DEVELOPMENT AND EVALUATION OF AN ADVANCED AUTOMATIC CRASH NOTIFICATION ALGORITHM FOR PEDIATRIC OCCUPANTS

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ABSTRACT

The objective of the study was to develop and evaluate a pediatric-specific advanced automatic crash notification (AACN) algorithm that uses a more comprehensive scoring system than the Abbreviated Injury Scale (AIS)-based severity to predict the risk that a child in a motor vehicle crash (MVC) is severely injured and requires treatment at a designated trauma center (TC). Though several research groups have developed AACN algorithms for adults, none have yet been developed for children. Given a child's constant growth and development, use of currently-developed AACN algorithms in children is problematic because they provide no method for modification of injury risk based upon a child's developmental stage.

A list of injuries associated with a pediatric patient's need for Level I/II TC treatment known as the Target Injury List was determined using an approach based on 3 facets of injury: severity, time sensitivity, and predictability. The inputs used to create the pediatric-specific AACN algorithm include the Target Injury List (TIL) and 12,058 MVC occupants from the National Automotive Sampling System-Crashworthiness Data System (NASS-CDS) 2000-2014. The algorithm uses multivariable logistic regression to predict an occupant's risk of sustaining an injury on the TIL from the following input variables: delta-v, number of quarter turns, belt status, multiple impacts, airbag deployment, and age group. The pediatric-specific AACN algorithm was optimized in order to minimize under triage (UT) and over triage (OT) rates with the goal of producing UT rates < 5% and OT rates < 50% as recommended by the American College of Surgeons (ACS).

The OT rates were 44% (frontal), 47% (near side), 43% (far side), 25% (rear), and 49% (rollover). The UT rates were 3% (frontal), 3% (near side), 2% (far side), 8% (rear), and 14% (rollover). Note there are not separate algorithms for each of the developmental age groups (due to sample size limitations), but these results are for the pediatric population as a whole.

Injury patterns change as children grow and develop. Current AACN algorithms in industry are not pediatric specific. The developed pediatric-specific AACN algorithm uses measurements obtainable from vehicle telemetry to predict risk of occupant injury and recommend a transportation decision for the occupant. The AACN algorithm developed in this study will aid emergency personnel in making the correct triage decision for pediatric occupants after a MVC, and once incorporated into the trauma triage network it can reduce response times, increase triage efficiency, and improve overall patient outcome.

INTRODUCTION

Motor vehicle crashes (MVCs) remain a leading cause of death and disability in children worldwide. According to the Centers for Disease Control (CDC), in 2013, MVCs were the leading cause of death among U.S. children aged 5-18 years and accounted for 3,012 deaths among those aged 0-18 years that year in the U.S. [1]. Furthermore, for every pediatric fatality due to a MVC, 18 children are hospitalized and 400 receive medical treatment of injuries sustained in crashes [2].

Advanced Automatic Crash Notification (AACN) systems can improve the speed and accuracy of field triage decisions by alerting control centers that a crash has occurred and utilizing vehicle, occupant, or crash data to predict which occupants are likely to have serious injuries [3-6]. Though several research groups have developed AACN algorithms for adults, none have yet been developed for children [7, 8]. AACN algorithms require an objective measure for defining seriously injured patients. Existing AACN algorithms, such as OnStar and URGENCY, use metrics based upon the Abbreviated Injury Scale (AIS), such as a maximum AIS of 3+ or an Injury Severity Score (ISS) of 15+, to define seriously injured patients [9, 10]. Other methods of injury scoring have been devised, and disputes remain about which severity scoring system best discriminates seriously injured patients from non-seriously injured patients [11-13]. To improve upon trauma severity scoring systems used by AACN algorithms and, thus, better evaluate an occupant's need for treatment at a trauma center after a MVC, an injury-based approach employing three facets of injury (severity, time sensitivity, and predictability) was developed in adults [14-18]. Given a child's constant growth and development, use of currently-developed AACN algorithms in children is problematic because they provide no method for modification of injury risk based upon a child's developmental stage.

Due to the differences between adults and children, the objective of the study was to develop and evaluate a pediatric-specific advanced automatic crash notification (AACN) algorithm that uses a more comprehensive scoring system than Abbreviated Injury Scale (AIS)-based severity to predict the risk that a child in a MVC is severely injured and requires treatment at a designated trauma center (TC). The overall goal of the pediatric AACN algorithm is to reduce response times, increase triage efficiency, and improve overall pediatric patient outcomes following a MVC.

METHODS

Based on National Automotive Sampling-Crashworthiness Data System (NASS-CDS) 2000-2014 data, pediatric MVC occupants 18 years and younger were analyzed and divided into four age classifications based upon injury patterns previously studied [19], which coincided with commonly used Centers for Disease Control groupings [20]. Thus, children were grouped into the following categories: 0-4, 5-9, 10-14, and 15-18 years. The most frequently occurring injuries comprising the top 95% of the cumulative weighted injury count were included on that age group's "Top 95% Injury List." The Top 95% List was comprised of 111 unique AIS codes for 0-4 year olds, 122 unique AIS codes for 5-9 year olds, 156 unique AIS codes for 10-14 year olds, and 194 unique AIS codes for 15-18 year olds. The Top 95% Lists for all 4 age groups included 250 distinct AIS 2+ injuries.

A list of injuries associated with a pediatric patient's need for Level I/II TC treatment, known as the pediatric Target Injury List (TIL), was determined using an approach based on 3 facets of injury: severity, time sensitivity, and predictability. Severity refers to the risk that a particular injury poses to mortality and morbidity.The Severity Score was determined by calculating unadjusted and adjusted mortality risk (MR) and disability risk (DR) [21, 22]. Time sensitivity refers to the urgency with which a particular injury requires treatment. The Time Sensitivity Score was determined based upon survey of expert physician opinion [23]. Predictability quantifies the extent to which injuries may be occult, or missed by first responders upon initial assessment. The Predictability Score was determined using two metrics: an Occult Score and a Transfer Score. The Occult Score was developed through the use of expert opinion. The Transfer Score was derived through the use of the National Inpatient Sample (NIS) database. The scores of each of these facets were computed for each injury on the Top 95% List for each age group. Each score was normalized on a zero to one scale in which scores closer to one were more severe, more time sensitive, and less predictable.

The inputs to the pediatic AACN algorithm include a pediatric TIL and NASS-CDS 2000-2014 cases. The TIL is determined by multiplying the Severity, Time Sensitivity, and Predictability Scores by a weighting coefficient and then summing these values to produce a Target Injury Score. Injuries exceeding a defined Injury Score Cutoff are then included on the TIL. The

TIL is not a static list and is capable of being varied in order to optimize the algorithm. Due to the low sample sizes across the four age groups and crash modes, all pediatric occupants were grouped together. As a result, the pediatric TILs were collapsed for all ages into one list; however, the algorithm still accounts for age as a model variable to predict injury risk and assesses the outcome measure using the age-specific TIL. Scores for injuries that appeared in only one group were copied in the collapsed list. Scores for injuries that appeared in two or more age groups were averaged together. The inclusion criteria for the pediatric NASS-CDS cases included occupants aged 0-18 years old with seat positions including driver, right front passenger, and second row passengers.

The algorithm uses multivariable logistic regression to predict the risk of an occupant sustaining an injury on the TIL for specified crash conditions. Five separate multivariable logistic regression models were created according to crash type: frontal, near side, far side, rear, and rollover crash. For the purposes of calculating outcome measures, injuries sustained by an occupant that did not appear on the age-specific TIL were discarded, even if that injury appeared in one or more of the other age-specific injury lists. The model parameters included in the algorithm were longitudinal delta-v, lateral delta-v, number of quarter turns, belt status, frontal airbag deployment, multiple impacts, age group, and side airbag deployment. Longitudinal delta-v was used for the frontal and rear models; lateral delta-v was used in the near side and far side models. For the rollover crash type, the number of quarter turns was binned into six categories: 1, 2, 3-4, 5-6, 7-8, 9-17. Side airbag deployment was included in the near side and rollover crash modes only. The Risk of any Target Injury is calculated with the cumulative distribution function (Eq. 1). Logistic regression analyses were performed using SAS 9.4 (SAS Institute, Cary, NC) and R 3.0.2 (R Foundation for Statistical Computing, Vienna, Austria). Note there are not separate algorithms for each of the developmental age groups (due to sample size limitations), but these equations are used for the pediatric population as a whole.

Risk of any Target Injury=

$$\frac{e^{(\alpha + \beta_1 DV + \beta_2 Belt + \beta_3 AB + \beta_4 MI + \beta_5 Age + \beta_6 SAB)}}{1+e^{(\alpha + \beta_1 DV + \beta_2 Belt + \beta_3 AB + \beta_4 MI + \beta_5 Age + \beta_6 SAB)}} \quad \textbf{(Eq. 1)}$$

where α*= intercept,* β_1*,* β_2*,* β_3*,* β_4*,* β_5*,* β_6*=parameter coefficients for: DV= longitudinal delta-v/lateral delta-v/number of quarter turns; Belt= belt status (0=no, 1= yes); AB= frontal airbag deployment (0= no, 1=yes); MI= multiple impacts (0= no, 1= yes); Age= age group (0= 0-4 YO, 1= 5-9 YO, 2= 10-14 YO, 3= 15-18 YO; **SAB= side airbag deployment (0=no, 1=yes, **only for near side and rollover).*

An overview of the algorithm including the data sources for the injury score facets, inputs to the algorithm including the TIL, NASS cases, and model parameters, and output of triage recommendation is show in Figure 1.

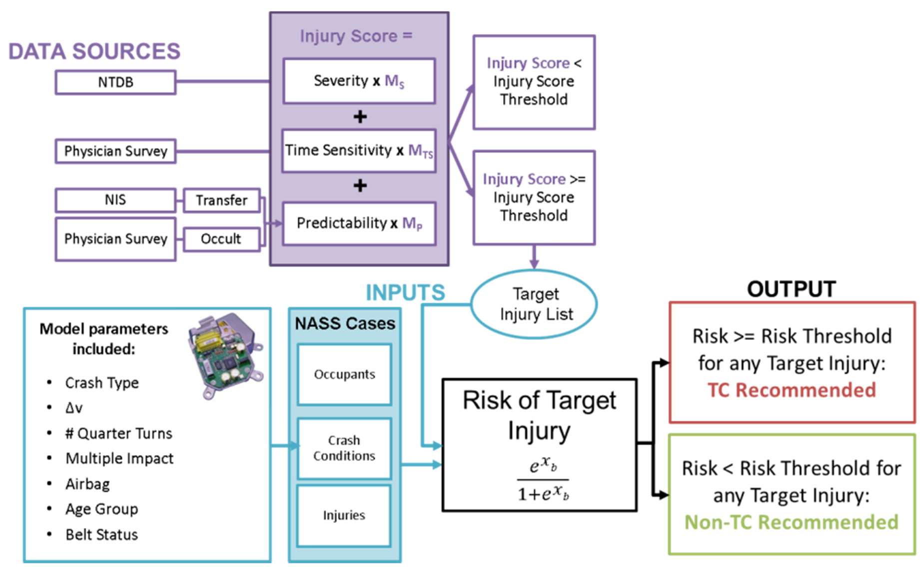

Figure 1. Overview of pediatric AACN algorithm. (Abbreviations M_P, predictability score multiplier; M_s, severity score multiplier; M_{TS}, time sensitivity score multiplier; NASS-CDS, National Automotive Sampling System - Crashworthiness Data System; NIS, National Inpatient Sample; NTDB, National Trauma Data Bank; TC, trauma center)

The pediatic AACN algorithm features five tunable parameters (termed "Variable Parameters") allowing for extensive optimization. The five Variable Parameters include the Severity Multiplier, Time Sensitivity Multiplier, Predictability Multiplier, Injury Score Cutoff, and a Risk Cutoff. The Severity Multiplier, Time Sensitivity Multiplier, Predictability Multiplier are the weighted coefficients used to produce the Target Injury Score. The Injury Score Cutoff is the threshold at which an injury is deemed to be included on the TIL. The Risk Cutoff is the threshold above which a case is deemed to need treatment at a Level I/II TC. The pediatric AACN algorithm was optimized for each crash mode.

The pediatric algorithm was optimized using a genetic algorithm that compared the algorithm decision for each NASS-CDS occupant to a dichotomous representation of their ISS. Occupants with ISS 16+ should be transported to a Level I/II TC. OTDA optimization minimized under triage (UT) and over triage (OT) rates with the goal of producing UT rates < 5% and OT rates < 50% as recommended by the American College of Surgeons (ACS) [24]. OT was assessed using the False Positive Rate (FPR) metric, also known as 1-Specificity [25-27]. This represents the proportion of mildly injured patients that went to a Level I/II TC. UT was assessed using the False Negative Rate (FNR) metric, also known as 1-Sensitivity [25-28]. This represents the proportion of seriously injured patients that did not go to a Level I/II TC.

RESULTS

A total of 12,058 NASS-CDS 2000-2014 cases met the inclusion criteria for training and evaluating the pediatric AACN algorithm. The number of cases meeting the inclusion criteria for each crash mode included 6,580 frontal cases, 776 rear cases, 2,457 rollover cases, 1,172 near side cases, and 1,073 far side cases.

The resulting OT and UT metrics for the optimized algorithm are listed in Table 1. The OT rates for frontal, rear, far side, near side, and rollover all met the 50% ACS recommendation. The UT rates for frontal, near side, and far side met the 5% ACS recommendation, while the rear UT rates fell within the 5-10% recommendation. The OT rates were 44% (frontal), 47% (near side), 43% (far side), 25% (rear), and 49% (rollover). The UT rates were 3% (frontal), 3% (near side), 2% (far side), 8% (rear), and 14% (rollover).

Table 1. Optimized algorithm triage rates by crash mode (F= frontal, NS= near side, FS= far side, R= rear, Roll= rollover.

Triage Rates	F	NS	FS	R	Roll
OT (%)	44.12	46.85	42.57	24.64	49.39
UT (%)	3.03	3.23	2.27	7.69	13.71
TP	192	120	43	12	214
TN	3566	557	591	575	1118
FP	2816	491	438	188	1091
FN	6	4	1	1	34

DISCUSSION

The pediatric AACN algorithm was developed with an injury-based approach that examined three injury facets to identify injuries necessitating treatment at a Level I/II trauma center. Large hospital and survey datasets containing information on injuries, mortality risk, treatment urgency, and hospital transfers were used in conjunction with large crash datasets with crash, vehicle, occupant, and injury data.

Traditionally, priority is given to the reduction of UT to lower mortality and morbidity with the understanding that some elevation in OT is necessary to prevent seriously injured patients from being undertriaged. The pediatric AACN algorithm reduced UT for all crash modes without elevating OT beyond the ACS guidelines. These results are very encouraging as the pediatric AACN algorithm uses crash characteristics obtainable from vehicle sensors and age group which could be easily be entered by parents into an AACN system in their vehicle and programmed to update automatically, as date of birth and current date would always be available in the system. Furthermore, at 14%, there is some room for improvement in UT for rollover crashes. Rollover crashes are complex events and determining the severity of the event is difficult due to many factors. These factors include vehicle geometry, vehicle deformation, and subsequent impacts which can alter the number of quarter turns a vehicle experiences. Additional data elements could be incorporated in the future to better quantify the severity as well as to better differentiate the types of rollovers.

CONCLUSIONS

This was the first AACN algorithm created specifically for children and, as such, it accounts for important differences in injury patterns and physiology across different stages of pediatric development. The pediatric AACN algorithm was optimized in order to minimize under triage (UT) and over triage (OT) rates with the goal of producing UT rates < 5% and OT rates < 50% as recommended by the American College of Surgeons (ACS). The pediatric AACN algorithm developed in this study will aid emergency personnel in making the correct triage decision for an occupant after a MVC, and once incorporated into the trauma triage network it can reduce response times, increase triage efficiency, and improve overall patient outcome.

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