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REASSESSING MECHANISM AS A PREDICTOR OF PEDIATRIC INJURY MORTALITY

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Abstract

Background—The use of mechanism of injury as a predictor of injury outcome presents practical challenges because this variable may be missing or inaccurate in many databases. The purpose of this study was to determine the importance of mechanism of injury as a predictor of mortality among injured children.

Methods—The records of children (<15 years old) sustaining a blunt injury were obtained from the National Trauma Data Bank. Models predicting injury mortality were developed using mechanism of injury and injury coding using either Abbreviated Injury Scale post-dot values (low-dimensional injury coding) or injury ICD-9 codes and their two-way interactions (high-dimensional injury coding). Model performance with and without inclusion of mechanism of injury was compared for both coding schemes, and the relative importance of mechanism of injury as a variable in each model type was evaluated.

Results—Among 62,569 records, a mortality rate of 0.9% was observed. Inclusion of mechanism of injury improved model performance when using low-dimensional injury coding but was associated with no improvement when using high-dimensional injury coding. Mechanism of injury contributed to 28% of model variance when using low-dimensional injury coding and <1% when high-dimensional injury coding was used.

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Conclusions—Although mechanism of injury may be an important predictor of injury mortality among children sustaining blunt trauma, its importance as a predictor of mortality depends on approach used for injury coding. Mechanism of injury is not an essential predictor of outcome after injury when coding schemes are used that better characterize injuries sustained after blunt pediatric trauma.

Keywords

wounds and injuries; mechanism of injury; predictive value of tests; child

1. INTRODUCTION

Previous studies have suggested that mechanism of injury is associated with injury outcome in children and adults and have argued for inclusion of this class of variable in trauma outcomes research.¹⁻³ The potential relationship between mechanism of injury and outcome is intuitive as different patterns of energy transfer occur with different mechanisms. Although most injury coding schemes can accommodate differences in the severity of a given injury (e.g., the grade of splenic injury), injury coding in some cases may not be sufficiently detailed to represent the actual severity of injury sustained. When injury coding is insufficiently detailed for specifying injury severity, mechanism of injury and other variables may serve as surrogates for the amount of injury-associated energy transfer and may improve the prediction of injury outcomes when included as covariates.

Although inclusion of mechanism of injury may have value in models predicting injury outcome, this variable has limitations that may impact its practical use. External cause of injury codes (E-codes) that are commonly used to classify mechanism of injury are frequently inaccurate in hospital discharge datasets. A review of studies evaluating the E-codes in hospital discharge data found that coding accuracy ranged from 64% when exact coding agreement was evaluated and 85% when broader coding groups were considered.⁴ In addition to limitations based on their accuracy, E-codes may be missing in some datasets requiring the use of methods for managing missing data.^{4,5} Missing mechanism of injury descriptions are also more frequently observed in patient populations at increased risk for adverse outcomes, such as children injured by child abuse.⁶ Although approaches such as multiple imputation have been used for managing missing data for trauma studies,⁷ the efficacy of these methods for managing missing values of mechanism of injury has not been studied.

Previous studies that have promoted the importance of including mechanism of injury in trauma outcomes studies have used statistical testing in multivariate models to define importance.¹⁻³ Standard tests of significance, however, are not sufficient to establish the importance of a given predictor when one or more predictors are correlated,⁸ a condition that likely occurs when mechanism of injury is combined with other predictors that are also each related to injury outcome. The purpose of this study was to reevaluate mechanism of injury as a predictor in models predicting mortality after pediatric injury using approaches that address the limitations of using standard statistical testing. A second purpose of this study was to evaluate how the importance of mechanism of injury differed when injuries were

coded using only severity within body regions and when injuries were coded using a more detailed, high-dimensional approach that included injury ICD-9 codes and their interactions.

2. METHODS

2.1 Data Overview

The Children's National Medical Center Institutional Review Board approved this study as an exempt protocol. We obtained the records of injured children (age <15 years old) sustaining an injury from a blunt mechanism in 2010 reported to the National Trauma Data Bank (NTDB), a database maintained by the American College of Surgeons. We excluded records of patients who were transferred during treatment or who had a missing discharge status. The dataset was further limited to patients who had at least one injury ICD-9 code in the range 800 to 959.9 exclusive of late effects of injury (905 to 909), foreign bodies entering through an orifice (930 to 939) and burns (940 to 949). The final dataset contained 62,569 records.

2.2 Development of Models

A directed acyclic graph can be developed that represents the dependencies between patient features such as age or weight (designated as variables in 'W'), mechanism of injury (designated as variables in 'X'), injuries that occurred (designated as variables in 'Y') and outcome after injury (designated as variables in 'Z') (Figure 1A). The purpose of this study was to test the hypothesis that injury outcome (Z) is 'conditionally independent' of mechanism of injury (X) when given the injuries that occurred (Y) (Figure 1B). This hypothesis can be restated as the assertion that it is sufficient to use the observed injuries (Y) to predict injury outcome (Z) and that inclusion of injury mechanism (X) as an additional class of predictors provides no significant improvement compared to using injuries alone. To test this conditional independence hypothesis, we developed models predicting in-hospital mortality based on different injury code representations and either the inclusion or exclusion of variables representing mechanism of injury.

Based on our previous work showing that mortality prediction after pediatric injury was improved when using high-dimensional data,⁹ we developed separate models using either low- or high-dimensional injury code representations. For low-dimensional injury code representations, we used Abbreviated Injury Scale (AIS) post-dot values (range 1–6) for each of nine body regions. We treated each pair of AIS post-dot values and body region as a binary variable. For high-dimensional injury code representations, we generated binary variables representing the occurrence of each ICD-9 injury code or the occurrence of any pair of ICD-9 codes in the same patient ('interaction' codes). The dataset used for this study contained 54 AIS post-dot:body region variables, 1,332 ICD-9 injury codes and 45,229 pair-wise ICD-9 injury code interactions. Based on external cause of injury codes (E-codes) listed in the CDC Matrix of E-code Groupings,¹⁰ we generated variables representing the 10 most common mechanisms of injury observed in the dataset.

Standard approaches for logistic regression use maximum likelihood can become unreliable due to overfitting as the number of predictors becomes very large. Regularized logistic regression is an approach that avoids the issue of overfitting by defining a regularization

parameter that serves to shrink regression coefficients toward zero.¹¹ Although not required when using low-dimensional injury code representations, for consistency we used regularized regression for both low- and high-dimensional injury code representations. We evaluated two regularization procedures to assess the approach that yielded optimal model performance: Laplacian and Gaussian. The Laplacian regularization in a way performs variable selection because it can push some of the estimated coefficients values to exactly zero. In contrast, Gaussian regularization is a procedure that performs only parameter estimate shrinkage and results in models that can include all predictors. Because many of these predictors are not numerically important, we only counted parameter estimates using Gaussian regularization with an absolute value greater than a parameter threshold of 10^{-4} .

2.3 Evaluation and Comparison of Models

We first used standard frequentist statistical approaches for evaluating model performance: Harrell's c-statistic to evaluate model discrimination and the Hosmer-Lemeshow χ^2 statistic to evaluate model calibration, the latter based on dividing patients into deciles of risk. To compare models with and without inclusion of mechanism of injury as a predictor, we used a frequentist approach (the change in the Akaike Information Criteria [AIC]) and a Bayesian approaches (the change in Deviance Information Criteria [DIC] and the Bayes factor).^{12–14} AIC is based on the maximized likelihood and the number of model parameters, with the optimal model having the smallest AIC value. The differences in AIC of the two models can be used to interpret the strength of evidence for one model versus another, with a difference less than two units conventionally indicating model similarity and a difference of >10 units indicating model dissimilarity.¹⁵ DIC is a Bayesian approach that can be used for model selection and is based on the posterior mean of the deviance and the effective number of model parameters, with the preferred model having a smaller DIC value. The Bayes factor is another approach that can be used to determine which model best fits the data and focuses on the ratio of the data likelihoods under the competing models. Hypothesis testing with Bayes factors can be more robust than frequentist hypothesis testing and offers interpretative advantages.¹⁴ We calculated AIC, DIC and the Bayes factor using packages available in the R statistical package.

2.4 Evaluation of the Relative Importance of Model Predictors

When evaluating predictors used in a model, it is useful to consider the importance of each predictor, both when considered by itself and in combination with other predictors. To evaluate the predictors used in each model, we computed the relative weight of each predictor in models using an adaptation of a previously described method.¹⁶ This method maps the original (and likely correlated) predictors to a mutually orthogonal set of predictors, so that the contribution of each predictor can be computed. To apply this approach of relative weight computation for high-dimensional data, we used numerical approximations to overcome some of the computational challenges posed by these methods. We first computed a singular value decomposition of the column-normalized training data matrix. This normalization disrupts the sparse structure of a high-dimensional data matrix by adding additional data elements, potentially making it computationally infeasible for the calculation to proceed. We therefore normalized only those columns that were less than 99% sparse (i.e., when at least 1% of the rows in the training data for a given column are non-

zero). This approximation preserved the sparseness of most columns without significantly impacting the normalization requirement. We also rounded the entries of the matrix linking the original and likely correlated predictors to their new, uncorrelated values through linear regression, by rounding values with an absolute value of less than 10^{-7} to zero. This method yields a relative weight for each predictor based on its contribution for predicting the dependent variable, with the relative weights of all predictors summing to one. Predictors with a higher relative weight have more importance for predicting the dependent variable than those with lower values.

3. RESULTS

3.1 Data Overview

The overall mortality observed in the dataset was 0.9% (Table 1). Although falls were the most common mechanism of injury, injuries sustained by children as motor vehicle occupants or as pedestrians were more common mechanisms among those patients who died. Children injured as a pedestrian struck by a motor vehicle had the highest mortality (4.1%) and represented 5.7% of records, while children injured in a fall had the lowest mortality (0.2%) and represented 53.1% of records.

3.2 Comparison of Model Performance

All models assessed had excellent discrimination and calibration based on assessment of the c-statistic and Hosmer-Lemeshow χ^2 statistic (Table 2). Using low-dimensional injury code representations, we observed an improvement in model performance when including mechanism of injury. This finding refuted the conditional independence hypothesis and supported a contribution of mechanism of injury when using low-dimensional injury coding. The use of high-dimensional injury representations resulted in improved model performance compared to low-dimensional data representations based on the c-statistics and Hosmer-Lemeshow statistic values. In contrast to findings using low-dimensional injury code representations, models generated using high-dimensional injury code representations supported the conditional independence hypothesis. We observed no qualitative difference in these findings when using either a Gaussian or Laplacian regularization procedure (Table 2).

An evaluation of the relative weights of model parameters was consistent with the comparisons of model performance when including or excluding mechanism of injury. In the models trained using low-dimensional injury representations, injury mechanism accounted for 28% of variance while injury codes accounted for the remaining 72%. In contrast, injury mechanism accounted for <1% of variance in the model using high-dimensional injury representations, while injury coding represented the largest contribution of model variance. Injury interactions accounted for 98% of model variance, while single ICD-9 codes accounted for only 1% (Table 3).

4. DISCUSSION

We have shown in this study that the impact of mechanism of injury on mortality prediction after pediatric injury depends on the injury coding scheme used, with its impact being high

when using a low-dimensional injury coding scheme and minimal when using a high-dimensional coding scheme. In contrast to the approaches used in the current study, previous studies promoting the value of mechanism of injury in trauma outcome studies defined the importance of mechanism of injury based on significance testing in multivariate models.¹⁻³ In multivariate regression, the statistical significance of an independent variable is an intuitive way to determine the ‘importance’ of the independent variable as a predictor. This approach, however, is appropriate only when all predictors are uncorrelated,⁸ a circumstance that is uncommon in models predicting injury outcome in which more than one predictor are likely to be associated with the outcome. In the case of observed or potential collinearity among a set of predictors, the importance of a given predictor can be evaluated by several methods, including comparing models generated with and without inclusion of each predictor or calculation of the relative importance of a given predictor. These approaches can determine the importance of a given independent variable even when collinearity may be present and can more rigorously evaluate the impact of mechanism of injury. Relative weight calculation is also useful because it can provide a metric for the importance of mechanism of injury.

The use of mechanism of injury can be problematic when included in studies of the outcomes after pediatric injury. Mechanisms of injury associated with significant morbidity and mortality vary by age^{17,18} and may be difficult to ascertain in specific pediatric populations.⁶ Because of evolving developmental milestones, the mechanism of injury associated with mortality after childhood injury also changes with age, even when subdivided into age intervals differing as little as a few months. For example, ‘falls from furniture’ is a common mechanism of injury associated with hospitalization and death among six-month old children, while ‘falls from playground’ is observed as an important mechanism of injury only among older age groups.¹⁸ Child abuse is an important mechanism of injury associated with injury mortality in infants and toddlers.¹⁹ Despite its importance as a mechanism of injury in this age group, ascertainment of this mechanism is challenging, with both missed and missing codes occurring among children injured by this mechanism.⁶ Both the diversity of mechanism of injury and these ascertainment challenges highlight the limitation of using mechanism of injury as a predictor of mortality in children and supports that use of a modeling approach that does not depend on mechanism of injury in some settings.

The findings in our current study suggest that inclusion of injury code interactions or other approaches that represent injury codes in a detailed way such as the use of a high-dimensional injury coding schemes (as presented in this paper), the ICD-9 Injury Severity Score (ICISS)²⁰ or the Trauma Mortality Prediction Model (TMPM-ICD9)²¹ may obviate the need for using mechanism of injury and circumvent the need to address potential challenges when ascertaining mechanism of injury. Injury code interactions that we used with high-dimensional injury coding are a representation of the additional effect of two injuries occurring together, above that occurring with either injury alone. For example, the occurrence of a severe head injury and a splenic injury together may influence the treatment options chosen as well as outcome.²² Our finding that ICD-9 code interactions have a substantially higher relative weight than single ICD-9 codes suggests the potential importance of inclusion of information about the simultaneous occurrence of injuries when

mechanism of injury may not be available or is unreliable. The large number of these interactions requires modeling approaches that can manage high-dimensional data.

Based on our findings, it is reasonable for mechanism of injury to remain as a component in trauma outcome studies when the injury coding and other covariates used as predictors may incompletely specify the severity of injury.¹⁻³ In these settings, mechanism of injury provides information about severity that may not be conveyed by injury coding. In a similar way, mechanism of injury is also useful as a predictor in prehospital triage schemes.²² Although the low specificity and sensitivity of mechanism of injury are known in this setting,²³ mechanism of injury is easily obtained and is useful when more accurate anatomic or physiological variables are not obtainable or are unreliable. In this setting, mechanism of injury may provide additional information about the severity of injury and potential patient outcomes that is incompletely conveyed by other observable information.

This study has several limitations. First, we limited our analysis to children sustaining only a blunt mechanism of injury to ensure the homogeneity of the study population. Our findings will require validation for penetrating and other types of injury among children. These findings should be compared with similar studies conducted on adult population data. Second, we considered only injury codes and mechanism of injury, not including other predictors such as age, vital signs or Glasgow Coma Scale values. While we excluded other variables to focus on the relative importance of injury codes and mechanism of injury, inclusion of additional variables that have a strong relationship with mortality may have altered the observed importance of mechanism of injury or injury codes as predictors. Based on the observed low relative importance of injury codes represented in a high-dimensional coding scheme, it is likely that changes in relative importance between mechanism of injury and injury codes would be most prominent in the low-dimensional model. Third, the focus of this study was to determine the role of mechanism of injury as a predictor of in-hospital mortality. Separate evaluation will be needed to determine its relationship with other measurements of injury outcome such as functional status after discharge. Finally, although the software that we used is publicly available, managing and performing analyses using high-dimensional injury code representations is challenging because of the amount of data preprocessing required. As the potential benefits of using high-dimensional data in this and other settings becomes more established, it is likely that user-friendly interfaces will be developed for processing and analyzing high-dimensional data, allowing for more widespread use.

5. CONCLUSIONS

In this study, we observed the importance of mechanism of injury as a variable contributing to the prediction of in-hospital mortality after blunt injury in children but found that its importance depended on the injury coding scheme used. When we used a low-dimensional injury coding scheme, mechanism had an important contribution to predicting injury mortality. In contrast, a significant contribution of mechanism of injury was not observed when we used a more detailed high-dimensional injury code representation. Our findings suggest that mechanism of injury may not be needed as a predictor of injury mortality in all models of injury outcome. When mechanism of injury is missing or potentially inaccurate,

this variable can be omitted when injury coding is sufficiently detailed to characterize the injury patterns associated with outcome. A high-dimensional injury coding scheme or other strategies that well-characterize injury patterns may be useful for analyzing trauma outcomes in datasets in which mechanism of injury is inaccurate or frequently missing.

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Figure 1. Directed acyclic graphs representing the proposed dependencies between mechanism of injury, anatomic injury and outcome after injury with (A) and without (B) inclusion of patient features.

Table 1

Summary Statistics

	Overall	Mortality (%)
Age		
0–4 yrs	20,996	1.2
5–9 yrs	19,355	0.7
10–14 yrs	22,218	0.8
Gender		
Female	22,799	0.8
Male	39,723	1.0
Mechanism of injury (%)		
Fall	53.1	0.2
Motor vehicle-occupant	11.1	2.9
Motor vehicle-motorcyclist	0.7	1.3
Motor vehicle-pedal cyclist	1.8	1.7
Motor vehicle-pedestrian	5.4	4.1
Pedal cyclist	5.8	0.2
Other pedestrian	0.8	2.5
Other transportation	8.2	0.9
Struck by, against	11.9	0.6
Machinery	0.4	1.5
Other	0.5	2.1

Table 2

Model Structure and Evaluation

Injury coding dimension	Inclusion of mechanism of injury	Penalization	# of predictors		c-statistic	Hosmer-Lemeshow statistic	AIC [†]	DIC [*]	DIC	Bayes Factor
			Entered	Selected						
Low	No	Gaussian	48	48	0.948	10.8	70.6	3453.3	100.1	15.0
	Yes		58	58	0.958	11.8		3352.6		
	No	Laplace	48	47	0.948	10.8		3451.4	100.7	14.5
	Yes		58	56	0.958	11.8	70.4	3351.3		
High	No	Gaussian	46,561	46,561	0.999	10.1	1.8	1733.9	1.6	NA [‡]
	Yes		46,571	46,571	0.999	10.0		1732.1		
	No	Laplace	46,561	1,967	0.998	10.1		1658.0	1.8	NA ^{‡§}
	Yes		46,571	1,902	0.998	9.9	2.2	1656.4		

* deviance information criteria;

† change in Akaike information criteria;

‡ not available because posterior distributions did not converge

Table 3

Evaluation of the Relative Weight of Model Parameters

Model		# of Variables in Final Model	Relative Weight
Low-dimensional injury coding	Mechanism of injury	10	0.28
	AIS post dot codes	48	0.72
High-dimensional injury coding	Mechanism of injury	10	<.001
	ICD-9 codes	1,332	0.02
	ICD-9 code interactions	45,229	0.98