COMPARISON OF SEVERITY AFFECTING FACTORS BETWEEN YOUNG AND OLDER DRIVERS INVOLVED IN SINGLE VEHICLE CRASHES

Sunanda DISSANAYAKE, Ph.D., P.E.
Assistant Professor
Department of Civil Engineering, Kansas State University
Kansas, USA

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Single vehicle crashes contribute to a significant amount of fatalities in the United States. At the same time, fatality crash involvement rates of young and older drivers are well above the average and both groups are identified as critical groups when it comes to highway safety. Therefore, the study described in this paper developed separate models to predict crash severity of single vehicle crashes by young and older drivers. By using the models, factors affecting towards increased crash severity were identified for each group and comparisons were made. Almost all the common identified factors influenced both driver groups in the same manner except in the case of alcohol and drug usage, which indicated an interesting finding in the case of crash severity of older drivers. Speeding and non-usage of a restraint device were the two most important factors affecting towards increased crash severity for both driver groups at all severity levels. Additionally, ejection and existence of curve/grade were determinants of higher young driver crash severity at all levels. For older drivers, having a frontal impact point was a severity determinant at all levels. County of residence and weather condition were not effective in making any changes with respect to crash severity at any level, while some other factors had a minimal affect. Findings of this study are beneficial in investigating the potential ways of reducing crash severity, which could also be influential in reducing the occurrence of crashes as well.

Key Words: Crash severity, Safety, Logistic regression, Driver age differences, Modeling

1. INTRODUCTION

According to the assessments of injuries and fatalities in traffic crashes by the National Highway Traffic Safety Administration (NHTSA), approximately 42,850 persons died in an estimated 38,356 motor vehicle traffic crashes in the United States in 2002[1]. This represents an increase of 1.7% fatalities from the 42,116 reported in 2001 and is the highest level of fatalities since 1990**.** An additional 2,914,000 persons were injured on U.S. public roads and highways in the calendar year 2002. Single vehicle crashes account for a considerable number of these traffic crashes in the United States[2]. This situation is worsened by the fact that the majority of single vehicle crashes (56.8 %) end up as fatal crashes as indicated in Table 1.

Table 1 Single vehicle crashes by severity level, 2001-United States

Severity of the Crash	Single Vehicle	Multiple Vehicle	Total	% of Single Vehicle Crashes
Fatal	21,477	16,318	37,795	56.8
Injury	589,000	1,414,000	2,003,000	29.4
Property-Damage-Only	1,297,000	2,985,000	4,282,000	30.2
All	1,907,000	4,416,000	6,323,000	30.1

On the other hand, both young and older drivers are often identified as having critical highway safety needs[3]. As indicated by crash statistics, both groups experience higher fatality involvement rates than the average driver population[2]. This is graphically illustrated in Figure 1 based on the fatality rate per 100,000 licensed drivers. Based on the figure, young drivers aged 16–25 years had a fatality involvement rate of 63.36, which is the highest among all the groups. It is an important task for the highway safety community to look at the ways of reducing this alarming death rate of young people.

When a more accurate measure of exposure such as number of vehicle miles traveled is taken into consideration, older drivers show much higher fatality involvement rates[4]. According to the changes that are taking place within the age structure of the United States population, transportation needs and related highway safety issues of the elderly are becoming increasingly important as well. The majority of this elderly population is going to be dependent on automobiles for their mobility needs, thereby increasing the proportion of older drivers in the general driving population.

Even though both young and older drivers are identified as critical groups with regard to highway safety, their driving and other characteristics are completely different, making a comparison sensible. Looking into the

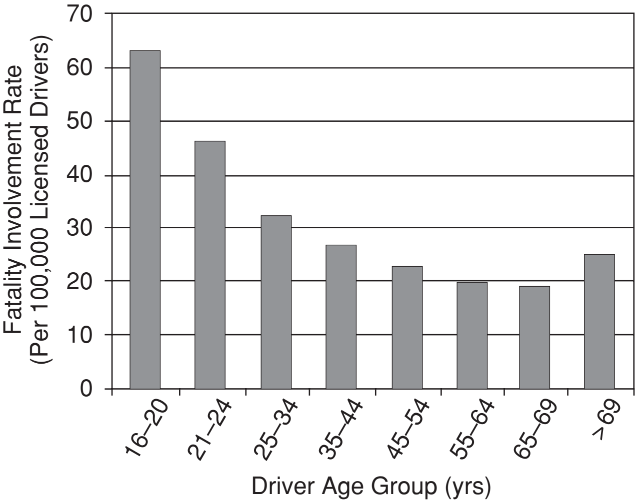

Fig. 1 Fatality involvement rate by driver age group 2001-United States

ways of improving the highway safety situation of these two groups, older and young drivers, could be addressed by using two approaches. One approach is to try to reduce the number or the frequency of crashes by each group. The second approach would be to try to reduce the severity of crashes. The analysis conducted in this study attempted to address the issue through the second approach. On the other hand, it could be envisioned that the conditions affecting increased traffic crash severities are also contributing towards the occurrence of crashes as well.

Understanding the causes and situations under which drivers are more likely to be fatally or more severely injured will help towards improving the overall highway safety situation. Accordingly, this study developed separate models to identify the factors that are contributing towards increased crash severity of older and young drivers involved in single vehicle crashes and makes a comparison between the affecting factors.

2. PAST STUDIES

A considerable amount of literature is available on the general subject of crash vulnerability of older drivers[5,6,7]. Similarly, a significant amount of literature is available on the safety issues related to young drivers as well [8,9,10,11]. 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 passengers, drivers or crashes include the following. A study conducted by applying the techniques of categorical data analysis to built 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[7]. Driver errors were found to have a small effect, while personal characteristics of age and gender were generally insignificant, as found in this study. Another study by Mercier et[5] 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. 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 [12]. 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)[13]. A disaggregate model of road accident severity based on sequential logit models, was developed in Canada, using Ontario road accident database[14]. O'Donnel and Conner[15], 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 ordered logit and probit models. Another study used logistic regression to analyze Pennsylvania vehicle crash data to identify the driver, highway, and environmental factors that differentiate run-off-road (ROR) crashes from non-ROR crashes[16]. Nested logit formulation was used in Washington as a means to predict the accident severity given that an accident had occurred[17]. Ordered probit models have also been used to identify specific variables significantly influencing levels of injury in two-vehicle truck-car rear-end collisions on divided roadways and single vehicle large truck collisions[18,19]. However, there were no published studies available to the author regarding the comparison of severity affecting factors based on age group.

3. METHODOLOGY

3.1 Model format

When identifying the factors affecting crash severity of young and older drivers, this study utilized logistic regression, which was identified as appropriate due to the discrete nature of the dependent variable, which was the crash severity. The purpose of the model development was to identify roadway, environmental, vehicle, and driver related characteristics that affect the severity of single vehicle crashes by young and older drivers and to make a comparison among them. Ordinal response logistic regression was tested first and it was found to be unsatisfactory due to the violation of the common slope parameter assumption. Additionally, even a single severity level difference was considered as important, leading to the development of a set of sequential binary logistic regression models for each driver group considered in this study. Each ordered level of the sequential structure was selected as indicated in Figure 2. This formulation was based on five crash severity levels, fatal (within 30 days), incapacitating, non-incapacitating, injury and property damage only (no injury).

Each ordered level of the model was a binary logistic regression model, where 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,

$$Logit(p_i) = \log[p_i/(1-p_i)] = \alpha + \beta' X_i$$

where,

p_i = Prob. $(y_i = y_1 \mid X_i)$ is the response probability to be modeled, and y_1 is the first ordered level of y,

α = intercept parameter,

β' = vector of slope parameters, and

X_i = vector of explanatory variables.

3.2 Data

Traffic crash data for the development of models in this study came from the Florida Traffic Crash Data-

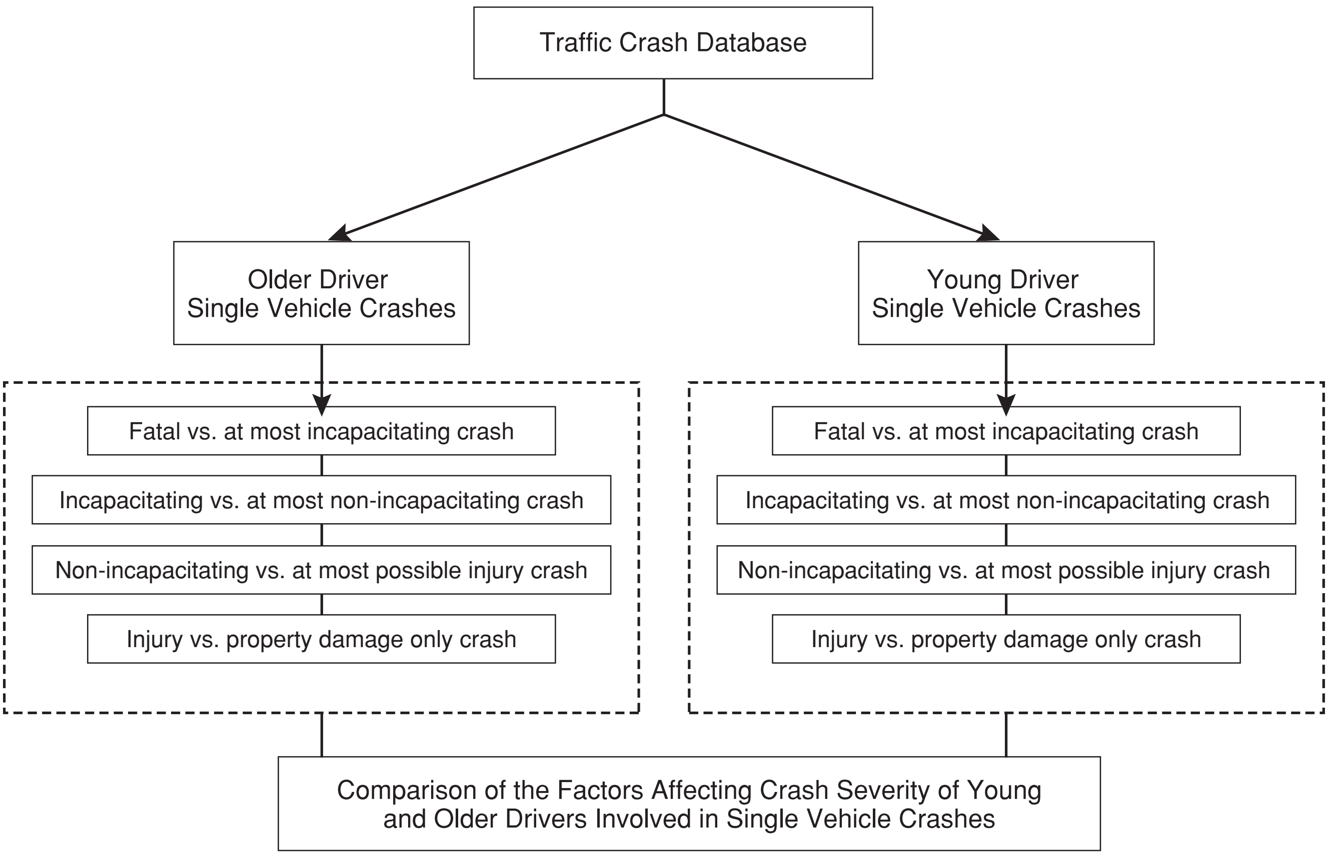

Fig. 2 Formulation of the model structures

base, which provided sufficiently large sample sizes for both young and older drivers involved in single vehicle crashes. It was obtained from the State Data Program that is maintained by the National Center for Statistics and Analysis (NCSA) established under National Highway Traffic Safety Administration (NHTSA) in the United States[20]. The State Data Program provides a comprehensive and illustrative census of motor vehicle crash patterns and trends for the 17 states in the State Data System at this time: California, Florida, Georgia, Illinois, Indiana, Kansas, Maryland, Michigan, Missouri, New Mexico, North Carolina, Ohio, Pennsylvania, Texas, Utah, Virginia, and Washington. South Carolina joined the State Data System in January 2003 and NHTSA is actively seeking additional members[21].

3.3 Age group definitions

Previous studies have used somewhat inconsistent categorizations when it comes to the labeling of young and older drivers. For the purpose of this study young drivers were considered as 16–25 year olds. Those drivers older than 65 years were considered as old drivers.

3.4 Model development

Crash records related to drivers of the two groups involved in single vehicle crashes were extracted from the Florida Traffic Crash Database obtained from the State Data Program. Since the weight and the type of vehicle might also affect the crash severity outcome, only the automobiles were considered in order to control for that. Logistic regression model development was then carried out by using PROC LOGISTIC procedure available in SAS[22]. In this procedure, severity levels had to be ordered from more severe to less severe[23]. Thus, in the case of binary logistic regression models, the event of interest (crashes with high severity) always received the rank order number 1. This situation arises due to the fact that by default, PROC LOGISTIC models the probability of the response that corresponds to the lower ordered value.

3.5 Explanatory variables

Explanatory variables that could possibly be considered as affecting crash severity were selected from all the available variables in the crash database. They fell into four categories: driver-related factors, vehicle-related factors, roadway-related factors, and environmental-related factors. A detailed list of all the selected explanatory variables considered in the model development is given in Table 2. All of the explanatory variables were treated as dichotomous variables (0 and 1) except the travel speed, which was a continuous variable.

Table 2 Explanatory variables considered in the modeling process

Variable	Description When Response =1
BDWTHER	Weather is not clear.
DAYLIGHT	Crash occurred during day light condition.
RURAL	Crash occurred in a rural area.
PERDEF	Physical condition of the driver is a factor in the crash.
PEJECT	Driver has ejected in the crash.
MALE	Driver is a male.
CNTY_RES	Driver is a resident of the same county.
FAULTC	Driver is at fault for the crash.
RESTR	A restraint device is used.
GR_CUR	A curve or a grade exists at the crash location.
FREEWY	Crash occurred on a freeway.
VFOLT	Vehicle is at fault for the crash.
IMP_SIDE	Impact point is side of the vehicle.
IMP_FRNT	Impact point is front of the vehicle.
AL_DRG	Driver is under influence of alcohol or drugs.
SPEED	Actual speed of the vehicle at the time of the crash.

3.6 Model fitness

In the analyses using SAS, results provide two criteria known as AIC and SC that are useful for comparing models and two other criteria (–2 LOG L) and Score to 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. AIC (Akaike Information Criterion) and SC (Schwarz Criterion) are adjustments to the –2 LOG L score based on the number of explanatory variables in the model and the number of observations used. For a given set of data, the AIC and SC are goodness-of-fit measures that can be used to compare one model with another, with lower values indicating a more desirable model. (–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. The LOGISTIC procedure provides this Chi-square value along with the degrees of freedom, and a p-value for this statistic. A significant p-value (Ex. $p<0.05$) provides the evidence that at least one of the regression coefficients for an explanatory variable is nonzero. Score is a score statistic, which has an asymptotic Chi-square distribution under the null hypothesis. The procedure outputs the chi-square value, degrees of freedom, and a p-value for this statistic. All four parameters were utilized in this study to evaluate the model fitness.

4. ANALYSIS RESULTS

Results of the models at each level that include model coefficients and Odds Ratios are provided in Tables 3 through 5. Odds Ratio is a measure of the strength of the relationship between the explanatory variable and the event of interest. When the Odds Ratio is farther away from 1 (depending on the sign of the coefficient) the strength of the relationship increases. The following are the descriptions of the comparison of the identified severity affecting factors for young and older drivers involved in single vehicle crashes.

4.1 Fatal vs. at most incapacitating crashes

There were five factors (whether the driver was at fault, restraint device usage, existence of curve or grade, having a side impact point, and speed of the vehicle) that were identified as important for both young and older drivers. The relationship between each of the factors and the outcome, fatal crash as against at most incapacitating crash was consistent. However, some factors were more strongly influential towards increased crash severity of one group than the other. For example, a young driver who is at fault in a crash is much more likely to die in a single vehicle crash than an older driver at fault in a similar crash. In addition to that, lighting condition at the time of the crash, influence of alcohol and drugs, and driver ejection had an affect towards an increased crash severity of young drivers, but they were not significant in making any difference in older driver injury severity. Having a frontal impact point increased the possibility of a fatal crash for older drivers, but it was unimportant for young drivers.

Table 3 Modeling results for fatal vs. at most incapacitating crash

Explanatory Variable	Older Driver Model		Young Driver Model	
	Coefficient	Odds Ratio	Coefficient	Odds Ratio
INTERCEPT	−5.0069	-	−4.795	-
DAYLIGHT	-	-	−0.572	0.56
PEJECT	-	-	1.736	5.67
FAULTC	−1.3684	0.255	−3.328	0.04
RESTR	−1.2752	0.279	−1.36	0.26
GR_CUR	0.4820	1.619	0.629	1.88
IMP_SIDE	0.8202	2.271	0.851	2.34
IMP_FRNT	1.3056	3.690	-	-
AL_DRG	-	-	1.346	3.84
SPEED	0.0456	1.047	0.026	1.03

"-": Variable is not significant or Odds Ratio is not applicable.

4.2 Incapacitating vs. at most non-incapacitating crash

Again, there were five variables (rural crash location, driver ejection, being a male, restraint device usage,

Table 4 Modeling results for incapacitating vs. at most non-incapacitating crash

Explanatory Variable	Older Driver Model		Young Driver Model	
	Coefficient	Odds Ratio	Coefficient	Odds Ratio
INTERCEPT	−3.1223	-	−2.530	-
DAYLIGHT	-	-	0.219	1.25
RURAL	0.5500	1.733	0.484	1.62
PEJECT	1.0224	2.78	1.528	4.61
MALE	−0.1913	0.826	-0.292	0.75
RESTR	−0.7934	0.452	−0.875	0.42
GR_CUR	-	-	0.229	1.26
FREEWAY	−0.4188	0.658		
IMP_FRNT	0.4784	1.613	-	-
AL_DRG	−0.6821	0.506	-	-
SPEED	0.0398	1.041	0.02	1.02

"-": Variable is not significant or Odds Ratio is not applicable.

Table 5 Non-incapacitating vs. at most possible injury crash

Explanatory Variable	Older Driver Model		Young Driver Model	
	Coefficient	Odds Ratio	Coefficient	Odds Ratio
INTERCEPT	−2.2822	-	−1.286	-
RURAL	0.6039	1.829	0.554	1.74
PERDEF	0.2177	1.243		
PEJECT	0.6394	1.895	0.802	2.23
MALE	−0.3523	0.703	−0.338	0.71
RESTR	−0.4942	0.61	−0.645	0.53
GR_CUR	0.3029	1.354	0.324	1.38
VFOLT	-	-	0.125	1.33
IMP_SIDE	-	-	0.203	1.23
IMP_FRNT	0.6643	1.943	0.284	1.33
AL_DRG	−0.5783	0.561	-	-
SPEED	0.0359	1.037	0.012	1.01

"-": Variable is not significant or Odds Ratio is not applicable.

Table 6 Injury vs. property damage only crash

Explanatory Variable	Older Driver Model		Young Driver Model	
	Coefficient	Odds Ratio	Coefficient	Odds Ratio
INTERCEPT	−2.2566	-	−1.068	-
DAYLIGHT	0.2834	1.328	0.202	1.22
RURAL	0.4566	1.579	0.512	1.67
PERDEF	0.2925	1.34	-	-
PEJECT	-	-	1.48	4.37
MALE	−0.3727	0.689	−0.736	0.48
RESTR	−0.1842	0.832	−0.319	0.73
GR_CUR	0.2797	1.323	0.187	1.21
IMP_SIDE	−0.2885	0.749	−0.242	0.79
IMP_FRNT	0.5639	1.758	-	-
AL_DRG	−0.6629	0.515	0.436	1.13
SPEED	0.0370	1.038	0.020	1.02

"-": Variable is not significant or Odds Ratio is not applicable.

and speed) that were significant at this level for both young and older drivers. The nature of the relationship in each case was consistent across both driver groups. However some factors for example, ejection of the driver, has a very strong effect (higher Odds Ratio) on increased severity of young drivers than it is for older drivers. Additionally, three more factors were identified as significant for older drivers, but not for young drivers. Those were freeway crash location, having a frontal impact point, and alcohol/drug usage. Driving under daylight condition was an influential factor for young drivers only.

4.3 Non-incapacitating vs. at most possible injury crash

Seven common variables, (rural crash location, driver ejection, being a male, restraint device usage, existence of curve or grade, having a frontal impact point, and speed) were identified as affecting severity at this level, which were related to the outcome in the same way in the case of both young and older drivers. Similar to the above-discussed two levels, the effect of ejection was more critical for young drivers. Two additional variables in the older driver model were, physical condition of the driver, and usage of alcohol/drugs. As for the young driver group, vehicular faults, and having a side impact point, were identified as influential in addition to the seven common variables.

4.4 Injury vs. property damage only crash

There were more common variables included in both young and older driver models at this level, which were daylight conditions, rural crash location, being a male, restraint device usage, existence of curve/grade, having a side impact point, usage of alcohol/drugs, and speed. Two additional variables included in the older driver model were, physical condition of the driver, and having a frontal impact point, whereas the young driver model included the ejection of the driver.

4.5 Discussion

Travel speed of the vehicle at the time of the crash (SPEED) and restraint device usage are the two most powerful factors affecting severity at all levels, equally important for both young and older drivers in single vehicle crashes. As indicated by the positive sign of the variable SPEED, the higher travel speed always leads to increased crash severity, which is explainable based on the laws of physics. Similarly, it is an obvious fact that the usage of a restraint device reduces the possibility of having a higher severity irrespective of the driver age and severity level (Negative coefficient of RESTR).

As for the older driver models, having a frontal impact point also affected towards increased crash severity at all levels in addition to speed and restraint device usage. Additionally, three other variables, usage of alcohol and drugs, being a male, and rural crash locations are capable of affecting severity at the three lower levels of older driver models. Female older drivers and crashes in rural areas tend to be of higher severity, where as an interesting observation could be made related to the usage of alcohol or drugs. When an older driver is under the influence of alcohol or drugs the severity of the crash tends to be lower, which is contradictory to young drivers in similar crashes. A possible explanation could be that elderly, when they are aware of the fact that they are under the influence of alcohol or drugs may be somewhat cautious (even though they are incapable of avoiding crashes) when driving.

In young driver models, two more variables, ejection of the driver and the existence of grade or curve/grade become significant at all levels. As indicated by a high Odds Ratio, crash severity is highly affected by the ejection of the young driver. Additionally, young drivers who lack driving experience are not capable of handling or negotiating curves and grades well and tend to have higher severity crashes at such locations.

County of residence (CNTY_RES) and weather condition (BDWTHER) are not effective in making any changes with respect to crash severity at any level. As indicated by the CNTY_RES, driver familiarity with the area in which he/she is driving is not a determinant in crash severity, however outcome from BDWTHER should be interpreted in the pretext that the crash data for the modeling came from Florida, where no seriously hazardous bad weather related driving conditions such as icy roads are existent. Driver or vehicle faults in single vehicle crashes were also of very minor importance.

5. CONCLUSIONS

This paper developed two sets of sequential binary logistic regression models for young and older drivers involved in single vehicle crashes with the intention of identifying and comparing severity affecting factors. The methodology provided a reasonably satisfactory way of achieving these objectives, even though drawbacks such as the accuracy and reliability of police reported crash data and inter-relationships between considered independent variables could be existent.

All of the factors identified influenced both driver groups in a uniform way, except the influence due to alcohol and drugs, which was surprisingly capable of reducing crash severity of older drivers. Speeding and not using a restraint device were the two most important factors affecting towards increased crash severity for both driver groups at all severity levels. This emphasized the need for further efforts towards increasing the seat belt usage rates among drivers. Additionally, ejection and existence of curve/grade were determinants of higher young driver crash severity at all levels. For older drivers, having a frontal impact point was a severity determinant at all levels.

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