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Using multiple imputation and propensity scores to test the effect of car seats and seat belt usage on injury severity from trauma registry data

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Abstract

Background—Missing data and the retrospective, nonrandomized nature of trauma registries can decrease the quality of registry-based research. Therefore, we used multiple imputation and propensity scores to test the effect of car seats and seat belt usage on injury severity in children involved in motor vehicle crashes.

Methods—All children admitted after injury from motor vehicle crashes who had complete data on seat belt or car seat usage from 2003 to 2006 were included in the study. The sample was divided into children younger than 4 years ($n = 130$) or 5 years or older ($n = 575$) and analyzed for seat belt usage, car seat usage, injury severity score, revised trauma score, and Glasgow Coma Scale score. Data were analyzed before and after matching on propensity scores after multiple imputation.

Results—There were no outcome differences between car seat users and non-car seat users. However, there were significant improvements in injury severity score (7.0 vs. 10.1, $P = .002$) and revised trauma score (7.6 vs 7.3, $P = .013$ for seat belt users compared to nonusers) even after matching on propensity score.

Conclusion—Multiple imputation and propensity scores demonstrated the efficacy of seat belts, but not car seat in this preliminary study. This statistical method can strengthen registry-based research.

Keywords

Multiple imputation; Propensity score; Trauma registry; Passenger safety

There are several obstacles to performing randomized, prospective trials in pediatric trauma, including the inability to control interventions, the unpredictability of trauma events, and the difficulty of obtaining informed consent from acutely injured children and their legal guardians. As a result, pediatric trauma research studies are often based on nonrandomized, retrospective samples of patients. These studies are often considered inferior to randomized, controlled clinical trials. However, the propensity score is a method that can be used to test the causal effects in observational studies in settings where it is not possible to randomize

interventions [1,2]. For example, propensity score methodology can be used to determine if male smokers have higher medical expenditures than males who never smoked [1].

Missing data is another major problem in retrospective research using large databases such as a pediatric trauma registry [3]. For example, logistic regression requires records with complete information. Traditional approaches to missing data, such as deleting records with incomplete data (which reduces sample size and increases bias) or completing missing data with single means or medians (which under-estimates variability), can lead to erroneous conclusions. Multiple imputation is a statistical method for filling in missing data with plausible values; it addresses the problem of missing data elements in a research database.

The purpose of this study was to use car seat safety data to demonstrate how multiple imputation and propensity scores can be used to analyze pediatric trauma registry data with missing data in an environment where it is not possible to randomize interventions.

1. Methods

1.1. Sample

The sample included all motor vehicle crash occupants recorded in the trauma registry from 2003 to 2006 of a level 1 pediatric trauma center. The sample included all patients younger than 4 years ($n = 130$) or 5 to 15 years of age ($n = 575$) who had complete data on car seat or seat belt usage. In the group of patients younger than 4 years, 83 (64%) of 130 were restrained in car seats. In the group of patients 5 to 15 years of age, 339 (59%) of 575 were restrained. Data collected from each record included demographics, injury severity score (ISS), revised trauma score (RTS), and Glasgow Coma Scale (GCS) score. This study was approved by the institutional review board of Children's Hospital.

1.2. Data cleaning

The data were prepared by running frequencies and deleting obvious typographical errors (relatively uncommon) and making text responses consistent, for example, $m = M =$ male (relatively common). There were 2 data fields related to restraint in the trauma registry: "Protective Device" and "Protective Device Applied." Because Ohio law requires children younger than 4 years to be in a car seat, if a child was younger than 4 years and the protective device was anything other than a car seat, then Protective Device was designated "car seat" and Protective Device Applied was designated "No."

1.3. Imputation of missing data

All covariates including outcome measures were used when creating multiple imputation data sets. This method has been described by other researchers [4]. The procedure for multiple imputation was a Markov Chain Monte Carlo method using Jeffrey's prior [5]. Markov Chain Monte Carlo refers to a collection of methods for simulating random draws from nonstandard distributions.

1.4. Propensity scores

In the usual analysis with multiple imputation, the analyst creates multiple data sets and performs the required analysis separately for each data set. A final model is developed using the estimated parameters from the multiple data sets to obtain the proper variability of the imputed missing values. In this analysis, the logistic regression is an intermediate step rather than the final step, so the problem was approached slightly differently. Separate logistic regressions were generated from each imputed data set. Rather than combining them into a single data set, the conditional probabilities of seat belt use were computed for each data set. We imputed 15 complete data sets providing 15 records for each patient. We then randomly

selected 1 of the 15 records for each patient to include in the final data set. Users and nonusers of restraint were matched on the conditional probabilities (propensity scores) from the final data set. Matching was accomplished by rounding propensity scores to 1 decimal point and matching the subjects. The general approach was motivated by Collins et al [6] and preserved the sample original variability while filling in the missing values.

1.5. Logistic regression models for computing propensity scores

For Protective Device = car seat; age <5; cause = motor vehicle crash (MVC)

$$\text{Logit (Protective Device Applied)} = b_0 + b_1 (\text{age}) + b_2 (\text{male}) + b_3 (\text{black}) + b_4 (\text{weight}) + b_5 (\text{age}) \times (\text{weight}) + b_6 (\text{population density}) + b_7 (\text{median income})$$

For Protective Device = seat belt; age ≥ 5; cause = MVC

$$\text{Logit (Protective Device Applied)} = b_0 + b_1 (\text{age}) + b_2 (\text{male}) + b_3 (\text{black}) + b_4 (\text{weight}) + b_5 (\text{age}) \times (\text{weight}) + b_6 (\text{population density}) + b_7 (\text{median income})$$

Propensity score computed as

$$p(\text{Protective Device Applied}) = \exp[(Bx_i)/(1 + \exp(Bx_i))]$$

1.6. Statistical analysis

The imputation/propensity method of analysis was compared to a standard analysis in which only complete records were included in the analysis. The amount of missing data was noted. Differences in covariates and outcome variables based on the presence or absence of restraint were tested with *t* test and χ^2 .

2. Results

Analysis of the trauma registry for motor vehicle occupants included 130 children younger than 5 years with available car seat information and 575 children between 5 and 15 years of age with seatbelt information. The amount of missing data is identified in Table 1.

There were 68 missing data patterns in the data set that included the variables for population density, median household income, race, weight, ISS, GCS, RTS, and total length of stay. The relative efficiency for the multiple imputation varied from .971 to .999. There were no differences between car seat and non-car seat users for the covariates used to impute propensity scores for patients under 5 admitted to the hospital using either the traditional or multiple imputation data (Table 2). There were significant differences between seatbelt users and non-seatbelt users in age and weight with the traditional method of dropping cases with missing data (Table 3). The propensity score matching removed this difference and yielded equivalent groups.

Table 4 presents the results of the 2 methods of analysis for car seats. The groups were evenly matched on propensity score. There were no differences in injury severity between car seat and non-car seat users before or after matching. Table 5 shows significant differences in injury severity between seatbelt and non-seatbelt users before and after matching.

3. Discussion

A major concern of using trauma registry data to answer epidemiological questions is possible bias owing to missing data. In addition, the lack of randomization of interventions, such as the use of passenger restraints, is a barrier to exploring causal relationships. This study demonstrated an approach to analyzing registry data with missing data in an

environment where it was not possible to randomize interventions. The statistical methods used here allowed this observational study to approximate a randomized experiment as closely as possible. This should be the goal for all observational studies [1].

There were no statistically significant differences in injury severity owing to car seat use as analyzed by either the “traditional” method or by multiple imputation. There were significant differences in severity of injury with seatbelt use by both methods of analysis. In the case of seatbelts, there was a difference in the demographics of children who were using restraints. The methods discussed eliminated the bias by imputing the missing data and matching on propensity scores.

Although multiple imputation has been used to predict pediatric trauma mortality from national data [7], this is first study to our knowledge to use these statistical methods to study pediatric injury prevention. Nevertheless, there was a significant limitation in our study: injuries were only recorded in the trauma registry if the patients were admitted to the hospital. The number of hospital admissions *prevented* by properly applied passenger restraints was unknown. Therefore, we cannot draw conclusions on the effectiveness of restraints in reducing crash-related injuries with this bias present. In addition, there was large amount of missing data in the registry on whether or not restraints were used. We did not impute the restraint usage variable. Future research might consider this analytic approach using national or regional crash data that include restraint usage, the crash energy vectors, and the presence or absence of physical injury [8].

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Table 1

Missing covariate values

Percent missing data in the trauma registry	Car seat (n = 130)	Seatbelt (n = 575)
Age	0%	0%
Sex	0%	0%
Race	14%	10%
Weight	15%	13%
Population density of residence zip code	34%	36%
Household median income of residence zip code	34%	36%

Table 2

Covariates used to create propensity scores for matching car seat and no-car-seat patients

Car seat covariates used for computing the propensity score (mean [SD])	Traditional complete data with missing values		Matched on propensity score after multiple imputation	
	No car seat	Car seat	No car seat	Car seat
Weight	13.5 (3.6)	13.6 (5.2)	.87	13.2 (5.0)
Age	2.33 (1.0)	2.43 (1.5)	.68	2.26 (1.0)
African American	26%	15%	.14	22%
Male	57%	48%	.26	60%
Population density in resident neighborhood (people/mile ²)	519 (512)	460 (484)	.58	477 (499)
Household median income per year (\$)	35,722 (14,576)	41,478 (18,062)	.12	37,461 (15,203)
				41,748 (19,721)
				.28

Race and sex *P* values are compared with χ^2 tests. Weight, age, population density, and household median income were compared with *t* tests.

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Table 4

Effect of using a car seat on severity of injury

Car seat outcome	Traditional complete data prematched with missing values				Matched on propensity score after multiple imputation			
	No car seat		Car seat		No car seat		Car seat	
	Mean (SD)	n	Mean (SD)	n	Mean (SD)	n	Mean (SD)	n
ISS	7.4 (8.0)	12	8.7 (10.9)	73	7.3 (7.8)	45	9.2 (13.8)	45
RTS	7.3 (1.6)	11	7.4 (1.2)	70	7.2 (1.6)	45	7.4 (1.2)	45
GCS	13.8 (3.1)	12	13.7 (3.0)	74	13.8 (3.1)	45	13.7 (3.0)	45
LOS total	3.6 (8.1)	8	3.3 (6.1)	45	3.9 (7.0)	45	3.6 (4.5)	45
Propensity score: conditional probability of using a car seat					.43 (.14)		.38 (.14)	

All comparisons were with *t* tests. LOS, length of stay.

Table 5

Effect of using a seatbelt on severity of injury

Seat belt outcome	Traditional complete data prematched with missing values			Matched on propensity score after multiple imputation		
	No seatbelt	Seatbelt	P	No seatbelt	Seatbelt	P
	Mean (SD)	Mean (SD)	n	Mean (SD)	Mean (SD)	n
ISS	10.0 (11.9)	6.5 (9.4)	197	10.1 (11.9)	7.0 (9.1)	196
RTS	7.3 (1.4)	7.6 (9.4)	278	7.3 (1.4)	7.6 (0.8)	196
GCS	13.6 (3.6)	14.4 (2.3)	281	13.5 (3.6)	14.4 (2.3)	196
LOS total	4.1 (6.8)	3.6 (10.3)	177	3.8 (6.1)	3.4 (9.9)	196
Propensity score: conditional probability of using a seatbelt				.43 (.09)	.43 (.09)	.950

All comparisons were with *t* tests.