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Development of Severity Models for Vehicle Accident Injuries for Signalized Intersections in Rural Areas

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Abstract

The objective of this paper is to establish a statistical relationship correlating crash severity with weather, traffic maneuvers, and specific roadway geometrics at four-legged signalized intersections in rural areas. In this paper, the probability of the levels of injury severity is examined by applying ordered probit regression models for all crash types, single-vehicle crashes, two-vehicle crashes, and three or more-vehicle crashes. The study results suggest that in terms of crash severity for all crash records, more vehicle occupants, sharper horizontal curves, higher speed limits, and manner of collisions play major roles for more serious injuries, while presence of protected left lane, wider median widths, and higher traffic flows, and more driveways are associated with less injury severity of intersections. By the number of vehicles involved in crashes, the variable shows variations in the models and magnitudes of the estimates.

Keywords: *accident injury, severity, signalized intersections, ordered probit models, safety*

1. Introduction

Safety and efficiency are the two primary concerns of transportation engineering. Traffic accidents place a huge financial burden on society and the public always want policy makers to provide safer road conditions. Safety is, therefore, of considerable interest to both policy makers and transportation engineers.

Numerous research has been conducted in the field of highway safety. But as the nodes of the highway network, intersections should receive more attention for safety analyses than other highway elements because many intersections are found to be crash-prone spots from a safety point of view. This is partially caused by the complicated interactions between roadway users within the influence area of an intersection. When reaching an intersection, drivers are confronted with a lot of choices to make such as either to stop or keep going, or going either left or right. The complex vehicle movements at intersections directly lead to a traffic conflict, and if a driver cannot avoid the traffic conflict, a vehicle crash will occur. Therefore, intersection safety should be a high priority of traffic agencies, and traffic agencies should provide enormous and also efficient highway safety management efforts.

Accident prediction modeling is helpful for assessing risk factors and design issues at intersections. To the end, a good number of studies analyzed the causation of accident frequencies using Poisson, Negative Binomial and other models. There is, however, comparatively little research work on accident severity. Especially, there are no established accident prediction models for crash severity in rural signalized intersections. Few research means that the information for the research is not adequate and thus, more studies are required. Especially, signalized intersections are rare on rural two-lane highways, so it is difficult to develop meaningful research for the safety improvement at rural signalized intersections, which limits highway agencies to choose best accident modification factors among the available candidates. For example, there are only 50 signalized rural intersections in Georgia.

The objective of this paper is to establish a statistical relationship correlating crash severity with weather, traffic maneuvers, and specific roadway geometrics at four-legged signalized intersections in rural areas. The methodology used to derive the statistical model, including the selection of the appropriate model, is first described in the paper. This is followed by a description of the data and a discussion on model calibration and estimation. Lastly, the results and implications of the findings are presented.

2. Literature Review

There exists a well-developed literature documenting linkages between vehicle accidents and geometric design of road sections. For example, Miaou et al. (2003) investigated statistical relationships between traffic crashes and traffic flows at urban four-legged signalized intersection in Toronto. Poch and Mannering (1996) have investigated negative binomial models of crash counts in Washington. The findings of their research provide the accident reduction benefits of various proposed improvements on operationally deficient intersections. Persaud and Dzbik (1993) used generalized linear models with both macroscopic and microscopic accident data for freeway sections. In their study, they identified some difficulties with conventional modeling techniques and used an empirical Bayesian procedure to refine the estimates of generalized linear models. Kulmala (1995) studied the safety of main road junctions with the help of accident prediction models. They made separate models for 915

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three-arm and 847 four-arm junctions and applied Poisson and Negative Binomial techniques for injury accidents. They found that the most important variables are the magnitude and distribution of motor vehicle volumes. They also note that the risk of accidents increase as the traffic share of the minor road increases. Ivan et al. (1999) estimated annual crash rates as a function of traffic density and land use, as well as ambient light conditions and time of day. Their model specification relied on a Poisson distribution for predicting both single and multi-vehicle highway crash rates. Their results show that traffic intensity explains differences in crash rates even when controlling for time of day and light conditions, and that these effects are quite different for single and multi-vehicle crashes.

Among all the existing literature, the most relevant papers for the work presented in this paper are those of O'Donnell and Connor (1996) and Kockelman and Kweon (2002). In the paper by O'Donnell and Connor (1996), they assessed the probabilities of four levels of injury severity as a function of eleven road user attributes and compared ordered logit and ordered probit specificatons. Their results suggest that injury severity are affected by speed, vehicle age, occupant age, gender, blood alcohol levels, seatbelt usage, manner of collision, vehicle make and type. Kockelman and Kweon (2002) used ordered probit models to examine the risk of different injury levels. Their results suggest that pickups and sport utility vehicles are less safe than passenger cars under single-vehicle crash conditions. In two-vehicle crashes, however, these vehicle types are associated with less severe injuries for their drivers.

3. Data Description

The data for the study are based on a total of 50 four-legged signalized highway intersections in rural areas. The data used for model calibration were obtained from four data sources: crash files, roadway characteristic (RC) files, aerial photographs, and geographic information system (GIS) maps. Crash and RC files were available for 1999 and 2000. RC files provided detailed information on road characteristics. Digital Orthophotography Quarter Quadrangles (DOQQs) aerial photos were used from 1994 and 2000 to extract information regarding intersection angle and degree of horizontal curvature of selected intersections by overlapping with GIS roadmaps.

Four crash data sets were prepared for model estimation. These all derive from the 1999 and 2000 Georgia crash files. The crash files also include fatal, serious, visible, complaint, and no injury (PDO). The crash records contain a variety of information including weather conditions, roadway conditions, vehicle maneuvers etc. reported at the time of the accident.

Based on underlying theories of crash causation and to establish a suitable statistical model that enabled the examination of possible relationships between accident frequencies, geometric, and traffic characteristics of intersections, a total of 55 possible explanatory variables were considered. Traffic volumes, including left-, right-, and u-turn volumes were estimated from average annual daily traffic (AADT). Geometric elements included vertical and horizontal curves, sight distances, hazard ratings around the intersection, terrain, presence of exclusive left-and right-turn lanes, lane and shoulder widths, median types and widths, driveways intensity, signal control types, etc.

Table 1 describes the key variables available in the analysis, their units, and the abbreviation used in model estimation results. Table 2 shows the summary statistics of the variables discussed in this paper.

4. Methodology

The ordered probit models are usually motivated in a latent (ie. unobserved) variables framework. The general specification of each single-equation model is

$$y_i^* = x_i'\beta + \varepsilon_i \tag{1}$$

where y_i^* is a latent variable measuring the risk of injury faced by accident victim i, x_i is a vector of variables determining the discrete ordering for observation, n, β is a vector of estimable parameters, and ε_i is a random error term.

It is assumed that all error terms have zero mean and that the error terms for different accident victims are uncorrelated. In a small departure form standard models of ordered multiple choice, it is also assume that the disturbance term is heteroskedastic (i.e. the variance of the disturbance term can vary from one accident victim to another):

$$Var(\varepsilon_i) = Var(y_i^*) = [\exp(z_i'\gamma)]^2 \tag{2}$$

where z_i is a vector of observed nonstochastic explanatory variables, which may or may not include some of the elements of x_i, and γ is a vector of unknown parameters.

Using the equation (1), observed ordinal data, y_i, for each observation are defined as

$$y_i = \begin{cases} 0 \ if -\infty \le y_i^* \le \mu_1 \ (no\ injury) \\ 1 \ if \ \mu_1 \le y_i^* \le \mu_2 \ \ (complaint\ of\ pain) \\ 2 \ if \ \mu_2 \le y_i^* \le \mu_3 \ \ (visible\ injury) \\ 3 \ if \ \mu_3 \le y_i^* \le \mu_4 \ \ (severe\ injury) \\ 4 \ if \ \mu_4 \le y_i^* \le \infty \ \ (fatal\ injury) \end{cases} \tag{3}$$

where μ are estimable parameters that define y*, which corresponds to integer ordering.

The μ are parameters that are estimated jointly with the model parameters. The estimation problem then becomes one of determining the probability of specific ordered responses for each observation, n.

This determination is accomplished by making an assumption on the distribution of ε. If ε is assumed to be normally distributed across observations with mean = 0 and variance = 1, an ordered probit model results with ordered selection probabilities as follows:

$$\begin{aligned} P(y=1) &= \Phi(-\beta X) \\ P(y=2) &= \Phi(\mu_1 - \beta X) - \Phi(\beta X) \\ P(y=2) &= \Phi(\mu_1 - \beta X) - \Phi(\beta X) \\ &\vdots \\ P(y=I) &= 1 - \Phi(\mu_{I-2} - \beta X) \end{aligned} \tag{4}$$

where $\Phi(.)$ is the cumulative normal distribution,

Table 1. Key Variables Available in Analysis

Variables	Description
SEVERITY	no injury(0), complaint of pain(1), visible injury(2), severe injury(3), and fatal injury(4)
ACC_MONTH	Month of accident occurred
NO_VEH	The number of vehicles in collision
NO_OCC	The number of occupants in vehicles
WEATHER	Weather: clear, cloudy, rain, snow, sleet, fog, and other
SURF_COND	Surface condition: dry, wet, snowy, loy,and other
ROAD_CHAR	Road character: straight and level, straight on grade, straight on hillcrest, curve and level, curve on grade, and curve on hillcrest
MEDWIDTH1	The major road median width in feet
RTLN2	The number of right turn lane on the minor road
PROT_LT1	1 if protected left turn lane on major road, 0 otherwise
PROT_LT2	1 if protected left turn lane on minor road, 0 otherwise
COMDRWY1	The number of commercial driveways on the major road within 250 feet of the intersection center
DRWY1	The number of commercial and residential driveways on the major road within 250 feet of the intersection center
COMDRWY2	The number of commercial driveways on the minor road within 250 feet of the intersection center
DRWY2	The number of commercial and residential driveways on the minor road within 250 feet of the intersection center
LIGHT	Light at intersection: no(0), yes(1)
SD2	Sight distance on minor road (feet)
SDL1	Left-side sight distance on major road (feet)
VEI2	Average curve grade rate along minor road within 800 feet of the intersection center
VCEI2	Sum of absolute change of grade in percent per hundred feet for each crest curve on minor road any portion of which is within 250 feet of the intersection center, divided by the number of such curves
HEICOM	(1/2)(HEI+HEI2)
SP1	The average posted speed on major road in vicinity of the intersection. (mph)
SP2	The average posted speed on minor road in vicinity of the intersection. (mph)
AADT1	Annual average daily traffic on major road (vehicles per day)
AADT2	Annual average daily traffic on minor road (vehicles per day)
MANNER_OF	Manner of collision: angle, head on, rear end, sideswipe-same direction, sideswipe-opposite direction, and not a collision with a motor vehicle

$$\Phi(\mu) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty} EXP\left[-\frac{1}{2}w^2\right]dw \tag{5}$$

In the equation 4, threshold μ_0 is set equal to zero without loss of generality. For estimation, the equation 4 is written as

$$P(y=i) = \Phi(\mu_i - \beta X) - \Phi(\mu_{i+1} - \beta X) \tag{6}$$

where μ_i and μ_{i+1} represent the upper and lower thresholds for outcome i.

The likelihood function is:

$$L(y\backslash\beta,\mu) = \prod_{n=1}^{N}\prod_{i=1}^{I}[\Phi(\mu_i - \beta X_n) - \Phi(\mu_{i+1} - \beta X_n)]^{\delta_{in}} \tag{7}$$

where δ_{in} is equal to 1 if the observed discrete outcome for observation n is i, and zero otherwise.

This equation leads to a log-likelihood of

$$LL = \sum_{n=1}^{N}\sum_{i=1}^{I}\delta_{in} LN[\Phi(\mu_i - \beta X_n) - \Phi(\mu_{i+1} - \beta X_n)] \tag{8}$$

Maximizing this log likelihood function is subject to the constraint $0 \le \mu_1 \le \mu_2 K \le \mu_{I-1}$. If the assumption is made that ε in the equation 1 is logistically distributed across observations with mean = 0 and variance = 1, an ordered logit model results, and the derivation proceeds the same as for the ordered probit model. Because the ordered probit model is not afflicted with the estimation difficulties encountered in estimating the multinomial probit model for unordered discrete data, the ordered probit is usually chosen over the ordered logit because of the underlying assumption of normality.

5. Results and Discussions

This section discusses the development of the models. The crash prediction models were estimated using the LIMDEP econometric software. Ordered probit regression models were estimated separately for driver injury status in all crashes, single-vehicle crashes, two-vehicle crashes, and three or more crashes. A 90% confidence interval was used as an acceptable cutoff for statistical significance. The parameters of the ordered probit models are estimated by the method of maximum likelihood.

The models include many theoretically appealing variables

Table 2. Summary Statistics of Key Variables

Variables	Frequency	Mean	Median	Minimum	Maximum
SEVERITY	449	0.36	0	0	4
no injury complaint of pain visible injury severe injury fatal injury	335(74.6%) 60(13.3%) 44(9.8%) 7(1.6%) 3(0.7%)				
ACC_MONTH	449	6.63	7	1	12
NO_VEH	449	1.97	2	1	5
1 2 3 or more vehicle	43(9.5%) 381(84.9%) 25(5.6%)				
NO_OCC	449	2.97	2	1	64
ROAD_CHAR	449				
straight and level straight on grade straight on hillcrest curve and level curve on grade curve on hillcrest	329(73.3%) 87(19.4%) 12(2.7%) 12(2.7%) 7(1.6%) 2(0.5%)				
MEDWIDTH1	449	1.57	0	0	13
RTLN2	449	0.78	1	0	2
PROT_LT1	449	0.35	0	0	1
No Yes	292(65.0%) 157(35.0%)				
PROT_LT2	449	0.18	0	0	1
No Yes	369(82.2%) 80(17.8%)				
COMDRWY1	449	2.74	3	0	8
DRWY1	449	2.96	3	0	8
COMDRWY2	449	2.53	2	0	10
DRWY2	449	2.76	2	0	11
LIGHT	449	0.47	0	0	1
No yes	237(52.8%) 212(47.2%)				
SD2	449	1119	1117	237	2000
SDL1	449	839	857	135	2000
VEI2	449	2.05	1.88	0	7.79
VCEI2	449	1.72	1.38	0	8.4
HEICOM	449	2.53	1.09	0	12.71
SP1	449	44.5	45	25	55
SP2	449	40	40	25	55
AADT1	449	8943	8700	430	15200
AADT2	449	3464	3000	420	10400
MANNER_OF	449				
Angle head on rear end sideswipe-same direction sideswipe-opposite direction not a collision with a motor vehicle	193(43.0%) 12(2.67%) 163(36.3%) 26(5.8%) 9(2.0%) 46(10.2%)				

with the intent to explain as much of variation in injury crash as possible, given knowledge of crash causation and the available set of potential explanatory variables. The "best" models discussed in the following section were selected by comparing several "candidate" models. When all candidate models were compared, the goodness-of-fit measures discussed previously were used, in addition to inspection and theoretical appeal of model coefficients and their associate statistical significance. This paper only shows the "best" models and the "second best" models from Table 3 to 6 and discussed below.

5.1 Models for All Crash Records

Table 3 provides the estimation results of ordered probit models of drivers' injury severity, as applied to drivers across all crashes. Since the dependent variable or injury index increases with injury severity, positive coefficients suggest the likelihood of more severe injuries. Thus, more vehicle occupants, shaper horizontal curves, and higher speed limits on major roads are associated with increased injury severity.

In contrast, presence of protected left lane is associated with decreased injury levels, as shown in the second best model. Although the results from the previous studies (Miaou et al., 2003; Kulmala, 1995; Ivan et al., 2000; Oh et al., 2004; Lyon et al., 2004) showed that traffic flows increase crash frequencies, this study shows that AADT on major roads are associated with decreased injury levels, which indicates higher traffic flows reduces the likelihood of more severe injuries than lower traffic flows. It is probably because higher traffic flows lead to more traffic conflicts but also reduces speeds of approaching vehicles to intersections. Wider medians on major roads decrease injury levels than narrower medians, as expected. More commercial driveways on minor roads were found to be a factor reducing injury severity.

The study results also show that the manners of collision are a significant factor for injury severity. Angle, head on and rear end collisions are particularly serious, contributing to more severe injury levels than sideswipe collisions on the same and opposite direction.

5.2 Models for Single-Vehicle Crash Records

Like the models for all crash records, protected left lane, driveways, and traffic flows are significantly associated with injury levels, but sight distance, vertical curves, presence of light, and road characteristic variables are newly included in the models (shown in Table 4).

For the main model for single-vehicle crashes, more driveways on major roads is associated with decreased severity levels, while the second best model includes more commercial driveways on major roads leads to lower levels of severity. Higher crest vertical curves on minor roads also contribute to more severe injury levels, as shown in the second best model. In contrast, presence of protected left turn lane, presence of light, longer left sight distance from major roads, and more AADT on major road are associated with decreased injury levels. The model results also shows that road characteristics from "Straight and Level" to "Curved on Hillcrest" are significantly associated with severity levels.

5.3 Models for Two-Vehicle Crash Records

Model results for two-vehicle crash records are similar to the model results for all crash records. Table 5 shows the estimation results of the probit models. Like the models for all crashes, the model results suggest that injury severity rises with higher number of occupants, sharper horizontal curves, and higher speed limits, while lower number of commercial driveways, higher traffic flows on major, the manners of collsions as significant variables for lower severity levels. Vertical curves and number of driveways on minor roads are, however, newly founded as important for these types of crashes. Injury severity rise for two-vehicle crashes with more vertical curvature out to 800 feet (244 meters) on minor road approaches. One may

Table 3. Model Results for All Crashes

Variables	Best Model (p-value)	Second Best Model (p-value)
Intercept	2.5946 (0.0437)	2.1237 (0.0983)
NO_OCC	0.0700 (0.0000)	-
MEDWIDTH1	-0.0372 (0.0339)	-0.0518 (0.0058)
PROT_LT1	-	-0.3575 (0.0273)
COMDRWY2	-0.0731 (0.0544)	-
HEICOM	0.0547 (0.0167)	0.0622 (0.0079)
SP1	0.0285 (0.0018)	0.0220 (0.0119)
LOG of AADT1	-0.4989 (0.0003)	-0.3982 (0.0049)
MANNER_OF	-0.1430 (0.0012)	-0.1532 (0.0004)
ρ^2	0.176	0.151
χ^2	51.28	34.38
Number of observations	449	449

Table 4. Model Results for Single-Vehicle Crashes

Variables	Best Model (p-value)	Second Best Model (p-value)
Intercept	4.4278 (0.0858)	4.0905 (0.0939)
ROAD_CHAR	-	0.3070 (0.0141)
PROT_LT2	-1.4709 (0.0727)	-
COMDRWY1	-	-0.1840 (0.0405)
DRWY1	-0.1082 (0.0852)	-
LIGHT	-	-1.168 (0.0903)
SDL1	-0.00461 (0.0043)	-
VCEI2	-	0.0971 (0.0984)
LOG of AADT1	-0.4347 (0.0907)	-0.8569 (0.0444)
ρ^2	0.378	0.257
χ^2	19.23	13.05
Number of observations	43	43

wonder vertical curves on minor roads are more significant than those on major roads. The maximum, mean, and median of vertical curves on minor roads are 13.5, 1.91, and 1.39, respectively, while those for major roads are 11.9, 1.45, and 1.19. That is, minor roads need to be better built to reduce the injury severity level. Regarding the effects of driveways, the findings of this research suggests high access management through better channelization can decreases severe injury levels. In addition, the model results show that the month of accident occurrence is associated with increased severity levels, which indicates that the severity of injury varies seasonally.

5.4 Models for Three or More-Vehicle Crash Records

Table 6 provides the estimation results of probit models of injury severity, as applied to drivers across three or more-vehicle crashes. Unlike the models for other crash types, the model results show that the number of vehicles involved in collisions is associated with the injury severity, which implies that if more vehicles are involved in crashes it would result in more serious injuries.

The model results suggest that road characteristic variable, like the models for single crashes, affects the injury severity. In contrast, presence of right turn lane on minor roads, longer sight distance from minor roads, and more AADT on minor roads reduce the injury severity levels. With regard to speed, numerous studies (Parker, 1997; Navon, 2002; Shinar, 1999) have demonstrated positive and negative safety effects of speed. Some studies indicate that fast speeds are not hazardous and perhaps even safer because turning and/or lane changing maneuvers occur more frequently when the average speed of traffic is lower.

Table 5. Model Results for Two-Vehicle Crashes

Variables	Best Model (p-value)	Second Best Model (p-value)
Intercept	2.5080 (0.0991)	2.5844 (0.0931)
ACC_MONTH	-0.0397 (0.0639)	-0.0428 (0.0479)
NO_OCC	0.1439 (0.0262)	0.1328 (0.0386)
COMDRWY2	-0.0945 (0.0215)	-
DRWY2	-	-0.1089 (0.0073)
VEI2	-	0.0786 (0.0569)
HEICOM	0.0577 (0.0206)	-
SP1	0.0306 (0.0024)	0.0293 (0.0051)
LOG of AADT1	-0.4620 (0.0035)	-0.4531 (0.0041)
MANNER_OF	-0.2690 (0.0001)	-0.2715 (0.0001)
ρ^2	0.197	0.195
χ^2	53.69	52.83
Number of observations	381	381

Table 6. Model Results for Three or More-Vehicle Crashes

Variables	Best Model (p-value)	Second Best Model (p-value)
Intercept	1.6201 (0.1134)	4.4835 (0.0955)
NO_VEH	2.5258 (0.0073)	1.9344 (0.0089)
ROAD_CHAR	1.1404 (0.0295)	0.8766 (0.0622)
RTLN2	-0.7941 (0.1074)	-
SD2	-	-0.0027 (0.0457)
SP2	-0.1495 (0.0509)	-0.2051 (0.0121)
LOG of AADT2	-0.5468 (0.0841)	-
ρ^2	0.480	0.456
χ^2	24.77	23.56
Number of observations	25	25

Other studies have revealed that higher speeds considerably increase crash involvement because speeding reduces the distance that drivers have to react and avoid crashes and lengthens stopping distances, which in turn increases both the likelihood of crashing and the severity of crashes. The findings in this study suggest that the safety effects of speed are different across crash types. For three or more-vehicle crashes, injury severity falls with higher speed limits on minor roads, which suggests opposite safety effects to the other crash types. This finding may, however, be limited by the relatively small sample size (n=25) used.

6. Conclusions

Many literatures confirm that Poisson formulation or Negative Binomial formulation is superior to other modeling methodologies to describe the statistical properties of the accident frequency. However, modeling the accident frequency needs to aggregate the accident data and conducts the macroscopic impact analysis with a few significant variables. In order to reveal the safety factors and develop effective countermeasures, there are needs to examine a variety of characteristics of accident natures. It is, thus, meaningful to reveal safety factors affecting injury severity levels in more detail using a large disaggregated cross-section data.

A variety of factors can come into play when vehicles crash on intersections. It is because intersections require complicated interactions between roadway users as the nodes of the highway network. In order to reveal the safety factors for four legged signalized intersections in rural area, this study estimated the parameters of ordered probit models based on the ordinal nature of injury levels. Especially, the focus of this study has been on different levels of injury by different number of vehicles involved in collisions.

The model results show variations in the safety factors by crash types and suggest that there should be different remedies to improve the safety of intersections. For all crash records, the results show that more vehicle occupants, sharper horizontal curves, higher speed limits, and manner of collisions play major roles for more serious injuries, while presence of protected left lane, wider median widths, and higher traffic flows, and more driveways improve the safety of intersections. By the number of vehicles involved in crashes, the variable showed variations in the models and magnitudes of the estimates.

In terms of crash severity for single-vehicle crashes, road surface conditions, presence of protected left lane, driveways, presence of light, vertical curves, sight distance, and traffic flows are statistically significant. Presence of protected left turn lane, presence of light, longer left sight distance from major roads, more driveways on major roads, and higher traffic on major roads are associated with decreased injury levels, while higher crest vertical curves on minor roads also contribute to more severe injury levels. The model results also shows that road characteristics from "Straight and Level" to "Curved on Hillcrest" are significantly associated with the severity levels of injury.

For three or more-vehicle crashes, road characteristics, number of vehicle involved in collisions, presence of right turn lane, sight distance, traffic flows, and speed limits are significant factors for the severity levels of injury. These findings may, however, be limited by the relatively small sample size used.

Finally, in this research, statistical relationships between crash severity, weather, traffic maneuvers, and specific roadway geometrics were established. Although the ordered probit model can be elegantly developed and perhaps statistically satisfied, there still remains the unresolved question of using it as a means of assessing safety impact. It is because identification of significant explanatory variables explains some association with the severity levels of injury but may not imply the causation of injury severity. Research into this important area, therefore, should be continued.

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