Advanced Automatic Crash Notification Algorithm for Children

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Abstract

Background: Advanced automatic crash notification (AACN) can improve triage decision-making by using vehicle telemetry to alert first responders of a motor vehicle crash and estimate an occupant's likelihood of injury. The objective was to develop an AACN algorithm to predict the risk that a pediatric occupant is seriously injured and requires treatment at a Level I or II trauma center.

Methods: Based on 3 injury facets (severity; time sensitivity; predictability), a list of Target Injuries associated with a child's need for Level I/II trauma center treatment was determined. Multivariable logistic regression of motor vehicle crash occupants was performed creating the pediatric-specific AACN algorithm to predict risk of sustaining a Target Injury. Algorithm inputs included: delta-v, rollover quarter-turns, belt status, multiple impacts, airbag deployment, and age. The algorithm was optimized to achieve under-triage ≤5% and over-triage ≤50%. Societal benefits were assessed by comparing correctly triaged motor vehicle crash occupants using the AACN algorithm against real-world decisions.

Results: The pediatric AACN algorithm achieved 25% to 49% over-triage across crash modes, and under-triage rates of 2% for far-side, 3% for frontal and near-side, 8% for rear, and 14% for rollover crashes. Applied to real-world motor vehicle crashes, improvements of 59% in under-triage and 45% in over-triage are estimated: more appropriate triage of 32,320 pediatric occupants annually.

Conclusions: This AACN algorithm accounts for pediatric developmental stage and will aid emergency personnel in correctly triaging pediatric occupants after a motor vehicle crash. Once incorporated into the trauma triage network, it will increase triage efficiency and improve patient outcomes.

Keywords: AACN; injury prediction; motor vehicle crash; pediatric trauma; triage

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What's New

Development of an advanced automatic crash notification (AACN) algorithm to predict the risk that a child in a motor vehicle crash is seriously injured and requires treatment at a Level I or II trauma center could save more lives.

Motor vehicle crashes (MVCs) are a leading cause of pediatric mortality and morbidity.[1] Advanced Automatic Crash Notification (AACN) can improve speed and accuracy of triage decisions by rapidly alerting public service answering points (PSAPs) of a MVC and utilizing crash/occupant data to predict likelihood of serious injury.[2−4] AACN uses telemetry data recorded during a crash by the vehicle's event data recorder (eg, speed, airbag deployment, belt status) to estimate the risk that an occupant sustained serious injury. AACN systems transmit this injury risk prediction to PSAPs who relay this information to Emergency Medical Services (EMS). By notifying PSAPs/EMS earlier and predicting severe injury, AACN can improve response times and triage decisions. Vehicle telemetry information is included in Step 3 of the "Field Triage Decision Scheme," adapted from the American College of Surgeons (ACS) and revised by an expert panel convened by the Centers for Disease Control and Prevention (CDC) and the National Highway Traffic Safety Administration (NHTSA).[5] These groups advocate for vehicle telemetry-based assessment of severe injury to improve triage. AACN can be used in the Field Triage Decision Scheme to augment assessment, speed up triage, and aid personnel who are less experienced with pediatric trauma.

AACN has been developed for adults,[6−11] but not for children specifically. The CDC, World Health Organization, and American Academy of Pediatrics recognize the importance of pediatric triage, given the impact of trauma on children.[1,12,13] Children progress through developmental stages which affects the injuries they incur and the treatment thereof.[14] For example, children have pliable chest walls allowing for force deflection to organs without fractures.[15]

Trauma triage emphasizes transporting the “right patient” to the “right place” at the “right time.” The “right patient” refers to deciding who has sustained severe injuries warranting emergency treatment. For the seriously injured, the “right place” refers to a designated trauma center (TC), since treatment at TCs reduces mortality.[16,17] The “right time” refers to the interval within which treatment is required before injury-induced physiologic derangements become irreversible.

Treatment of children at designated TCs with injuries that could have been appropriately managed at non-TCs is over-triage. Over-triaging patients to TCs puts undue strain on resources and may impair care of more seriously injured patients. Assignment of children to non-TCs with severe injuries that require treatment at TCs is under-triage. Mortality risk within 24 hours is 9.3% higher if seriously injured pediatric patients are under-triaged.[17] AACN leverages crash/occupant data to predict likelihood of serious injury and inform triage decisions (TC vs non-TC).

Adult AACN algorithm use in children is problematic because there is no modification of injury risk based on pediatric age. Though pediatric MVC injury patterns have been described,[14] there is a lack of data-driven quantification of risk of particular MVC injuries across pediatric development.

Objectives: (1) Develop and evaluate an AACN algorithm to predict the risk that a pediatric MVC occupant is seriously injured and requires treatment at a Level I or II TC. (2) Evaluate the societal benefits of improved pediatric triage with AACN algorithm implementation.

METHODS

INJURY FACETS

A pediatric AACN algorithm was developed to evaluate the need for Level I/II TC treatment based on an injury facet-based (severity, time sensitity, predictability) modeling approach validated previously for adults.[9] While the Abbreviated Injury Scale (AIS) classifies injury severity based on threat to life on a scale of 1 (minor) to 6 (maximum),[18] the 3 injury facets offer a comprehensive characterization of aspects important for triage. The National Automotive Sampling-Crashworthiness Data System (NASS-CDS) is a representative sample of minor, serious, and fatal US MVCs with injuries coded in the AIS lexicon.[18] Children from NASS-CDS years 2000−14 were stratified into four age groups (≤4, 5−9, 10−14, 15−18 years) coinciding with CDC groupings[19] and differing pediatric MVC injury patterns.[14] Across the four age groups, a total of 250 distinct AIS codes comprised the 95% most frequent AIS2+ pediatric injuries in cumulative weighted NASS-CDS data (Appendix).

The severity, time sensitivity, and predictability facets of pediatric injuries quantified previously (Appendix)[20−24] were used to develop a Target Injury List (TIL) of injuries associated with need for Level I/II TC treatment. These facets represent distinct and uncorrelated injury characteristics which, when linked with MVC conditions, can help guide patient triage and treatment needs. A Severity Score for each injury was quantified using the National Trauma Data Bank to compute mortality (MR_{MAIS}) and disability (DR_{MAIS}) risks associated with a given injury (Equation 1).[23,24] Time sensitivity was quantified from surveying the opinions of healthcare providers and medical experts on the need for an injury to be treated at a Level I/II TC and the urgency.[22] A Predictability Score quantifying an injury’s likelihood of being missed during initial assessment was the summation of Occult and Transfer Scores (Equation 2). The Occult Score was computed from physcian and EMS survey opinions rating potential for an injury to be missed by on-scene first responders.[21] The Transfer Score (TrS_{MAIS}) quantified how often an injury was present in National Inpatient Sample patients transferred from a non-TC to a Level I/II TC.[20] Scores of each injury facet (severity, time sensitivty, predictability) were computed for each of the 95% most frequent injuries within each age group (Appendix), and normalized from 0 to 1, with higher scores being more severe, more time sensitive, and less predictable.

Severity Score

$$= 0.9 * [1 - (\ln MR_{MAIS} / \ln A)] + 0.1 * DR_{MAIS} \tag{1}$$

where A = 0.002 ages ≤ 4; A = 0.0015 ages 5 to 9; A = 0.0013 ages 10 to 14; A = 0.00049 ages 15 to 18; Severity Score = 0.1*DR_{MAIS} for injuries with MR_{MAIS} = 0.

Predictability Score

$$= (0.5 * \mathit{Occult\ Score}) + (0.5 * TrS_{MAIS}) \tag{2}$$

ALGORITHM

Based on our approach for adults (Fig. 1),[9] pediatric AACN algorithm inputs included a pediatric TIL, and crash, age, and injury data from NASS-CDS. The pediatric TIL contains injuries associated with an occupant’s need for Level I/II TC treatment. To maximize sample size, Severity, Time Sensitivity, and Predictability Scores for injuries in different age groups were combined into a single list of 250 AIS codes comprising the most frequent pediatric injuries. Scores for injuries appearing in ≥2 age groups were averaged. To create the pediatric TIL, a Target Injury Score was computed for each of the 250 injuries by summing Severity, Time Sensitivity, and Predictability Scores, after weighting each by a variable multiplier (Fig. 1). Injuries on the pediatric TIL have Target Injury Scores greater than or equal to a variable Injury Score Threshold. The multipliers and Injury Score Threshold are varied during the algorithm optimization; thus,

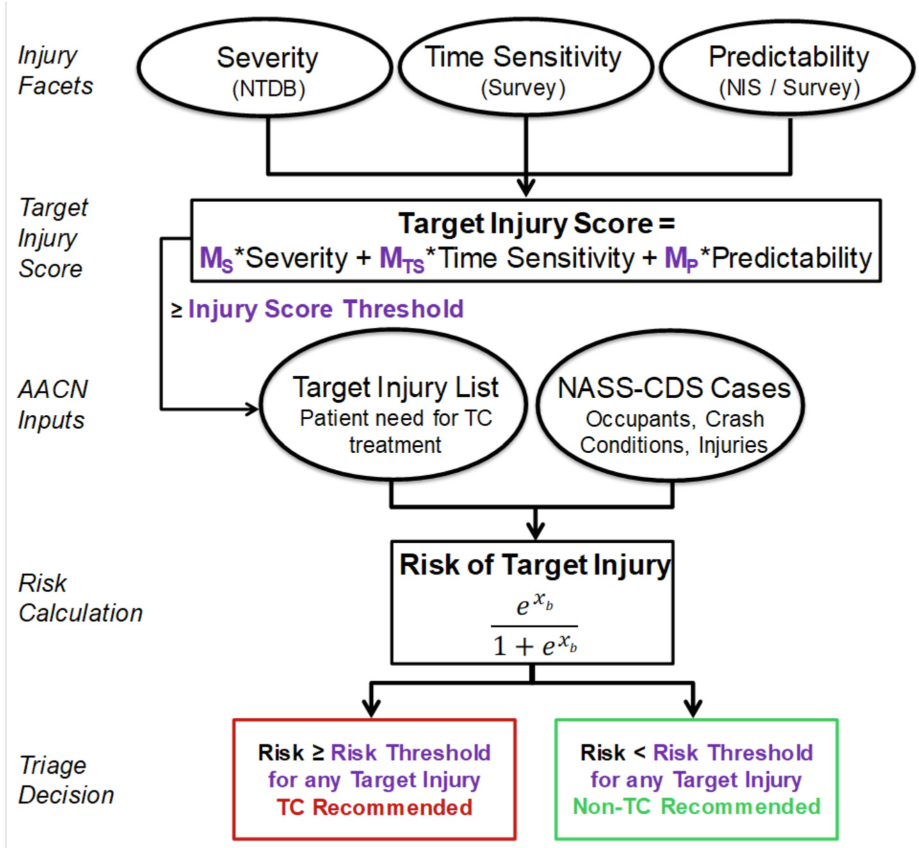

Figure 1. *Pediatric AACN algorithm overview with five tunable parameters indicated with purple text. M_s indicates severity score multiplier; M_{TS}, time sensitivity score multiplier; M_P, predictability score multiplier; NASS-CDS, National Automotive Sampling System - Crashworthiness Data System; NTDB, National Trauma Data Bank; NIS, National Inpatient Sample; TC, trauma center.*

injuries making it onto the pediatric TIL are predictive of a child's need for Level I/II TC treatment. Example TIL injuries include a grade V spleen laceration, complex vault fracture, and diaphragm rupture.

The algorithm was trained and evaluated using weighted NASS-CDS 2000−14 cases of drivers, right-front passengers, or second-row passengers ages ≤18 (Table 1). Cases with vehicles >10 years old were excluded in NASS-CDS 2009−14 due to missing injury/occupant information. Separate multivariable logistic regression models were created for each crash type: frontal, near-side, far-side, rear, rollover. Logistic regression was used to predict an occupant's risk of sustaining an injury on the pediatric TIL for specified crash conditions. The model's outcome measure was assessed using the age-specific injury lists (Appendix), where occupants with ≥1 injury on the TIL for their age group were coded as sustaining a Target Injury. Occupants with injuries not appearing on their age-specific TIL were not considered to have sustained a Target Injury, even if that injury appeared on another age-specific TIL.

Models were adjusted by longitudinal delta-v (frontal/rear crashes), lateral delta-v (near-side/far-side crashes), number of quarter-turns (rollover crashes), belt status, frontal airbag deployment, multiple impacts, age group, and side airbag deployment (near-side/rollover crashes). Rollovers were crashes with ≥1 quarter-turn; quarter-turns were stratified as: 1, 2, 3 to 4, 5 to 6, 7 to 8, 9 to 17.[9] Risk of any Target Injury for frontal, rear, and far-side (Equation 3), and near-side and rollover (Equation 4) crashes was computed in SAS (v.9.4, Cary, NC) and R (v.3.0.2, Vienna, Austria).

Risk of any Target Injury for frontal, rear and far-side crashes:

$$\frac{e^{(\alpha\ +\ \beta_1 DV\ +\ \beta_2 Belt\ + \beta_3 AB\ +\ \beta_4 MI +\ \beta_5 Age)}}{1+e^{(\alpha\ +\ \beta_1 DV\ +\ \beta_2 Belt\ + \beta_3 AB\ +\ \beta_4 MI +\ \beta_5 Age)}} \tag{3}$$

Risk of any Target Injury for near-side and rollover crashes:

$$\frac{e^{(\alpha\ +\ \beta_1 DV\ +\ \beta_2 Belt\ + \beta_3 AB\ +\ \beta_4 MI +\ \beta_5 Age + \beta_6 SAB)}}{1+e^{(\alpha\ +\ \beta_1 DV\ +\ \beta_2 Belt\ + \beta_3 AB\ +\ \beta_4 MI +\ \beta_5 Age + \beta_6 SAB)}} \tag{4}$$

where α = intercept, β_1, β_2, β_3, β_4, β_5, β_6 = coefficients for: DV = longitudinal delta-v, lateral delta-v, or number of quarter-turns; Belt = (0 = unbelted, 1 = belted); AB = frontal airbag deployment (0 = no, 1 = yes); MI = multiple impacts (0 = no, 1 = yes); Age = (0 =≤ 4yrs, 1 = 5 to 9 yrs, 2 = 10 to 14 yrs, 3 = 15 to 18 yrs; SAB = side airbag deployment (0 = no, 1 = yes).

The algorithm is optimized for each crash mode using five tunable parameters: Severity, Time Sensitivity, and Predictability Multipliers; Injury Score Threshold

Table 1. National Automotive Sampling System-Crashworthiness Data System (NASS-CDS) Variables and Definitions/Criteria

Variable	Definition/Criteria
Seat position	Driver, front right passenger, or second row passenger
Age	0 < Age ≤ 18 years
Case sampling weight	Valid and greater than 0
AIS code	Valid or missing (no injury)
Belt status	Belted: belted with a child restraint system, lap belt, and/or shoulder belt Unbelted: no belt or child restraint system used
Frontal Airbag Deployment	Deployed: Airbag deployed during crash as a result of impact Non-deployed: Airbag non-deployed or not available
Side Airbag Deployment *Near-side and rollover crashes only	Deployed: Airbag deployed during crash as a result of impact Non-deployed: Airbag non-deployed, not equipped, or missing information
Multiple Impacts	Yes: number of events in crash sequence > 1 No: number of events in crash sequence = 1
Crash Type	
Frontal	General area of deformation (GAD1) "Frontal" and Principal Direction of Force (PDOF1) 300−60^0 or any GAD1 and PDOF1 330−30^0 and absolute value of longitudinal delta-v > 0
Near-side	Front right or second row right passenger with GAD1 "Right" and PDOF1 40−140^0 or Driver or second row left passenger with GAD1 "Left" and PDOF 220−320^0 and absolute value of lateral delta-v > 0
Far-side	Driver or second row left passenger with GAD1 "Right" and PDOF1 40−140^0 or Front right or second row right passenger with GAD1 "Left" and PDOF 220−320^0 and absolute value of lateral delta-v > 0
Rear	GAD1 = "Back" and PDOF1 non-missing and absolute value of longitudinal delta-v > 0
Rollover	Number of quarter-turns > 0 but ≤ 17 Note: Rollover is categorized first; so, any case that is any other crash type (frontal, far-side, near-side, rear) and rollover is categorized as rollover

AIS indicates Abbreviated Injury Scale; GAD1, General area of deformation; and PDOF1, Principal direction of force.

(described earlier); and a Risk Threshold for any Target Injury Fig. 1). If occupant risk calculated (Equations 3-(4) meets or exeeds the Risk Threshold for any Target Injury, the algorithm recommends triage to a Level I/II TC. Optimization was completed using a Covariance Matrix Adaptation Evolution Strategy genetic algorithm[25] comparing the algorithm decision for each occupant to their Injury Severity Score (ISS). Occupants with ISS≥16 were assumed to require triage to a Level I/II TC,[26−28] and the optimization sought to minimize under-triage (≤5%) and over-triage (≤50%) per ACS guidelines.[28] Over-triage was assessed using the false positive rate, representing the proportion of mildly injured occupants triaged to a Level I/II TC.[26] Under-triage was assessed using the false negative rate,[26,27] representing the proportion of seriously injured occupants not triaged to a Level I/II TC.

Cross-Validation

While algorithm training and evaluation used the same NASS-CDS dataset, 10-fold cross-validation was conducted to confirm each crash type model was not over-fitted and that consistent triage results were achieved when training and evaluating with different datasets. NASS-CDS data was divided into 10 uniformly distributed folds. A new set of regression models (optimized with new tunable parameters) was constructed from cases in 9 folds (#1−9), and models were then evaluated using fold #10 to compute over-/under-triage. This is repeated 10 times, using a distinct 9-fold set for training and the remaining fold for over-/under-triage evaluation. The 10 sets of results produced indicate how well the method for constructing the model generalizes.

Benefits

Societal benefits were estimated by comparing the number of correctly triaged occupants using the AACN algorithm versus real-world MVC triage decisions. Real-world triage decisions in NASS-CDS were determined based on each child's ISS (≥16 vs <16) and their destination (TC vs non-TC). AACN algorithm triage rates were applied to these occupants to estimate the differential in over-/under-triage and the number of children who would benefit from improved triage with AACN implementation.

Results

Algorithm

The algorithm was trained/evaluated on pediatric occupants in frontal (n = 6580), near-side (n = 1172), far-side (n = 1073), rear (n = 776), and rollover (n = 2457) crashes. Tunable parameter values and model parameter estimates from algorithm optimization are in Table 2, along with triage rates by crash mode. The algorithm produced over-triage rates of 44% (frontal), 47% (near-side), 43% (far-side), 25% (rear), and 49% (rollover). Under-triage rates of 3% (frontal; near-side) and 2% (far-side) met ≤5% ACS criteria,[28] while 8% under-triage for rear crashes fell within the 5% to 10% recommendation. Under-triage for rollover crashes was 14%.

Table 2. Optimal Tunable Parameters Selected, Logistic Regression Model Parameter Estimates for Equations 3–4, and Triage Rates by Crash Mode

Crash Mode: Total, n = 12,058	Frontal n = 6,580	Near-side n = 1172	Far-side n = 1073	Rear n = 776	Rollover n = 2457
Optimal Tunable Parameters					
Severity Score Multiplier	0.595	0.544	0.707	0.528	0.746
Time Sensitivity Score Multiplier	0.586	0.650	0.773	0.713	0.714
Predictability Score Multiplier	0.250	0.320	0.380	0.897	0.266
Injury Score Threshold	0.782	0.705	0.706	0.794	0.619
Risk Threshold for any Target Injury	0.002	0.013	0.009	0.003	0.023
Model Parameter Estimates					
α, Intercept	−6.674	−6.021	−7.436	−5.858	−2.294
β_1, Delta-v (kph) or # Quarter-Turns	0.077	0.129	0.131	0.068	−0.102
β_2, Belt Status	−2.052	−0.886	−1.170	−1.956	−1.816
β_3, Frontal Airbag Deployment	−0.503	0.955	0.278	1.396	0.744
β_4, Multiple Impacts	0.678	0.382	0.203	0.786	0.824
β_5, Age Group = 5−9 years	−0.865	−0.227	0.528	−1.967	−0.699
β_5, Age Group = 10−14 years	0.615	−0.014	1.331	−1.392	−0.626
β_5, Age Group = 15−-18 years	0.023	0.126	1.084	−2.235	−0.306
β_6, Side Airbag Deployment	—	−0.931	—	—	1.261
Triage Rates					
Over-triage (false positive rate)	44.12%	46.85%	42.57%	24.64%	49.39%
Under-triage (false negative rate)	3.03%	3.23%	2.27%	7.69%	13.71%
True Positives	192	120	43	12	214
True Negatives	3566	557	591	575	1118
False Positives	2816	491	438	188	1091
False Negatives	6	4	1	1	34

CROSS-VALIDATION

Ten-fold cross-validation produced results consistent with those using the entire dataset to train/evaluate, particularly within crash modes with larger sample sizes (Fig. 2). In frontal crashes (n = 6580), cross-validation produced 16% to 49% over-triage (mean = 34%) and 0% to 11% under-triage (mean = 3.5%) across folds, compared to 44% over-triage and 3% under-triage in the full dataset. Cross-validation of rollovers (n = 2457) also showed stability and similarity (over-triage 34%−50%, mean = 43%; under-triage 9%−30%, mean = 14%) to the full dataset (over-triage 49%; under-triage 14%). Near-side, far-side, and rear crashes had smaller samples; even smaller samples are created in cross-validation, which may explain wider triage ranges. Due to small samples for some crash modes, and since similar results were obtained in cross-validation compared to the full dataset (particularly within frontal/rollover crashes with larger samples), we felt confident in the AACN algorithm that was developed via training/evaluation on the full dataset.

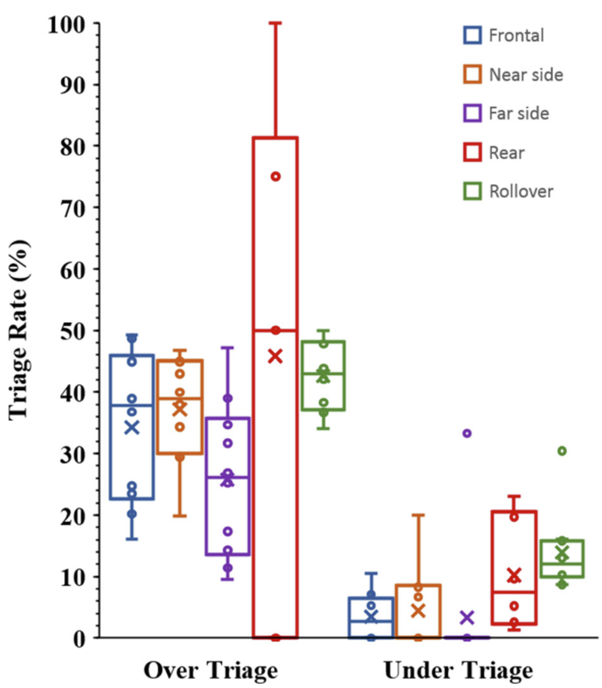

Figure 2. *Box and whisker plot of the over-triage and under-triage rates produced for the 10 folds used in cross-validation for each crash mode. Individual fold results are plotted with circle markers, and the mean of the 10 folds is indicated by an "×."*

BENEFITS

Benefits analyses included 8605 unweighted occupants (1,975,247 weighted) with hospital destination data (Table 3). Across all crash modes, under-triage was 14% and over-triage was 60% in 15 years of unweighted NASS-CDS data, indicating real-world triage rates do not meet ACS guidelines.[28] Applying the AACN algorithm triage rates in Table 2 to these occupants by crash mode, rates were reduced to 6% under-triage and 44% over-triage. With the pediatric AACN algorithm, it is estimated a TC recommendation would be made for 57 seriously injured children who were under-triaged to a non-TC in NASS-CDS (56% improvement). Likewise, a non-TC recommendation would be made for 1213 minimally injured children who were over-triaged to a TC in NASS-CDS (26% improvement). In total, an estimated 1270 children would be correctly triaged with the pediatric AACN algorithm that were not previously.

Benefits analysis of population-weighted NASS-CDS data revealed 17% under-triage and 56% over-triage, which also falls short of ACS guidelines.[28] Applying

Table 3. Benefit Analysis Summary for Pediatric AACN Algorithm

Number/Proportion of Pediatric Occupants Triaged	Unweighted (n = 8605) UT	Unweighted (n = 8605) OT	Weighted (n = 1,975,247) UT	Weighted (n = 1,975,247) OT
Occupants incorrectly triaged in NASS-CDS, n (%)	102 (14)	4688 (60)	9099 (17)	1,073,752 (56)
Occupants incorrectly triaged based on AACN, n (%)	44 (6)	3475 (44)	3709 (7)	594,331 (31)
Incorrectly triaged occupants predicted to be triaged correctly with the AACN, n (%)	57 (56)	1213 (26)	5389 (59)	479,421 (45)

AACN indicates advanced automatic crash notification; NASS-CDS, National Automotive Sampling System-Crashworthiness Data System, UT, under-triage; and OT, over-triage.

AACN algorithm triage rates reduces under-triage to 7% and over-triage to 31% within the US population. Over 15 years, this would result in under-triage improvement for 5389 (59%) children and over-triage improvement for 479,421 (45%) children, for an estimated 484,810 total children who would now be triaged correctly with AACN. Thus, we estimate a potential benefit of improved MVC triage decision-making for 32,320 children annually (one-fifteenth of the 484,810 occupants) with nation-wide implementation of the pediatric AACN algorithm. Annually, reduction in under-triage attributable to AACN would translate to more appropriate care for 359 seriously injured children, potentially decreasing MVC mortality and morbidity. Similarly, impact of AACN in lowering over-triage would reduce unnecessary utilization of TCs for 31,961 minimally injured children annually, potentially lowering healthcare costs and burden on TCs.

Discussion

To identify injuries requiring Level I/II TC treatment, the pediatric AACN algorithm utilizes three injury facets to appropriately triage children based on the TIL. The AACN algorithm reduced under-triage for all crash modes without elevating over-triage beyond ACS guidelines and thereby increased triage efficiency to contribute to improving pediatric patient outcomes following an MVC. A 56% improvement in under-triage and 26% improvement in over-triage can be gained utilizing the pediatric AACN algorithm. The benefit of improved triage decision-making for 32,320 children annually would occur if the AACN algorithm had nation-wide implementation, with more appropriate care for 359 seriously injured children potentially saving more lives.

The algorithm produced over-triage rates that met the ≤50% ACS recommendation for all crash scenarios. In 15 years of unweighted real-world data across all crash modes, the under-triage rate was 14% and over-triage rate was 60% among MVC occupants, meaning that real-world triage rates did not meet ACS guidelines. Applying the AACN algorithm, triage rates were reduced to 6% under-triage and 44% over-triage, meeting ACS guidelines.[28] Studies have reported that 22% to 43% of major pediatric trauma is under-triaged, with those in rural areas having an under-triage rate of 32%, alarmingly above ACS' ≤5% guideline.[17,28,29] The greatest goal of AACN is to reduce under-triage by identifying the severely injured. NHTSA guidelines tout the benefits of AACN in reducing fatalities by 1.6% to 3.3% and more than doubling the lives saved compared to earlier notification alone.[30]

One study found 17% of pediatric trauma patients in road accidents received non-EMS transport (private/public vehicle or walk-in).[31] Among seriously injured pediatric patients transported via non-EMS, 45% required inter-facility transfer after presenting to an adult TC. A recent systematic review found no protocol had the sensitivity needed to achieve the ≤5% under-triage ACS goal.[32] The need for overall improvement in pediatric triage is evident and AACN is a way to do this for all occupants. While on-scene assessment adds valuable patient factors (eg, airway compromise, impalement), AACN incorporates telemetry factors (eg, delta-v) that are unknown otherwise, but indicative of severe injury.

Improving triage efficiency requires knowledge of the occupants' injuries to adequately transport to the correct location be it a TC or non-TC. The data reveal that no single triage method currently meets ACS guidelines. Our results are encouraging as the pediatric algorithm uses crash characteristics obtainable from vehicle sensors and age which could easily be entered by parents into an AACN system in their vehicle. Age could update automatically thereby assisting triage according to the developmental stage and growth of the child. If the caregiver is severely or fatally injured in the MVC, the AACN system can still ensure the child is triaged appropriately. The right place requires trauma management expertise and appropriately-sized equipment for a child's age.[33]

The pediatric AACN algorithm would serve to improve the national trauma system by providing quicker system learning and feedback through combining developmental and triage data captured by the algorithm with real-world outcomes. A retrospective multi-institutional assessment of the Field Triage Decision Scheme for pediatric and adult trauma patients found children had higher under-triage (16%) compared to nonelderly adults, further highlighting the need for pediatric triage improvement.[34] All phases of pediatric patient care could be improved with feedback to prehospital transport and facilities (TC; non-TC) combining transfer, discharge, and patient outcomes data. EMS are not as exposed to critically ill children and the skillset for pediatric triage is not uniform.[13,33] This impacts the triage of children and highlights a gap for improvement where AACN could contribute. In addition, integrating uniformity into AACN algorithm design and their reported metrics cannot be ignored to aid in rapid and ongoing improvement of the system and universal comparison of outcomes. The societal impact of improving the pediatric trauma system as a whole cannot be overstated.

Limitations

Limitations of the injury facet scoring and NASS-CDS have been reported.[14,20−24] Briefly, focusing on the most frequent injuries within each age group produced a different mix of injuries on each age-specific list (Appendix), but this was deemed appropriate since prevalence of different injuries and their need for TC treatment can vary across pediatric age groups. Severity and Transfer Scores were computed via retrospective analysis of large hospital datasets, but some age-specific injury analyses had limited sample sizes.[20,23,24] Use of consensus opinion to determine Time Sensitivity and Occult Scores has limitations; however, rigorously designed surveys of medical experts were used to quantify these facets of injury that are important to triage, but not otherwise captured in hospital data. While NASS-CDS is a representative US sample of minor, serious, and fatal crashes, it only includes tow away crashes and does not record injuries for older vehicles (>10 yrs). Lastly, while ~20% of pediatric occupants have child restraint system (CRS) use that is suboptimal,[14] this was not accounted for due to the limited sample size and the potential to impede AACN implementation as it would be complex for a vehicle to determine proper CRS use.

Another limitation exists in developing the algorithm which used the same dataset for training and evaluation due to reduced sample sizes. Cross-validation folds of 2, 3, 4, 5, 10, and 20 were examined and results were not sensitive to the number of folds. The limited NASS-CDS sample size did not allow for algorithm optimization to specific age groups, which could improve performance in future studies. While older children (ages 16+) have been included in adult AACN algorithms,[9,10] future studies are needed to compare performance of pediatric versus adult algorithms for children whose physiology may be "adult-like". Future field studies of crashes with and without AACN technology are needed to verify the estimated societal benefits to children; however, AACN is not widely implemented at this time, and algorithms in use focus on adults.

There is room for improvement in under-triage for rollover crashes. Rollovers are complex and determining the severity of the event is challenging. Use of the genetic optimization also poses a limitation as there is potential no global optimum is found. However, results met or slightly exceeded ACS target criteria, and therefore the optimization was deemed suitable. This pediatric AACN algorithm was developed utilizing ACS recommendations that were current at the time the study was conducted,[28] and while the under-triage rate remains the same, updated ACS 2014 guidelines of 25% to 35% for over-triage are noted.[35]

This study focused on identifying occupants with serious injury (ISS ≥16) with the assumption that these occupants require triage to a Level I/II TC,[26−28] but it did not distinguish between pediatric-designated versus adult TCs nor assess hospital care since this is not captured in NASS-CDS. The AACN algorithm does not account for crash location and associated transport times to TCs vs. non-TCs. In places where transport time is very long (eg, rural areas), it may be appropriate for occupants to be stabilized at a non-TC and later transferred to a TC. AACN contributes additional information to the Field Triage Decision Scheme protocol, but does not replace it entirely; thus, a holistic approach is warranted, with EMS considering AACN predictions, patient vital signs/obvious injuries, along with the transport times to surrounding TCs versus non-TCs to make the most appropriate triage decision for a given child.

Conclusion

This is the first AACN algorithm created specifically for children. The algorithm accounts for age-specific differences in injury patterns and risk across different stages of pediatric development. The pediatric AACN algorithm can aid with triage decision-making after a MVC and can increase triage efficiency and improve outcomes for pediatric occupants.

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Supplementary Data

Supplementary data related to this article can be found online at https://doi.org/10.1016/j.acap.2022.02.016.

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