PERGAMON

Accident Analysis and Prevention 34 (2002) 609–618

ACCIDENT ANALYSIS & PREVENTION

www.elsevier.com/locate/aap

Factors influential in making an injury severity difference to older drivers involved in fixed object–passenger car crashes

Sunanda Dissanayake *, Jian John Lu

Department of Civil and Environmental Engineering, ENB118, University of South Florida, 4202 E Fowler Avenue, Tampa, FL 33620, USA

Received 20 December 2000; received in revised form 4 May 2001; accepted 7 May 2001

Abstract

To identify factors influencing severity of injury to older drivers in fixed object–passenger car crashes, two sets of sequential binary logistic regression models were developed. The dependent variable in one set of models was driver injury severity, whereas for the other it was the crash severity (most severe injury in the crash). For each set of models, crash or injury severity was varied from the least severity level (no injury) to the highest severity level (fatality) and vice versa. The source of data was police crash reports from the state of Florida. The model with the best fitting and highest predictive capability was used to identify the influence of roadway, environmental, vehicle, and driver related factors on severity. Travel speed, restraint device usage, point of impact, use of alcohol and drugs, personal condition, gender, whether the driver is at fault, urban/rural nature and grade/curve existence at the crash location were identified as the important factors for making an injury severity difference to older drivers involved in single vehicle crashes.

Keywords: Older drivers; Crash modeling; Highway safety; Logistic regression; Injury severity

1. Introduction

The percentage of elderly population in the United States is experiencing a rapid growth. According to the current trends, between the years 2020 and 2030, it is estimated that 20% of the population will be 65 years or older (U.S. Census Bureau, 1996). According to the current trends, the majority of the elderly population relies on automobiles for most of their transportation needs. Although preserving the mobility of elderly as drivers is a primary concern, traffic safety statistics indicate that older drivers as a group experience a far greater risk of injury and fatality when using the roadways (NHTSA, 1998). Based on the statistics, the number of crashes involving older drivers is less than the average, since they drive less. However, on a per mile driven basis they experience higher crash involvement than many other driver age groups (TRB, 1988). In addition, the elderly are more likely to be killed or severely injured when involved in a crash. Decreased physical and mental capabilities of the elderly combined with frailty reduce their desire to maintain mobility through the use of automobiles. This problem is even more acute when considering the fact that today's highway environment in most cases is based on the performance characteristics of average population rather than those of older drivers (Dissanayake et al., 1999).

Understanding the causes and situations under which older drivers are more likely to be fatally or more severely injured will help towards improving the overall highway safety situation of older drivers. The purpose of this study was therefore to identify the roadway, environmental, vehicle, and driver related factors that are influential in making an injury or crash severity difference to older drivers involved in crashes. In order to accomplish that, two sets of models were developed based on sequential binary logistic regression and the best model was selected based on model fitness and the predictive capability to identify the influential factors towards making a severity difference (Dissanayake, 1999).

* Corresponding author. Tel.: +1-813-974-0888; fax: +1-813-974-2957

E-mail addresses: dissanay@eng.usf.edu (S. Dissanayake), lu@eng.usf.edu (J.J. Lu).

0001-4575/02/$ - see front matter
PII: S0001-4575(01)00060-4

2. Past studies

There has been a considerable number of studies on the development of injury or crash severity models, even though the studies conducted particularly on older drivers are rare. The general models developed in the past to identify the most important parameters which are crucial in reducing or increasing the level of injury severity of the passengers, drivers or crashes include the following.

A study conducted by applying the techniques of categorical data analysis to build a structural model relating driver characteristics and behaviors to type of crash and injury severity found that the driver behaviors of alcohol and drug use and lack of seat belt use greatly increased the odds of more severe crashes and injuries (Kim et al., 1995). Driver errors were found to have a small effect, while personal characteristics of age and sex were generally insignificant, as found in this study. Another study by Mercier et al. used logistic regression to assess whether age or gender or both influenced severity of injuries suffered in head-on automobile collisions on rural highways (Mercier et al., 1997). Individual variables included age of the driver or passenger, position of the vehicle, and the form of the protection used, along with a set of interactive variables. Stewart discussed the applications of classification and regression tree methods (CART) in roadway safety studies and used it to estimate measures of driver injury severity when the crash consisted of a vehicle striking a fixed object on the roadside (Stewart, 1997). Effects of vehicle air bags on the severity of off-road, fixed object crashes were studied by using crash data from three states, Illinois, North Carolina, and Utah obtained from the Highway Safety Information System (HSIS) (Council et al., 1997). A retrospective case control study examined the relationship between the risk of dying for Michigan motor vehicle crash drivers and the type of county of crash occurrence as rural or non-rural, while adjusting for crash characteristics, age, sex, and the medical resources in the county of crash occurrence (Maio et al., 1992). A disaggregate model of road accident severity based on sequential logit models was developed in Canada, using an Ontario road accident database (Nassar et al., 1994). O'Donnell and Connor (1996) presented statistical evidence showing how variations in the attributes of road users could lead to variations in the probabilities of sustaining different levels of injury in motor vehicle accidents by using data from New South Wales, Australia, using an ordered logit and probit model. A more recent study used logistic regression to analyze the 1994/1995 Pennsylvania vehicle crash data to identify the driver, highway, and environmental factors that differentiate run-off-road (ROR) crashes from non-ROR crashes (McGinnis et al., 1999). Another study used the nested logit formulation as a means of predicting the accident severity given that an accident has occurred (Shankar et al., 1996). An ordered probit model was used in another study to identify specific variables significantly influencing levels of injury in two-vehicle truck–car rear-end involvement collisions on divided roadways (Duncan et al., 1998).

3. Data and methods

3.1. The dataset

For the model building process in this study, Florida Traffic Crash Database obtained from the State Data Program that is maintained by the National Center for Statistics and Analysis (NCSA) established under the National Highway Traffic Safety Administration (NHTSA) was used. The State Data Program is a collection of data from 17 states containing police reported accidents for the last 10 years. Florida is one of the 17 states where the NCSA maintains a database and all the crash related variables are recorded in three sub-files: Accident File, Vehicle File, and Person File (NCSA, 1998). Accident File contains the general crash characteristics describing the environmental and roadway conditions at the time of the crash. Vehicle File contains the information describing the vehicles involved in the crash. This file also includes some driver characteristics. The Person File includes the information describing the characteristics of all the people involved in the crash. All three sub files could be combined together by using the common variable, case number.

Since it was required to consider the factors that were solely associated with older drivers, this research considered the single vehicle crashes where older drivers hit some kind of fixed object. For the purpose of this study, drivers aged 65 years or more were considered as older drivers. Two response variables that were very strongly correlated were used in two separate model development processes. One variable was the injury severity of the older driver involved in the crash, which is coded as: no injury, possible injury, non-incapacitating injury, incapacitating injury, fatal (within 90 days), non-traffic fatality, and unknown. In the model building process, non-traffic fatalities and unknown severities were discarded and other injury outcomes were used in the model building process. The other response variable tested was the crash severity, which is defined as the most severe injury sustained by any occupant or non-occupant involved in the crash. As only the fixed object crashes were treated in this study, concern for non-occupants did not arise here. This variable has also been recorded under the same element values as for injury severity and the five different levels of crash severity were used as the ordinal responses. Among a large set of explanatory variables that may be capable of making a difference in the crash or injury severity, the most influential set of variables were selected in the logistic regression procedure while removing some of the strongly related explanatory variables. Three years of data from 1994 to 1996 were used in the modeling process and data from 1993 were used in validating the model.

3.2. Logistic regression modeling

The purpose of the model development was to identify the highway, environment, vehicle, and driver related characteristics that are more likely to produce more severe injuries for older drivers involved in fixed object–passenger car crashes. Since the outcome, i.e. injury/crash severity is of a discrete nature, logistic regression was identified as a suitable approach to identify the important factors. Thus, logistic regression modeling, where the probability of occurrence of a discrete dependent variable is predicted by using a set of independent variables was utilized. The regression coefficient of a certain independent variable provides an explanation of the type of influence that variable is having on the outcome, crash or injury severity in this case. As the initial attempts to develop ordinal logistic regression models failed due to lack of fitness, a binary logistic regression model approach was utilized in this study.

In binary logistic regression models, the relationship between a dichotomous or binary response variable and one or more explanatory variables are modeled. The logistic regression model uses the explanatory variables to predict the probability that the response variable takes on a given value. The response variable takes one of the two binary values in the case of binary logistic regression models. For a binary response variable y, the linear logistic regression model has the form:

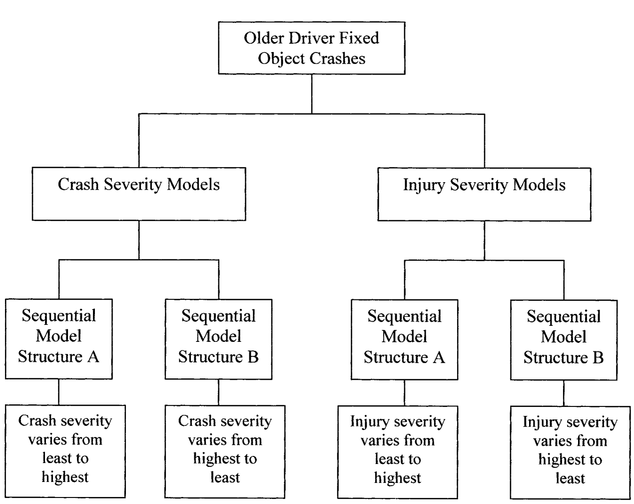

Fig. 1. Structural organization of the model development process.

$$\text{logit}(p_i) = \log[p_i/(1-p_i) - \alpha + \beta' X_i]$$

where p_i = prob. $(y_i = y_1|X_i)$ is the response probability to be modeled, and y_1 is the first ordered level of y, α is the intercept parameter; β' is the vector of slope parameters, and X_i is the vector of explanatory variables.

This logistic regression equation models the logit transformation of the ith individual's event probability, $p_{i,}$ as a linear function of the explanatory variables in the vector, $X_{i.}$ A more general class of models share the feature that a function $g = g(\mu)$ of the response variable is assumed to be linearly related to the explanatory variables. The function g is known as the 'link function'. There are other common link functions like the Normit function used in probit analysis and the complementary log–log function. Since the logit function has advantages, like being able to be more easily interpreted, it was used in developing the crash/injury severity models for older drivers. More theoretical information on link functions is available in the book *Discrete Choice Analysis* (Ben-Akiva and Lerman, 1993).

As the study dealt with older drivers, identifying the factors influential in making even a small injury or crash severity difference was considered to be important. Therefore, several sets of sequential binary logistic regression models were developed as represented in Fig. 1. The other advantage of using a sequential binary approach over the other methods is that it is capable of accounting for the dependency between different levels of severity. Details related to the two sequential model structures where the severity varied from lowest level to the highest and vise versa are given in Fig. 2a, b, respectively.

3.3. Criteria for assessing model fit

SAS programming language allows the user to print tables and statistics to help analyze and evaluate the estimated logistic regression models developed using the LOGISTIC procedure (SAS Institute, 1998a). Results of testing the null hypothesis: BETA = 0 provides two criteria (AIC and SC) that are useful for comparing models. Two other criteria (− 2 log L and Score) test the null hypothesis that all regression coefficients are zero. Except for the score statistic, all of the criteria are based on the likelihood for fitting a model with intercepts only or fitting a model with intercepts and explanatory variables. The details of these four criteria are as follows.

1. AIC is the Akaike information criterion, which is a goodness-of-fit measure that could be used to compare one model to another, with lower values indicating a more desirable model.

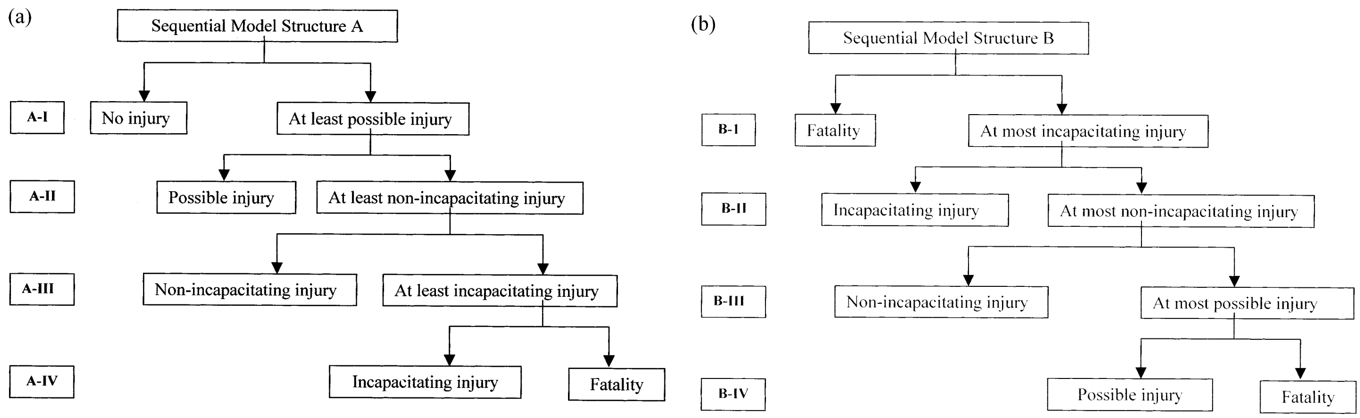

Fig. 2. (a) Sequential model structure A. (b) Sequential model structure B.

2. SC is the Schwarz criterion, which is also a goodness-of-fit measure that can be used to compare one model to another, with lower values indicating a more desirable model.
3. $-2 \log L$ is the -2 log likelihood statistic, which has a Chi-square distribution under the null hypothesis that all regression coefficients of the model are zero, which provides a P-value for the Chi-square statistic. A significant P-value (for example a P value less than 0.05) provides the evidence that at least one of the regression coefficients for an explanatory variable is non-zero.
4. Score is a score statistic, which also outputs the chi-square value, degrees of freedom, and a P-value for this statistic.

3.4. Selected explanatory variables

Out of all the variables related to crashes, the variables that could be considered as related to crash or injury severity were sorted out. These selected explanatory variables fell into four categories: driver-related, vehicle-related, roadway-related, and environmental-related factors. A detailed list of all the selected explanatory variables considered in the model development is given in Table 1. All of the explanatory variables were treated as dichotomous variables (0 and 1) except the travel speed, which is a continuous variable. At the early stages of the modeling process, travel speed and speed limit, which were strongly correlated, and were tested separately in the models. It was found that travel speed was a better indicator in predicting injury severity than speed limit. Thus, the model developments were continued with travel speed.

3.5. Other considerations

It is important to emphasize the fact that the models developed in this research are based on crash data, and hence they explain the effects of individual characteristics and behaviors on crash and injury severity given that the person is involved in a crash. In other words, the models developed are conditional crash and injury severity models, conditional in the sense that the crash has occurred. However, it is possible that many of the factors that increase the odds of severe crashes and injuries might also increase the probability of the occurrence of the crash as well. The other concern about the models developed is due to the well-known concern about the accuracy of the data gathered from the police reported crashes. A common bias may be that police are not called or do not file reports on very minor crashes. The percentage of under reporting is lowest with fatalities and increases with less severe injury levels. As the models treat the outcomes of crashes and not rates, the effect of this bias is not important. However, accuracy of recording the crash or injury severity level might have a significant influence on the model accuracy. The determination of this severity is usually done by a police officer at the scene of the crash and reported on a Florida Traffic Crash Report Form.

In addition to controlling for drivers age, and the crash type where only the fixed object crashes were treated, a third controlling condition was the type of vehicle. As there might be a relationship between the properties of the vehicle to the type of the severity experienced in the crash, and as the sample sizes were not sufficiently large enough for developing separate models, only passenger cars were considered in this study. All other types of vehicles including sports utility vehicles, mini-vans, pick-up trucks, buses, motorcycles, etc., were excluded from the analyses.

4. Research findings

4.1. Crash severity models

When considering older driver fixed object crashes, 3 years of crash data in Florida yielded a valid sample size of 7637. Results of crash severity modeling, which utilized sequential binary logistic regression model structures A and B are given in Table 2. One of the important observations that can be made through the above results is that the travel speed and restraint device usage remained as important parameters for all of the crash severity models. Having a front impact point in the crash was also identified in most of the models as an important factor towards having a more severe crash. Gender, urban/rural nature, and the presence of a roadway curvature were the other more important factors in making a crash severity difference. Effect of weather condition does not seem to be making any difference towards changing the crash severity. On the other hand, the B model series or considering the severity levels sequentially from fatal to no injury identified more explanatory variables as important than that of the sequential models where severity was changed from no injury to fatal.

Table 1
List of explanatory variables treated in the modeling process

Category	Variable	Description
Driver-related	AL_DRG	= 1 If driver is under influence of alcohol or drugs = 0 if not
	PERDEF	= 1 If the physical condition of the driver is a factor = 0 if not
	PEJECT	= 1 If the driver has ejected in the crash = 0 if not
	MALE	= 1 If the driver is a male = 0 If the driver is a female
	SPEED	Actual speed of the vehicle at the time of the crash
	CNTY_RES	= 1 If the driver is a resident of the same county = 0 if not
	FAULTC	= 1 If the driver is at fault for the crash = 0 if not
	RESTR	= 1 If a restraint device is used = 0 if not
Roadway-related	RURAL	= 1 If the crash occurred in a rural area = 0 if not
	GR_CUR	= 1 If there is a curve or grade at the crash location = 0 If the location is straight and level
	FREEWY	= 1 If the crash occurred in a freeway = 0 if not
Vehicle-related	VFOLT	= 1 If the vehicle is at fault for the crash = 0 if not
	IMP_SIDE	= 1 If the impact point is side of the vehicle = 0 if not
	IMP_FRNT	= 1 If the impact point is front of the vehicle = 0 if not
Environmental-related	BDWTHER	= 1 If the weather is not clear = 0 If the weather is clear
	DAYLIGHT	= 1 If the crash occurred during day light condition = 0 if not

4.2. Injury severity models

Details about the sequential binary logistic injury severity models are given in Table 3. These models were based on 3 years of crash data in Florida, which yielded a valid sample size of 7371. Frequencies for older driver injury severity are different from that of the crash severity, since crash severity is classified based on the most severe consequence of the crash. Therefore in certain cases, crash severity might have resulted due to an injury occurring to an occupant other than the driver, making the injury frequency different from crash frequencies. Similar to crash severity models, injury severity models also identified travel speed and restraint device usage as important variables for all the models. In addition, the fact that the driver is at fault for the crash was also an important factor in creating different injury severity at all levels. Weather or light conditions as well as the county of residence were not significant at all for any of the binary injury severity models.

4.3. Model fitness

In the above crash and injury severity models, lower AIC and SC values for the models with the selected set of explanatory variables indicated more desirable models. Also, significant P-values (<0.05) for $-2 \log L$ and Score indicated that at least one of the regression coefficients is non-zero. The residual Chi-square values were examined for evaluating the effectiveness of the remaining explanatory variables, which had not been entered into the models. A P-value smaller than 0.05 for the residual Chi-square for each case indicates that at least one of the remaining parameter coefficients is non-zero. Examination of all the residual Chi-square values showed that they all were greater than 0.05. As such it can be decided that the effect of the variables that have not been entered to the models were minimal.

In addition, SAS provides several measures of association to help assess the quality of the logistic regression model (SAS Institute, 1998b). It gives the percentage of concordant, discordant, and tied observations, and the number of observation pairs upon which the percentages are based. From the numbers of concordant and discordant pairs of observations, four rank correlation indexes, Somers' D, Gamma, Tau-a, and c were calcu-

Table 2
Crash severity modeling results

Variable	Model							
	Sequential model A				Sequential model B			
	A-I	A-II	A-III	A-IV	B-I	B-II	B-III	B-IV
INTERCEPT	−1.4877	0.6282	−0.4082	−1.4659	−5.0069	−3.1223	−2.2822	−2.2566
AL_DRG	−0.7794	[a]	[a]	[a]	[a]	−0.6821	−0.5783	−0.6629
PERDEF	0.3457	[a]	[a]	[a]	[a]		0.2177	0.2925
PEJECT	0.8140	[a]	[a]	[a]	[a]	1.0224	0.6394	[a]
MALE	−0.3990	[a]	[a]	0.3976	[a]	−0.1913	−0.3523	−0.3727
SPEED	0.0458	0.0155	0.0144	0.0122	0.0456	0.0398	0.0359	0.0370
CNTY_RES	[a]	−0.2589	[a]	[a]	[a]	[a]	[a]	[a]
FAULTC	[a]	[a]	−0.2669	−1.2737	−1.3684	[a]	[a]	[a]
RESTR	−0.4856	−0.6346	−0.5911	−0.5722	−1.2752	−0.7934	−0.4942	−0.1842
RURAL	0.6695	0.3515	[a]	[a]	[a]	0.5500	0.6039	0.4566
GR_CUR	0.3845	[a]	[a]	0.4512	0.4820		0.3029	0.2797
FREEWY	0.2856	[a]	[a]	[a]	[a]	−0.4188	[a]	[a]
VFOLT	[a]	−0.1620		[a]	[a]	[a]	[a]	[a]
IMP_SIDE	[a]	[a]	[a]	[a]	0.8202	[a]	[a]	−0.2885
IMP_FRNT	0.7950	0.1908	[a]	[a]	1.3056	0.4784	0.6643	0.5639
BDWTHER	[a]	[a]	[a]	[a]	[a]	[a]	[a]	[a]
DAYLIGHT	0.2182	[a]	[a]	[a]	[a]	[a]	[a]	0.2834

[a] Variable is not significant.

Table 3
Injury severity modeling results

Variable	Model							
	Sequential model A				Sequential model B			
	A-I	A-II	A-III	A-IV	B-I	B-II	B-III	B-IV
INTERCEPT	−1.6661	0.1776	−0.4387	−1.1970	−4.7155	−3.6090	−2.6546	−2.4147
AL_DRG	−0.6536	[a]	[a]	[a]	[a]	−0.4242	−0.3172	−0.7619
PERDEF	0.6829	[a]	[a]	[a]	[a]	0.3033	0.3765	0.6971
PEJECT	0.9392	[a]	[a]	[a]	[a]	1.0256	[a]	[a]
MALE	−0.5607	[a]	[a]	[a]	[a]	−0.2998	−0.4245	−0.5850
SPEED	0.0497	0.0160	0.0151	0.0152	0.0482	0.0443	0.0381	0.0393
CNTY_RES	[a]	[a]	[a]	[a]	[a]	[a]	[a]	[a]
FAULTC	−0.3465	−0.2627	−0.3705	−1.6250	−1.9533	−0.3045	−0.3131	−0.1809
RESTR	−0.6765	−0.7101	−0.7031	−0.6430	−1.5031	−0.9942	−0.6575	−0.3495
RURAL	0.6034	0.2861	[a]	[a]	[a]	0.4974	0.5393	0.4568
GR_CUR	0.4597	[a]	[a]	[a]	0.4436	[a]	0.3557	0.3829
FREEWY	[a]	[a]	[a]	[a]	[a]	−0.5828	[a]	[a]
VFOLT	[a]	[a]	[a]	[a]	[a]	[a]	[a]	[a]
IMP_SIDE	[a]	0.3608	[a]	[a]	[a]	0.4692	[a]	[a]
IMP_FRNT	1.1817	0.4824	[a]	[a]	0.9062	0.8974	1.1081	0.9495
BDWTHER	[a]	[a]	[a]	[a]	[a]	[a]	[a]	[a]
DAYLIGHT	[a]	[a]	[a]	[a]	[a]	[a]	[a]	[a]

[a] Variable is not significant.

lated. In order to decide whether the crash severity models or injury severity models were giving a better predictive capability, these four indices were taken into consideration. In a relative sense, a model with higher values for these indices has better predictive ability than a model with lower values. Index values for both sequential binary logistic regression crash and injury severity models are given in Table 4, which indicates the injury severity model as having better predictive capability than crash severity models.

4.4. Model accuracy

In the case of binary response models classification tables may be used to measure the accuracy of the logistic regression model. In this case, the classification table uses logistic regression model to classify the observations as events or non-events. The LOGISTIC procedure produces a classification table that contains several measures of predictive accuracy for each probability cut point. That is, the model classifies an observation as an event if its estimated probability is greater than or equal to a given probability cut point. Otherwise, the observation is classified as a non-event. The classification table reports how well these classifications match the observed event or non-event status of each observation. To test the actual predictive accuracy of the logistic regression model the evaluation should be based on a different set of observations than those data used to fit the model, to avoid the bias of the results. As such, fixed object older driver crashes that occurred during 1993 were used to test the model accuracy. It should be noted here that crashes during the 3-year period from 1994 to 1996 were used in developing the models. The classification table for the binary regression logistic model A–I using a probability cut point of 0.5, yielded a total of 2426 injuries in which 1295 non-events were predicted as non-events and 607 events were predicted as events. The remainder represents the number of incorrect predictions. Thus the model accuracy can be calculated as: $(1295+607)\ 100/2426=78.4\%$. In the same way, classification tables were obtained for the other binary injury models and the summary of the predicted accuracies is given in Table 5. According to the table, sequential model structure B, where the injury severity models were developed from most severe (fatal) to less severe (no injury) gave a better predictive capability than model structure A. Therefore, model structure B was used in identifying the influential factors for the older driver injury severity.

4.5. Interpretation of the results

The values of the model coefficients and the corresponding odds ratios for each level of the sequential binary logistic regression models for this case are given in Table 6. The effects of some of the important explanatory variables towards increasing the severity of injuries are discussed in the following sections.

4.5.1. Travel speed

The travel speed remains as one of the most important parameters capable of generating different levels of injury severity. The positive sign of the coefficient indicates that the higher speed increases the possibility of causing more severe injuries, in line with the laws of physics. Its importance remains at almost the same level throughout all model levels, but is slightly more effective on higher severity levels.

4.5.2. Restraint device usage

Similar to what has been found in many other research studies, the use of a restraint device proved to be very important in making a difference in injury severity. As the negative sign of the coefficient indicates use of restraint devices significantly reduces the probability of having a more severe injury. The effect of usage is extremely high at higher injury severity levels and de-

Table 4
Summary of the indices for binary models

Index	A-I	A-II	A-III	A-IV	B-I	B-II	B-III	B-IV
Crash severity model								
Somers' D	0.571	0.272	0.215	0.395	0.656	0.509	0.500	0.468
Gamma	0.574	0.274	0.220	0.400	0.672	0.515	0.503	0.473
Tau-a	0.282	0.125	0.101	0.130	0.029	0.082	0.159	0.161
C	0.786	0.636	0.607	0.698	0.828	0.754	0.750	0.734
Injury severity model								
Somers' D	0.636	0.272	0.239	0.406	0.696	0.583	0.568	0.541
Gamma	0.638	0.276	0.246	0.417	0.715	0.588	0.571	0.544
Tau-a	0.300	0.126	0.111	0.0132	0.025	0.078	0.159	0.162
c	0.818	0.636	0.620	0.703	0.848	0.792	0.784	0.770

Table 5
Predictive accuracies for binary injury models

Model	A-I	A-II	A-III	A-IV	B-I	B-II	B-III	B-IV
Predictive Accuracy	78.4%	63.2%	64.5%	71.4%	81.1%	75.5%	72.6%	69.7%

Table 6
Summary of the injury model coefficients and odds ratios — model structure B

Variable	Model			
	B-I	B-II	B-III	B-IV
INTERCEPT	−4.7155	−3.609	−2.6546	−2.4147
AL_DRG	[a]	−0.4242 (0.654)	−0.3172 (0.728)	−0.7619 (0.467)
SPEED	0.0482 (1.049)	0.0443 (1.045)	0.0381 (1.039)	0.0393 (1.04)
PERDEF	[a]	0.3033 (1.354)	0.3765 (1.457)	0.6971 (2.008)
FAULTC	−1.9533 (0.142)	−0.3045 (0.737)	−0.3131 (0.731)	−0.1809 (0.834)
PEJECT	[a]	1.0256 (2.789)	[a]	[a]
RESTR	−1.5031 (0.222)	−0.9942 (0.370)	−0.6575 (0.518)	−0.3495 (0.705)
MALE	[a]	−0.2998 (0.741)	−0.4245 (0.654)	−0.585 (0.557)
RURAL	[a]	0.4974 (1.642)	0.5393 (1.715)	0.4568 (1.579)
GR−CUR	0.4436 (1.558)	[a]	0.3557 (1.427)	0.3829 (1.466)
IMP_FRNT	0.9062 (2.475)	0.8974 (2.453)	1.1081 (3.028)	0.9495 (2.584)
FREEWY	[a]	−0.5828 (0.558)	[a]	[a]
IMP_SIDE	[a]	0.4692 (1.599)	[a]	[a]

Numbers within parenthesis are the odds ratios.
[a] Variable is not significant.

creases with injury severity level even though it is still significant.

4.5.3. Impact point

If the impact point in the crash is the front of the vehicle, there is a high probability that it might result in a more severe injury. This variable also remains important at all levels of injury severity. The odds ratio for front impacts is very high. If the impact is on the side it has also been able to make a significant difference between incapacitating and non-incapacitating injuries. However, this has not remained important in making a difference in other injury severity levels.

4.5.4. Alcohol and drugs

A finding that might be a contrast for older drivers is that when alcohol and or drugs are involved the probability of causing a more severe injury decreases. A possible explanation may be that older drivers who are experienced drivers are somewhat cautious when they are aware that they have consumed alcohol. However, this variable has not been able to make any difference between creating a fatality and incapacitating injury.

4.5.5. Personal condition

When older drivers are involved in crashes, if they are not in good physical condition there is a high likelihood of having more severe injuries as explained by the positive coefficient of this parameter.

4.5.6. Gender

Older male drivers when involved in crashes have a higher probability of generating less severe injuries. In other words, females may have a higher probability of experiencing more severe injuries. However, gender is not an influential factor in making a difference between a fatality and an incapacitating injury.

4.5.7. Driver at fault

The negative sign of the variable indicates that when the driver is at fault in the crash, it is likely to result in a less severe injury. Even though it is hard to find a realistic explanation for this situation, this may be due to the fact that fixed object crashes have been considered in this study.

4.5.8. Rural and grade/curve

Both rural locations and places with curves or grades have a higher probability of generating more severe injuries, as indicated by the positive coefficient. The odds ratio for these are also high indicating high effect on injury severity.

4.6. Estimating the probabilities

The probability of occurrence of each of the injury severity levels, given that a crash has occurred can be estimated by using the models where the procedure is explained by using a hypothetical observation where AL_DRG = 0, SPEED = 40 mph, PERDEF = 0, FAULTC = 0, PEJECT = 0, RESTR = 0, MALE = 0, RURAL = 0, GR_CUR = 0, IMP_FRNT = 0, and IMP_SIDE = 0. By substituting these values in the selected injury severity model structure B:

$$\text{Logit } p_1 = -4.7155 + 0.0482 \times 40 = -2.7875$$

$$\text{Logit } p_2 = -3.609 + 0.0443 \times 40 = -1.837$$

$$\text{Logit} p_3 = -2.6546 + 0.0381 \times 40 = -1.1306$$

$$\text{Logit } p_4 = -2.4147 + 0.0393 \times 40 = -0.8427$$

where, p_1 = probability of occurrence of a fatality given that a crash has occurred, p_2 = probability of occurrence of an incapacitating injury given that at most an incapacitating injury has occurred, p_3 = probability of occurrence of a non-incapacitating injury given that at most a non-incapacitating injury has occurred, and p_4 = probability of occurrence of a possible injury given that at most a possible injury has occurred.

Therefore:

$\mathrm{Log}_e(p_1/1-p_1) = -2.7875$ and $p_1 = 0.058$.

$\mathrm{Log}_e(p_2/1-p_2) = -1.837$ and $p_2 = 0.1374$.

$\mathrm{Log}_e(p_3/1-p_3) = -1.1306$ and $p_3 = 0.243$.

$\mathrm{Log}_e(p_4/1-p_4) = -0.8427$ and $p_4 = 0.301$.

Using conditional probabilities:

Probability of occurrence of a fatality given that a crash has occurred = 0.058.

Probability of occurrence of at most an incapacitating injury given that a crash has occurred = 1 − 0.058 = 0.942.

Probability of occurrence of incapacitating injury given that a crash has occurred = (p_2) × (probability that at most incapacitating injury has occurred given that a crash has occurred) = 0.1374 × 0.942 = 0.1294.

Probability of occurrence of a non-incapacitating injury given that a crash has occurred = (p_3) × (probability that at most a non-incapacitating injury has occurred given that a crash has occurred) = 0.243 × 0.942 × 0.8626 = 0.1974.

Probability of occurrence of possible injury given that a crash has occurred = (p_4) × (probability that at most possible injury has occurred) = 0.301 × 0.942 × 0.8626 × 0.757 = 0.1851.

Probability of occurrence of no injury given that a crash has occurred = 1 − 0.058 − 0.1294 − 0.1974 − 0.1851 = 0.4301.

(Check: sum of all probabilities = 0.058 + 0.1294 + 0.1974 + 0.1851 + 0.4301 = 1.0).

5. Conclusions

This paper explains a study conducted for the identification of influential factors towards making an injury severity difference to older drivers in fixed object–passenger car crashes. Two sets of sequential binary logistic regression models were developed for crash severity and injury severity as the dependent variable where, two types of sequences were tested. The model that treated injury severity as the dependent variable in which severity was varied from fatality to no injury yielded the highest level of model fitness and also predictive capability. Thus, the important explanatory variables towards creating a different level of injury severity were identified using that model structure and possible explanations were given. Travel speed, restraint device usage, point of impact, use of alcohol and drugs, personal condition, gender, whether the driver is at fault, urban/rural nature and grade/curve existence of the crash location were identified as the most important factors for making an injury severity difference to older drivers involved in fixed object–passenger car crashes. However, it should be noted that the statistical models of injury severity depend on the accuracy of information provided in the traffic crash reports.

References

Ben-Akiva, M., Lerman, S.R., 1993. Discrete Choice Analysis: Theory and Applications to Travel Demand. The MIT Press, Cambridge, Massachusetts.

Council, F.M., Mohamedshah, Y.M., Stewart, J.R., 1997. Effects of Air Bags on Severity Indexes for Roadside Objects. Transportation Research Record 1581. Transportation Research Board, National Research Council, pp. 66–71.

Dissanayake, S., 1999. Evaluation of Highway Safety Needs of Special Population Groups, Doctoral Dissertation, Department of Civil and Environmental Engineering, University of South Florida, Tampa, Florida.

Dissanayake, S., Lu, J.J., Chu, X., Turner, P., 1999. Use of Multicriteria Decision Making to Identify the Critical Highway Safety Needs of Special Population Groups. Transportation Research Record 1693. Transportation Research Board, National Research Council, pp. 13–17.

Duncan, C.S., Khattak, A.J., Council, F.M., 1998. Applying the Ordered Probit Model to Injury Severity in Truck-passenger Car Rear-end Collisions, Transportation Research Record 1635. Transportation Research Board, National Research Council, pp. 63–71.

Kim, K., Nitz, L., Richardson, J., Li, L., 1995. Personal and behavioral predictors of automobile crash and injury severity. Accident Analysis and Prevention 27 (4), 469–481.

Maio, R.F., Green, P.E., Becker, M.P., Burney, R.E., Compton, C., 1992. Rural motor vehicle crash mortality: the role of crash severity and medical resources. Accident Analysis and Prevention 24 (6), 631–642.

McGinnis, R.G., Wissinger, L.M., Kelly, R.T., Acuna, C.O., 1999. Estimating the Influences of Driver, Highway, and Environmental Factors on Run-off-Road Crashes Using Logistic Regression. TRB Preprint, Annual Meeting of Transportation Research Board. National Research Council, Washington, DC.

Mercier, C.R., Shelley, M.C., Rimkus, J.B., Mercier, J.M., 1997. Age and Gender as Predictors of Injury Severity in Head-on Highway Vehicular Crashes. Transportation Research Record 1581. Transportation Research Board, National Research Council, pp. 37–46.

Nassar, S.A., Saccomanno, F.F., Shortreed, J.H., 1994. Road accident severity analysis: a macro level approach. Canadian Journal of Civil Engineering, National Research Council of Canada 21 (5), 847–855.

National Center for Statistics and Analysis, 1998. Users Manual: State Data Program for Florida. Federal Highway Administration, Washington, DC.

National Highway Traffic Safety Administration, 1998. Crash Data and Rates for Age-Sex Groups of Drivers —1996, Research Note, U.S. Department of Transportation, Washington D.C.

O'Donnell, C.J., Connor, D.H., 1996. Predicting the severity of motor vehicle accident injuries using models of ordered multiple choice. Accident Analysis and Prevention 28 (6), 739–753.

SAS Institute Inc., 1998a. SAS Users Manual. SAS Institute Inc, Cary, NC.

SAS Institute Inc., 1998b. Logistic Regression Examples Using the SAS System, Cary, NC.

Shankar, V., Mannering, F., Barfield, W., 1996. Statistical analysis of accident severity on rural freeways. Accident Analysis and Prevention 28 (3), 391–401.

Stewart, J.R., 1997. Applications of Classification and Regression Tree Methods in Roadway Safety Studies, Transportation Research Record 1542. Transportation Research Board, National Research Council, pp. 1–8.

Transportation Research Board, 1988. Transportation in an Aging Society: Improving Mobility and Safety of Older Persons, National Research Council, TRB Special Report 218, Vols 1 and 2, Washington D.C.

U.S. Bureau of Census, 1996. Population Projections of the United States by Age, Sex, Race, and Hispanic Origin: 1995 to 2050, Current Population Reports. U.S Government Printing Office, Washington, DC, pp. 25–1130.