ELSEVIER
Accident Analysis and Prevention xxx (2006) xxx–xxx
ACCIDENT ANALYSIS & PREVENTION
www.elsevier.com/locate/aap

Predicting severe head injury after light motor vehicle crashes: Implications for automatic crash notification systems

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Received 2 May 2005; received in revised form 24 January 2006; accepted 29 January 2006

Abstract

Motor vehicle crashes (MVC) are a leading public health problem. Improving notification times and the ability to predict which crashes will involve severe injuries may improve trauma system utilization. This study was undertaken to develop and validate a model to predict severe head injury following MVC using information readily incorporated into an automatic crash notification system.

A cross-sectional study with derivation and validation sets was performed. The cohort was drawn from drivers of vehicles involved in MVC obtained from the National Automotive Sampling System (NASS).

Independent multivariable predictors of severe head injury were identified. The model was able to stratify drivers according to their risk of severe head injury indicating its validity. The areas under the receiver-operating characteristic (ROC) curves were 0.7928 in the derivation set and 0.7940 in the validation set.

We have developed a prediction model for head injury in MVC. As the development of automatic crash notification systems improves, models such as this one will be necessary to permit triage of what would be an overwhelming increase in crash notifications to pre-hospital responders.

Keywords: Head injury; Motor vehicle crashes; Automatic crash notification systems

1. Introduction

Approximately 42,000 people die per year in the United States as a result of motor vehicle crashes (MVC). An estimated 2000–3000 of these deaths could be prevented through improvements in emergency medical system notification simply by reducing notification time to 1 min (Evanco, 1999). In fact, the average time that elapses from crash to emergency medical system (EMS) notification for fatal crashes averaged 7 min for rural MVCs. More importantly, approximately 30% of rural crashes have more than a 60-min interval between the crash event and arrival to hospital compared to only 7% of urban crashes (Champion and Cushing, 1999). These delays in reaching medical care during the golden hour of trauma resuscitation are crucial for the trauma patient's survival (Lerner and Moscati, 2001; Tallon, 2002; Pamerneckas et al., 2003).

The currently available technology within motor vehicles combined with satellite communication systems allows for timely notification of EMS to crash events. With 27 million crashes occurring annually, and a significant proportion of these crashes being minor in terms of injury likelihood, an automated system of crash notification would inundate the EMS systems within minutes (Champion et al., 1999a,b). A mechanism to identify crashes with a higher likelihood of injury would reduce the need for EMS response and could assist with a more focused deployment of resources to the crash scene. Furthermore, specific crash patterns may suggest a higher probability of specific injuries, such as traumatic brain, thoracic, or abdominal injuries, which could provide EMS providers with a tool to triage patients more accurately.

Several major motor vehicle manufacturers have included global positioning systems in their new car models, allowing for accurate location of a vehicle in a crash event. Many of

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doi:10.1016/j.aap.2006.01.008

these vehicles are also equipped with event data recording systems similar to those found in airplanes which provide detailed information of the vehicle's engine, restraint, airbag deployment, maneuvering, and braking status seconds before the crash event. These two features provide the necessary elements for an automatic crash notification system (ACNS) that could provide timely notification of the crash event as well as information regarding crash severity and injury likelihood (Champion et al., 1997, 1998, 1999a,b; Champion and Cushing, 1999).

We therefore utilized crash, vehicle, and occupant characteristics to develop a probability model for traumatic brain injury. Incorporation of such a model into automatic crash notification systems would provide the added ability to appropriately dispatch emergency personnel to those sites with a higher probability of injury. Furthermore, it would facilitate subsequent triage decisions of patients from the scene to centers with the appropriate level of neurosurgical capabilities.

2. Methods

2.1. The NASS database

Data for this cross-sectional study were obtained from the Crashworthiness Data System (CDS), a part of the National Automotive Sampling System (National Highway Traffic Safety Administration, 2003). The National Automotive Sampling System is operated by the National Center for Statistics and Analysis of the National Highway Traffic Safety Administration (NHTSA). The CDS is a nationwide annual probability sample of approximately 5000 light passenger vehicles (passenger cars, light trucks, vans, sport utility vehicles) that were involved in police-reported tow-away collisions. For each CDS case, trained investigators collect information on occupant, vehicle, and injury characteristics using three sources of data: official documents (e.g., police traffic crash reports; and vehicle, highway, and medical records); physical evidence (e.g., scene characteristics and vehicle damage profile); and interviews. In this analysis, the 1993–2001 CDS data files were used. Only persons sitting in the driver's seat were included in the analysis. Observations were weighted to reflect sampling probability and national characteristics.

2.2. Risk factor definitions

This analysis includes only those variables that could realistically be collected with existing technology and transmitted into an ACNS. These included variables related to the vehicle, its occupant, and the crash characteristics as recorded by the CDS investigators.

Driver related variables included standard demographic characteristics (e.g., age, gender) and the driver's height and weight. We excluded information regarding possible driver intoxication, because we expect that legal considerations will prohibit the use of vehicle technology that could obtain this information (e.g., a vehicle breathalyzer).

Variables pertaining to occupant safety and vehicle characteristics were obtained. Seat belt use was defined as the use of shoulder belt, lap belt, or lap and shoulder belt. Airbag deployment was defined as any evidence of driver side airbag deployment. Ejection, vehicle rollover, last driving maneuver performed prior to impact (braking, steering away from the impact, or accelerating) as well as windshield, steering wheel or dashboard damage were also assessed with respect to their ability to predict head injury. The direction of the impact in relation to the car was defined as front, rear, driver's, or passenger's side impact.

Injury severity is reported in the CDS database using the Abbreviated Injury Scale (AIS) (Association for the Advancement of Automotive Medicine, 1990). For the purposes of this analysis a victim with a severe head injury was defined as one with a head AIS of 2 or greater. This level of injury severity was chosen as it corresponds to a level of injury that would likely need neurosurgical consultation.

2.3. Statistical methods

Using the NASS sampling weights, a weighted logistic regression model of the probability of severe head injury was constructed from a derivation set comprising about a random 70% of the data and validated on the remaining 30%. Most of the predictors had a substantial portion of missing data. These data were missing in equal proportions in both the derivation and the validation sets. Assuming data were missing at random, we employed a 10-step conditional imputation procedure to fill in the missing values of the following variables: height, weight, seatbelt use, speed, braking status, steering status, accelerating status, eject status, rollover status, vehicle curb weight, airbag deployment status, windshield impact, frontal impact, panel damage, steering wheel damage, driver side impact, on speed, braking, steering, accelerating, and steering wheel damage. Imputation steps were performed using Royston's Stata-based code *uvis* and *mvis*, an implementation of the MICE method of multiple imputation (Royston, 2004; van Buuren et al., 2004). A single imputed dataset was constructed on 500 randomly chosen subsets, each approximately 1/20th the size of the derivation set. For each of the 500 bootstrap iterations, point estimates of covariates' odds ratios were obtained from the estimated coefficients of univariable logistic regression models, weighted according to the design of the NASS survey. The 95% confidence intervals were estimated from the 2.5th and 97.5th percentiles of the bootstrap results.

All statistically significant univariable predictors were then incorporated into one multivariable weighted model. This intermediate model was trimmed to the final model by retaining only the three predictors (seatbelt use, eject, delta speed) that remained significant.

We tested the performance of the final multivariable model prospectively using the validation set. Discriminatory performance of the model was internally validated, by comparing the receiver-operating characteristic (ROC) curve analysis in the derivation set with that of the validation set. ROC curves and areas under the curves for each set were determined using counts of non-missing records in each set and were not weighted. Analysis was performed using STATA Version 8.0 (Stata Corp LP, College Station, TX).

Table 1
Characteristics of the study population

Characteristic	Derivation set (n = 39,441)	Validation set (n = 17,025)
Male no. (%)	23636 (59.9%)	10303 (60.5%)
Age (years)	36.7	36.8
Height (cm)	172	171.9
Weight (kg)	76	75.9
Severe head injury	4464 (11.3%)	1894 (11.1%)
Year of accident—no. (%)		
1993	4573 (11.6%)	2060 (12.1%)
1994	4185 (10.6%)	1876 (11%)
1995	4520 (11.5%)	1929 (11.3%)
1996	4711 (11.9%)	1893 (11.1%)
1997	4510 (11.4%)	1888 (11.1%)
1998	4411 (11.2%)	1964 (11.5%)
1999	4200 (10.7%)	1882 (11.1%)
2000	4290 (10.9%)	1832 (10.8%)
2001	4041 (10.3%)	1701 (10%)

3. Results

The CDS database for the years 1993–2001 included 56,466 drivers. This is equivalent to a population of 28,877,696 drivers nationwide. Of these, 6358 sustained a head injury associated with an AIS ≥ 2. The dataset used to develop the model includes 39,441 drivers, with 11.3% sustaining a severe head injury. A further 17,028 drivers were allocated to the validation set, 11.1% of whom had severe head injuries (Table 1).

3.1. Univariable analysis

A total of 21 passenger and vehicle variables were tested for association with severe head injury and the results presented in Table 2. Of these only four were found to be significantly associated with a severe head injury ($P < 0.05$), since none of the 95% confidence intervals contained unity. These included seat belt use and crash characteristics (rollover during the accident, driver ejection from the vehicle and the change in velocity incurred during the crash).

3.2. Mulitivariable analysis

All factors found to be significant in the univariate analysis were then entered as a group into a multivariable logistic regression model. Variables with a $P < 0.05$ were retained. The result of this regression is the model presented in Table 3. The final model included seat belt use, driver ejection from the vehicle and the change in velocity of the vehicle during the crash.

3.3. Validation of the model

Using the validation set, the prediction model was able to stratify drivers according to their risk of severe head injury (Table 4). The risk of traumatic brain injury was arbitrarily classified as low (<10%), moderate (10–30%), and high (>30%).

When receiver-operating characteristic curves for the model in the derivation and in the validation sets were compared, the areas under the curves were 0.7928 in the derivation set and 0.7940 in the validation set (Fig. 1). This suggests only minimal degradation in performance of the model in the validation set.

Table 2
Univariable correlates of severe head injury in the derivation set

Covariate	Odds ratio estimate	95% confidence interval	P-value
Driver related variables			
Male	1.39	0.30, 3.53	NS
Age (years)	1.00	0.98, 1.06	NS
Height (cm)	1.02	0.98, 1.16	NS
Weight (kg)	1.01	0.99, 1.07	NS
Vehicle related variables			
Curb weight (kg)	1.00	0.99, 1.02	NS
Seat belt used	0.21	0.09, 0.81	<0.05
Airbag deployed	0.87	0.28, 2.15	NS
Accident related variables			
Rollover	3.67	1.25, 23.00	<0.05
Ejection	17.79	5.62, 216.74	<0.05
Windshield damage	1.25	0.51, 3.04	NS
Panel damage	1.13	0.44, 5.02	NS
Steering wheel damage	1.01	0.36, 8.25	NS
Change in vehicle velocity (km/h)	1.03	1.01, 1.11	<0.05
Last maneuver prior to accident			
Braking	0.63	0.21, 1.83	NS
Steering	1.25	0.41, 3.49	NS
Accelerating	0.40	0.02, 5.77	NS
Direction of impact			
Frontal impact	1.13	0.46, 3.14	NS
Rear end impact	0.90	0.25, 4.65	NS
Driver's side impact	0.76	0.21, 2.64	NS
Passenger's side impact	0.74	0.21, 2.85	NS

Table 3
Predictors of severe head injury identified by multivariable analysis

Covariate	Adjusted odds ratio estimate	95% confidence interval
Seat belt used	0.26	0.10, 0.66
Ejection	9.36	2.67, 65.85
Change in vehicle velocity (km)	1.03	1.00, 1.08

Table 4
Performance of the prediction rule in the derivation and validation sets

Predicted risk (%)	Derivation set severe head injury (%)	Validation set severe head injury (%)
0–10	6.62	6.18
10–30	27.93	28.83
30–100	47.20	43.82

4. Discussion

Automated crash notification systems reduce the time from the crash event to hospital arrival, primarily by reducing time between crash occurrence and notification of emergency medical services. With such a system EMS is notified an average of 44 s after the crash occurs (National Highway Safety Administration,

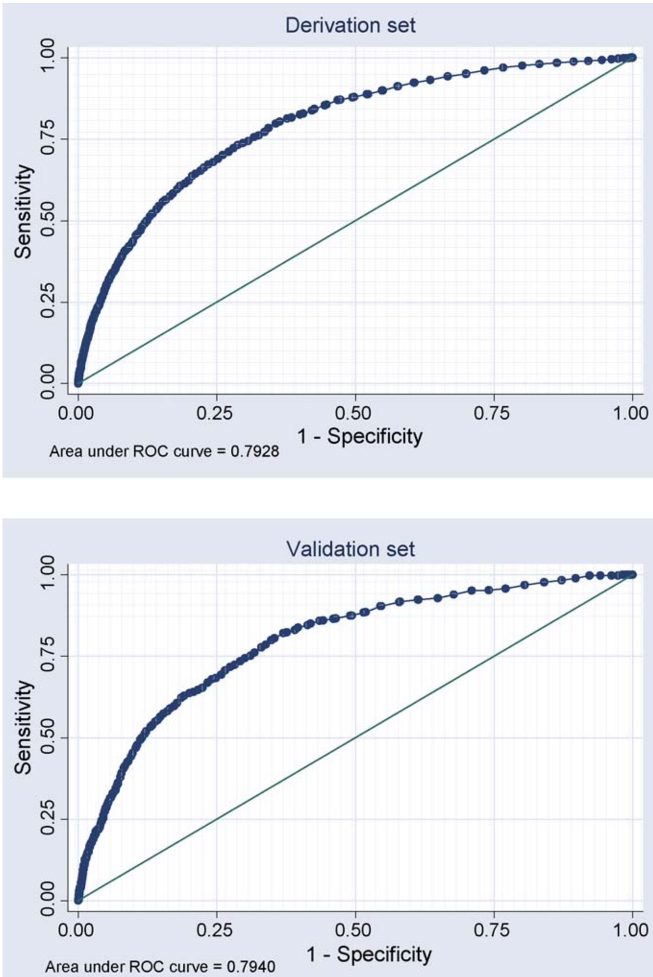

Fig. 1. Comparison of the receiver-operating characteristic (ROC) curves for the derivation set and the validation set. The area under the curve was 0.7928 for the derivation set and 0.7940 for the validation set. This suggests little degradation in the models performance when used for prospective testing.

2001), almost twice as fast as the 82 s average notification time in Connecticut, and significantly faster than the 18 min average notification time in South Carolina (Akella et al., 2003). Shorter notification times result in fewer fatalities, particularly in rural areas where the majority of crashes in the United States occur (Champion and Cushing, 1999; Funke et al., 2000).

In addition to providing a means of reduced notification time, the ACNS must determine which crashes should trigger EMS notification. Dispatch of EMS for minor collisions in which no injury occurs would overwhelm the system and divert resources needed to care for the seriously injured. Under-triage is equally problematic, when EMS is not notified of crashes with seriously injured or potentially seriously injured occupants.

In 2001, the National Highway Traffic Safety Administration (NHTSA) published the results of an initiative to create and operate an ACNS on a demonstration basis in a rural area. The crash characteristics included in the model were rollover, change in velocity, and direction of force. In the initial field trial, change in velocity was detected with 87% accuracy, principal direction of force with 100% accuracy, and rollover status with 93% accuracy. The outcome variable assessed was the probability of any body region to sustain a significant injury (AIS score of 2 or greater). We chose to focus upon traumatic brain injuries specifically as an initial step to refine the original work done by NHTSA. With more specific crash-injury profiles the ACNS technology can improve its efficiency in terms of triage and identify those patients with the most severe life-threatening injuries. Our study demonstrates that the likelihood of traumatic brain injury can be predicted with reasonable accuracy based upon variables that can and should be measured during the crash event.

We chose to test the ability of this model to predict traumatic brain injury using sensitivity and specificity measurements which are summarized by receiver-operating curves. This approach was utilized since triage tools are akin to screening tests for a disease. Generally, the accuracy of a screening test is best measured by such an approach. In further validating the model (Table 4) we arbitrarily categorized the risk into low to high categories. This is not to imply that these categories be utilized in determining subsequent triage decisions as other factors such as geographical location of adequate facilities must also be considered.

Currently, crash characteristics such as velocity of greater than 20 mph and intrusion have added little to our ability to accurately triage patients in terms of injury severity, and have actually been found to reduce specificity with little improvement in sensitivity (Henry et al., 1996a,b). One problem with using mechanism as a triage tool is that it may lead to considerable over triage of patients. Using event data recording systems will remove some of the inaccuracies related to the subjective estimates of crash severity and may, in turn, improve the correlation between the event and the likelihood of injury.

Choosing a lower threshold for EMS deployment and a higher threshold for triage to a level one trauma center would provide a mechanism to ensure that patients with a low potential for traumatic brain injury are at least brought to a level 3 or 4 trauma center while those at higher risk would be brought to a higher level of care.

In reviewing the factors found to be predictive of head injury seat belt use appear to be protective, while ejection from the vehicle and an increasing velocity of the crash both are predictive of a severe head injury. These results are consistent with previous studies. This reinforces the validity of our findings.

A study should be interpreted in the context of its limitations. Several limitations of this study must be addressed. First, the NASS dataset has a significant amount of missing data. This was particularly important with respect to the velocity of crashes. The amount of missing data was particularly significant for the change in velocity incurred during the crash. For this variable 49.9% of data was missing. We used imputation to estimate the values of the missing data. This method allows us utilize the full power of the NASS dataset however it increases the uncertainty about the odds ratio estimates. By randomly selecting our derivation and validation sets we ensured that data was missing in equal proportions in both sets. ACNS are increasingly prevalent. Data collected through these systems will allow the prospective validation of our prediction model on complete datasets.

Misclassification with any retrospectively analyzed dataset is another possible limitation; however, to significantly alter the model's accuracy, there would have to be differential misclassification of those confounders with respect to head injury. Since the data coders for NASS perform their crash variable coding independent of injury coding, there is little reason to believe that crash related variables would be coded differentially with respect to head injury. That is, any misclassification of crash related variables or injury severity would occur with equal likelihood, and therefore would not affect the overall estimates as to the likelihood of injury.

Application of this probability model requires intact global satellite communication between the vehicle and the emergency medical dispatch unit. The three variables we identified as significant predictors are not necessarily the variables currently examined by vehicle surveillance systems. The findings of this study should be utilized to guide the development of this technology so as to improve medical emergency resource utilization. Finally, the ability to detect and notify EMS of a crash event is only the first part in improving survival from crashes. Treating the injured rapidly and appropriately requires an intact trauma care system to provide efficient trauma assessment and care. In the absence of such a system, the maximum efficacy of an ACNS will not be attained.

From a health care standpoint, there must be no confusion about this technology. It is clear that automatic crash notification systems will play a key role in rural areas to reduce deployment times to crash scenes. The accuracy of triage, based upon the findings of this study, may be improved by use of this technology. As health care professionals, we must ensure that the political agenda of various interest groups does not outweigh the more important issue of improvement in pre-hospital response and triage for victims of motor vehicle related trauma.

This study identifies several important crash-related variables, which can be measured by vehicle surveillance systems and relates them to the likelihood of significant head injury. These findings need to be tested in actual crashes to determine the true accuracy of the model and the degree of improvement that may be gained in emergency response utilization and hospital triage. Furthermore, specific cut-off levels with respect to the probability of severe brain injury need to be developed to assist in triage of patients to higher levels of care based upon the model.

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