one quarter of the injured population were incorrectly flagged as uninjured. The specificity of a model, as described by Equation 6, indicates the percentage of a population which is correctly diagnosed as uninjured when they are indeed not injured. Ideally, high sensitivity and high specificity are desirable for a particular cutoff value for a predictive model.

Sensitivity and specificity values provide an indication of the ability of a model to predict an outcome based on a selected probability threshold. If the probability considered to be an indication of injury was lowered, more occupants would be flagged as injured. In some cases, the injury probability calculated using by logistic regression models may exceed the injury threshold for occupants who are not injured. This would be a false positive indication and would reduce model specificity. Conversely, if the probability threshold were raised, it is possible that a model prediction for an injured occupant may not reach or exceed the injury threshold value. This injured occupant would be improperly classified as uninjured and a false negative indication would result. This improper classification would reduce model sensitivity.

As probability threshold values are varied from 0% to 100%, the number of correct and incorrect classifications can be established for each possible cutpoint. One method to evaluate the overall performance of a model is to plot the sensitivity versus 1-specificity for each threshold. This form of binary result presentation is called Receiver Operating Characteristic curve or ROC curve. A perfect model will approach 100% sensitivity with 100% specificity. The shape of this curve would be a 90 degree angle with the vertex at (0,1). Conversely, an ineffective model would show little correlation between model prediction and observed behavior so that the resulting curve would approach a straight line at 45 degrees from the origin.

Figure 3 shows sensitivity and 1-specificity values for each crash mode at several deltaV values. At a 17 mph threshold, a 65.2% sensitivity rate would result with a false prediction rate of 18% for frontal collisions. The frontal curve is shown in bold and a series of threshold values are noted in 5 mph increments along the curve.

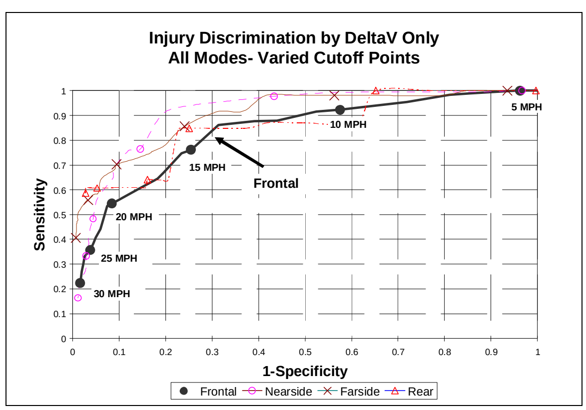

Figure 3. Single Variable Model Accuracy Based on DeltaV Only (with deltaV cutoff values)

Alternatively, a logistic regression model may be used to predict the risk of an MAIS3+ injury based soley on deltaV as shown in Table 3. Here, the intercept and regression coefficient values for the single parameter model are given. The maximum likelihood of MAIS3+ injury calculated using Equations 3 and 4 indicate that the risk of serious injury for a 30 mph crash is 43.6%. Parameter estimates for a regression model predicting Injury Severity Score (ISS) are also shown in Table 3. This model has been fit to predict the square root of ISS. As a result, the predicted ISS for a 30 mph deltaV crash event is 7.96.

Table 3. Logistic Regression and Simple Regression- 1 Parameter Model (all modes)

Model Type	Parameter (All Modes)	Estimate	Standard Error
P(MAIS3+)	Intercept	-4.1951	0.0587
	DeltaV	0.1301	0.00258
ISS Value	Intercept	-0.0776	0.02108
	DeltaV	0.0966	0.00112

These estimates of MAIS3+ injury risk and ISS level do not take any additional crash characteristics into account. When separated by crash mode, the parameter estimates for MAIS3+ injury are as shown in Table 4. Based on these model parameters, the risk of MAIS3+ injury for each mode is 38.9%, 83.8%, 47.8% and 19.9% for frontal, nearside, farside and rear impact crashes respectively for a 30 MPH deltaV. The predicted ISS values are 7.87, 21.35, 9.25 and 3.24 for each mode respectively based on model parameters shown in Table 5.

Table 4. Logistic Regression Models Predicting Probability of MAIS3+ Injury- DeltaV by Mode

Mode	Parameter	Estimate	Standard Error
Frontal	Intercept	-0.12626	0.03717
	Deltav	0.0977	0.00194
Nearside	Intercept	-0.19778	0.1151
	Deltav	0.1606	0.0061
Farside	Intercept	-0.25331	0.10488
	Deltav	0.10983	0.00543
Rear	Intercept	-0.2245	0.07375
	Deltav	0.05255	0.00429

Table 5. Simple Linear Regression Models Predicting ISS Score- DeltaV by Crash Mode

Mode	Parameter	Estimate	Standard Error
Frontal	Intercept	-0.06617	0.02604
	Deltav	0.09339	0.00135
Nearside	Intercept	-0.16719	0.09354
	Deltav	0.15466	0.00492
Farside	Intercept	-0.28818	0.08095
	Deltav	0.10973	0.00424
Rear	Intercept	-0.02787	0.06527
	Deltav	0.06802	0.00378

The significant variation in injury risk based on crash direction suggests that separate models for each mode may better predict the occurrence of injury compared to a single model which concurrently represents all crash modes. As such, separate models are presented for frontal, nearside, farside and rear impact crashes in the following sections. For each crash mode, parameter estimates are presented in two variable groupings. These groups are listed and described below.

Injury Prediction Based on Multiple Parameters

The main goal of this study is to develop injury predicting algorithms for implementation in vehicle Automatic Collision Notification Systems. With this goal in mind, the selection of model variables has been made in two stages where the first group includes variables which are currently available for processing by onboard systems. Some variables within the second group are not yet available from vehicles although results of this study support this change.

<u>Group 1- Existing Variable Set</u>

Data points included in model group 1 are shown in Table 6 below.

Table 6. Group 1 Model Variables

Variable	Description
DELTAV	Tot. DeltaV- High Severity Event
BELT	3-Point Belt Usage
BDPLY	Airbag Deployment
MODE	Crash Direction/Impact Mode
SEATPOS	Seating Position

Table 7. Group 1 Parameter Estimates and Standard Errors

Model Type	Parameter (Frontal)	Estimate	Standard Error
P(MAIS3+)	Intercept	-3.668	0.0986
	Deltav	0.1238	0.00392
	Belt	-0.8036	0.0738
	Bdply	-0.06	0.1004
ISS Value	Intercept	0.31879	0.04918
	Deltav	0.09204	0.00196
	Belt	-0.49677	0.03941
	Bdply	-0.04	0.0396

Currently, vehicles use this information for a variety of reasons including processing for occupant protection systems. During this study, it was assumed that this data is or could easily be made available for processing by injury predicting algorithms.

Model parameters for Group 1 logistic regression and simple linear regression models are shown in Table 7 for frontal crashes only. Model variables for each remaining crash mode are presented in Appendix Table A2 of this text. These models predict the likelihood of MAIS3+ injury and ISS respectively.

Group 2- Optimized Variable Set

The second level of model complexity considers additional parameters that may not be available through current sensor systems. These detailed models are presented to promote the addition of some, if not all, of these variables in order to maximize the accuracy of predictive models.

In the future, selected model parameters could be derived from basic occupant sensor technology. Upcoming regulatory requirements intend to improve the level of protection provided by advanced restraint systems through a better understanding of occupant factors (i.e. occupant height, weight, gender). These characteristics may provide additional data points for processing by on-board diagnostic systems. In the meantime, verbal communication of some data points listed below may significantly enhance the ability of ACN call takers to assess likely injury severity from remote locations.

Some of this information may also be generated through processing of raw information like vehicle acceleration profiles. Post crash processing of vehicle acceleration data may provide valuable information regarding the nature of a collision event if collected for a larger portion of the crash event. As an example, the acceleration profile for some narrow object collisions can be distinguished from profiles of other collision types due to its characteristic shape. These events are characterized by a prolonged period of moderate deceleration followed by a sharp increase in deceleration level once the narrow object begins interaction with more rigid engine and drive train components. This information could be used as a model input parameter to indicate a narrow object impact.

Processing of vehicle rotational information can be used to evaluate the potential for occupant compartment intrusion in the region of a seated occupant. During a side impact event, a sudden rotation of the vehicle could indicate loading in the front or rear third of the vehicle such that a yawing motion initiates. A side impact event that results in little or no rotation about the vehicle CG may indicate a high likelihood of interaction with the middle third of the vehicle leading to potential compartment intrusion.

Group 2 parameters were selected for optimized performance of each model by crash mode. In Table 8 below, variables selected for the Group 2 frontal model are shown. In addition, Table 9 contains parameter estimates and standard error values for logistic regression models predicting MAIS3+ injury and ISS level respectively. Variable selection and model parameters for each remaining crash type are given in Appendix Table A3 of this text.

Table 8. Group 2 Model Variables

Variable	Description
DELTAV	Tot. DeltaV- High Severity Event
BELT	3-Point Belt Usage
BDPLY	Airbag Deployment
MAXC1	Maximum Exterior Crush 1 (in.)
MAXC2	Maximum Exterior Crush 2 (in.)
NARROW	Narrow Object Collision
INTRUS	Intrusion Near Occupant (in.)
SQR_AGE	Occupant Age Squared

Table 9. Group 2 Parameter Estimates and Standard Errors

Model Type	Parameter (Frontal)	Estimate	Standard Error
P(MAIS3+)	Intercept	-4.1442	0.1426
	Deltav	0.0875	0.00696
	Belt	-0.8949	0.0895
	Bdply	-0.0205	0.0931
	maxc1	0.0182	0.00632
	maxc2	0.0404	0.016
	Narrow	0.3144	0.1145
	Intrus	0.109	0.00956
	EJP	0.8661	0.3985
	sqr_age	0.000309	0.000023
	Strim	0.2858	0.1231
ISS Value	Intercept	0.31007	0.04853
	Deltav	0.05735	0.00273
	Belt	-0.4282	0.03424
	Bdply	-0.0442	0.03156
	maxc1	0.00918	0.00251
	maxc2	0.03054	0.00634
	Narrow	0.16194	0.04938
	Intrus	0.08729	0.00427
	EJP	1.07523	0.19755
	sqr_age	0.00013	.00008
	Strim	0.43479	0.05773

MODEL PERFORMANCE

NASS/CDS 2000-2001 data and CIREN census files were used to evaluate the accuracy of each proposed model. Below, the performance of logistic regression models predicting the likelihood of MAIS3+ injury are presented in the form of ROC Curves. In addition, overall prediction counts for each crash mode are reported for each population tested. A similar evaluation of each linear regression model predicting ISS was performed; however, results of this analysis are not reported here.

For the purpose of future ACN technology, the communication of injury likelihood values (i.e. 0-100% risk of MAIS3+ injury) offers a more intuitive indication of injury risk than linear models predicting ISS. Although ISS models were discovered to yield somewhat more accurate injury predictions, MAIS3+ injury predictions are focused on here.

<u>NASS/CDS</u>

Each of the NASS/CDS populations tested is independent of the cases used to initially train the regression models. The distribution of crashes in the 2000 and 2001 NASS/CDS population includes a sample of 9,351 tow-away crashes representing a total of 4,745,144 occupants following weighting. This includes 3,122,193 drivers and 1,622,952 passengers. Appendix Table A1 shows the annual distribution of injured occupants by mode for the tow-away crash population.

It should be noted that the occupant counts for each of the four categories of planar crashes (frontal, nearside, farside and rear) do not include any occupants involved in rollovers or complete ejections. For this analysis, the occurrence of these events are not simply considered to be characteristics of other crash types but are serious enough to independently warrant rapid deployment of rescue services.

Within Appendix Table A1, the population of injured occupants involved in rollover events may include occupants who are completely ejected. However, the ejected populations listed do not include occupants who were involved in a rollover event at any point during the crash. Occupants involved in tow-away crash events where MAIS level is known are listed only once in Appendix Table A1.

Figures 4-7 show sensitivity and specificity values for each model by crash mode. To evaluate the overall accuracy of each model, classification rates were determined at a single MAIS3+ injury risk threshold value. These threshold values were selected through an evaluation of each respective ROC curve by mode. To select an injury risk threshold value, a point on each curve was identified where variation in threshold value led to equivalent changes in model sensitivity and specificity. The approximate slope of the ROC curve at this point is equal to one. The selection of this threshold value equally favors model sensitivity and specificity. For other applications, selection of this value must be made based on intended model application and tolerable false positive and false negative predictions.

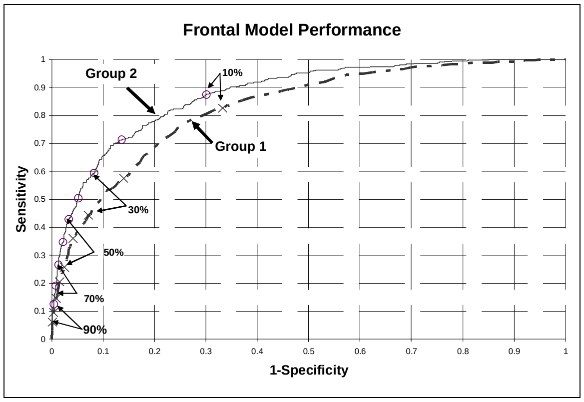

Figure 4. Group 1 and 2 Frontal Model Performance Curves (with probability thresholds)

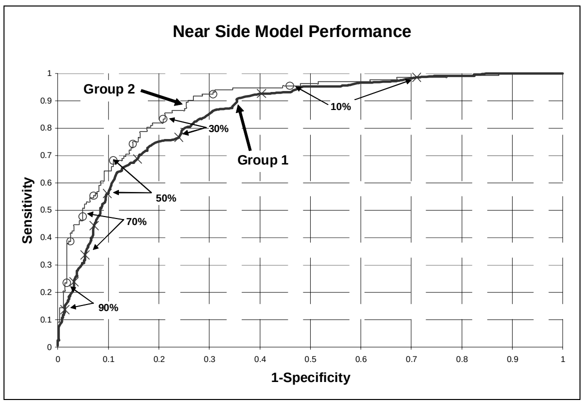

Figure 5. Group 1 and 2 Nearside Model Performance Curves (with probability thresholds)

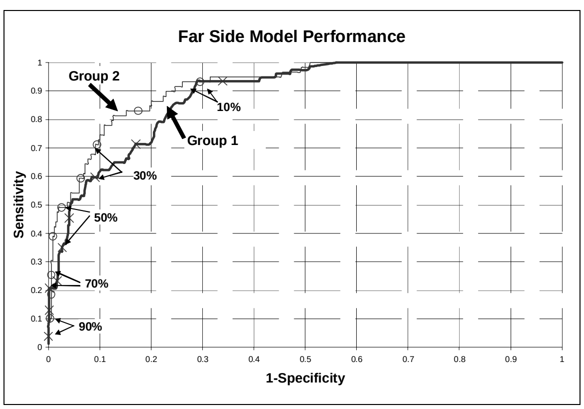

Figure 6. Group 1 and 2 Farside Model Performance Curves (with probability thresholds)

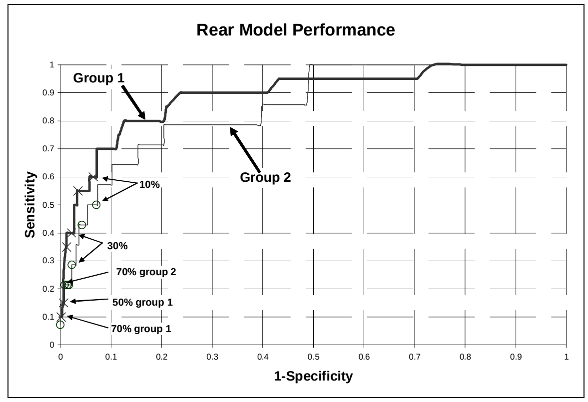

Figure 7. Group 1 and 2 Rear Model Performance Curves (with probability thresholds)

Table 10. Group 2 Model Performance at Selected Threshold Values (probability of MAIS3+ Injury)-NASS/CDS 2000-2001

Mode	Cutoff Probability	Sensitivity	1-Specificity
Frontal	19.2%	70.1%	11.2%
Nearside	29.7%	80.7%	18.0%
Farside	17.0%	78.3%	14.3%
Rear	8.4%	71.4%	11.2%
Total		74.2%	12.5%

Using threshold values (cutoff probabilities) as shown in Table 10, the overall sensitivity and specificity rates are shown by crash mode for the NASS/CDS test populations. If threshold values were shifted, model sensitivity and specificity parameters would vary in a way described by their respective ROC curve (Figures 4-7).

CIREN

The CIREN population includes 1,058 cases stored in NHTSA's database that are complete and available to date. This includes 762 drivers and 296 passengers involved in crashes where an occupant was transported to a Level I trauma center or was fatally injured. Within Table 10 below, prediction rates for Model Group 2 variables are presented. Within the CIREN crash population, too few rear impact crashes result in serious injury therefore model accuracy for this crash mode are not reported.

Table 10. Group 2 Model Performance at Selected Threshold Values (probability of MAIS3+ Injury)-CIREN Cases

Mode	Cutoff Probability	Sensitivity	1-Specificity
Frontal	19.2%	86%	41%
Nearside	29.7%	90%	27%
Farside	17.0%	65%	33%
Rear	*	*	*
Total		86.1%	39.6%

DISCUSSION OF RESULTS

During this study, two crash models of varied complexity were created to evaluate the benefit of multiple model parameters for injury prediction compared to models based soley on deltaV. Overall, model groups 1 and 2 significantly improve the accuracy of injury predictions; however, this improvement depends heavily on crash mode.

For frontal crashes, a 17 mph deltaV threshold correctly identifies 66.8% of MAIS3+ injured occupants with a false positive rate of 20% (uninjured classified as injured) when used alone. For Model Group 1, prediction rates improve somewhat where 70% of MAIS3+ injured occupants are detected with a false positive rate of 20%. The true benefit of additional model parameters can be recognized for the optimized Model Group 2 where 79% of MAIS3+ injured occupants are detected with a false positive rate of 20%.

For nearside collisions, deltaV alone provides better predictions of injury risk than those including additional attributes. For this crash mode, knowledge of restraints usage provides little information to assess injury risk. Although intrusion data provides a good indication of potentially harmful interaction with occupants, its inclusion in model Group 2 provides little improvement to model accuracy over deltaV alone.

For farside collisions, an 18 mph deltaV threshold correctly identifies 78% of MAIS3+ injured occupants with a false positive rate of 20% (uninjured classified as injured). For Model Group 1, prediction rates decline somewhat to where 72% of MAIS3+ injured occupants are detected with a false positive rate of 20%. For the optimized Model Group 2, 85% of MAIS3+ injured occupants are detected with a false positive rate of 20% for farside crashes.

For rear impacts, little benefit is observed when additional model attributes are considered (i.e. model group 2). It was discovered that model accuracy is degraded when addition parameters beyond deltaV and restraint usage are considered. In addition, standard errors for each reported estimate are high for this crash mode due to a limited population of severely injured occupants during rear impact crashes.

In total, the proposed models correctly identified 74.2% of the MAIS3+ injured occupants involved in tow-away crash events for NASS/CDS Cases from 2000 and 2001. 12.5% of the uninjured population was incorrectly classified as injured for this population. The thresholds selected for injury classification varied based on crash mode as shown in Table 10; however, the selection of this cutpoint must be made based on intended model application.

Applying threshold values as shown in Tables 10 and 11, each model was applied to recognize seriously injured occupants within the CIREN census. A model sensitivity of 86.1% and a specificity of 39.6% was found during classification of uninjured and injured crash involved populations.

As indicated by the low specificity value for this population, the number of false predictions for non-injured occupants within the CIREN sample far exceeds those for the NASS population. This occurs because each case included within the CIREN census was considered due to its high severity. It is likely that cases where no severe injury occurred and an occupant was brought to a Level I trauma center would have severe crash attributes compelling rescue providers to suspect injury based on apparent mechanism of injury. Interpretation of these severe characteristics (i.e. high deltaV, high crush, intrusion, old age) by injury predicting algorithms would naturally produce elevated indications of injury risk when, in fact no injury took place for these individuals. These missed cases suggest the need for improved estimates of occupant injury tolerance within proposed crash models.

CONCLUSIONS

It is well understood that rapid notification of rescue services and appropriate administration of medical care will reduce the likelihood of secondary injury or death of crash involved occupants. Methods to process crash conditions in order to estimate the likelihood of injury have been established and the accuracy of these methods has been reported. When compared with injury prediction based on deltaV alone, proposed models were shown to improve accuracy of injury estimates based on crash attributes available at the time of the crash.

For the NASS/CDS populations tested, the sensitivity of models predicting the likelihood of MAIS3 and higher injuries is 74.2% with an overall specificity of 87.5%. When compared with predictions based on deltaV alone, the use of proposed models offers a more accurate estimate of injury potential based on readily available crash information for frontal crashes and farside crashes. This improved accuracy is not readily observed for nearside and rear crashes.

In order to make use of any injury model including those based only on deltaV, methods to automatically collect and deliver crash information to the most appropriate individuals must be implemented. This effort will require continued cooperation between auto manufacturers, rescue providers and in hospital clinicians to collectively agree upon the most appropriate methods to reach this goal.

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APPENDIX 1. ADDITIONAL TABLES

Table A1.
NASS/CDS 2000-2001 and CIREN Case Injury Distributions (test populations)

CIREN	MAIS 0	MAIS 1	MAIS 2	MAIS 3	MAIS 4	MAIS 5	MAIS 6	Fatal
Frontal		46	128	355	81	39	0	100
Nearside		2	16	63	38	23	0	33
Farside		2	7	13	12	5	0	10
Rear		0	2	5	2	3	0	1
Rollover		2	7	19	10	6		3
Ejection		0	1	10	4	3	0	7
NASS/CDS	MAIS 0	MAIS 1	MAIS 2	MAIS 3	MAIS 4	MAIS 5	MAIS 6	Fatal
Frontal	1,060,732	819,312	83,314	28,223	5,200	2,484	36	8,845
Nearside	86,115	98,504	8,941	5,558	1,548	516	0	4,003
Farside	101,344	76,514	7,950	2,183	670	161	12	1,122
Rear	195,990	124,381	6,262	608	538	63	0	397
Rollover	150,687	203,556	32,822	11,452	5,111	1,218	0	8,394
Ejection	70	1,830	4,066	3,268	2,554	315	0	1,976

Table A2.
Logistic Regression Parameter Estimates for Model Group 1 (predicting probability of MAIS3+ Injury)

Parameter (Frontal Crashes)	Estimate	Standard Error	Pr>ChiSq
Intercept	-3.7089	0.0952	<.0001
Deltav	0.124	0.00374	<.0001
Belt	-0.8011	0.0652	<.0001
Bdply	0.03	0.0762	0.694

Parameter (Nearside Crashes)	Estimate	Standard Error	Pr>ChiSq
Intercept	-3.8684	0.2151	<.0001
deltav	0.1887	0.00987	<.0001
belt	-0.2758	0.1284	0.0317
bdply	0.2462	0.1829	0.1783

Parameter (Farside Crashes)	Estimate	Standard Error	Pr>ChiSq
Intercept	-3.8313	0.2376	<.0001
Deltav	0.1476	0.00997	<.0001
Belt	-1.1858	0.1591	<.0001
Bdply	0.1117	0.2206	0.6126

Parameter (Rear Crashes)	Estimate	Standard Error	Pr>ChiSq
Intercept	-4.8063	0.3885	<.0001
deltav	0.1395	0.0134	<.0001
belt	-1.1032	0.2738	<.0001
bdply	0.4726	0.5004	0.3449

Table A3.
Logistic Regression Parameter Estimates for Model Group 2 (predicting probability of MAIS3+ Injury)

Parameter (Frontal Crashes)	Estimate	Standard Error	Pr>ChiSq
Intercept	-4.1442	0.1426	<.0001
Deltav	0.0875	0.00696	<.0001
Belt	-0.8949	0.0895	<.0001
Bdply	-0.0205	0.0931	0.8256
maxc1	0.0182	0.00632	0.0039
maxc2	0.0404	0.016	0.0113
Narrow	0.3144	0.1145	0.006

Parameter (Nearside Crashes)	Estimate	Standard Error	Pr>Chi Sq
Intercept	-5.989	0.3173	<.0001
deltav	0.167	0.0122	<.0001
belt	-0.2638	0.1439	0.0668
narrow	1.099	0.2467	<.0001
intrus	0.0996	0.0126	<.0001
EJP	1.2517	0.3621	0.0005
AGE	0.0401	0.00335	<.0001

Intrus	0.109	0.00956	<.0001	FEMALE	0.0525	0.1338	0.6947
EJP	0.8661	0.3985	0.0298				
sqr_age	0.000309	0.000023	<.0001				
Strim	0.2858	0.1231	0.0202				

Parameter (Farside Crashes)	Estimate	Standard Error	Pr>ChiSq	Parameter (Rear Crashes)	Estimate	Standard Error	Pr>Chi Sq
Intercept	-4.7765	0.5135	<.0001	Intercept	-4.2287	1.1063	0.0001
Deltav	0.1557	0.0114	<.0001	deltav	0.1445	0.015	<.0001
Belt	-1.2287	0.1846	<.0001	belt	-1.2112	0.3179	0.0001
intru18	1.2028	1.061	0.2569	AGE	0.0147	0.00935	0.1162
EJP	1.3693	0.5745	0.0172	occht	-0.0215	0.0174	0.2171
AGE	0.0245	0.00449	<.0001				
Bmi	-0.0154	0.0168	0.3592				