A Comparison of Factors Associated with Run-off-Road and Non Run-off-Road Crashes

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Abstract—*Run-off-road (ROR) crashes have become a major cause of serious injuries and fatalities. Crash data from Kansas, United States of America (U.S.A.) is used in this study to examine the trends in ROR crashes related to non-ROR crashes. Various factors such as environment, roadway, driver, vehicle and factors contributing to ROR and non-ROR crashes were analysed developing crash severity models so that potential countermeasures can be developed to improve roadside safety. Different factors that affected on ROR crashes and non-ROR crashes were identified using the models. Results indicated that some variables are significantly related to ROR crash severity but not non-ROR crash severity and vice versa.*

Keywords— Run-off-road crashes, Roadside safety, Crash data analysis

I. INTRODUCTION

Road traffic safety is a primary concern globally due to the magnitude of its social and economic impact. According to the Global Plan for the Decade of Action for Road Safety, each year nearly 1.3 million fatalities, or more than 3,000 fatalities per day, occur due to traffic crashes (WHO 2011). In addition, 20 to 50 million more people suffer injuries due to motor vehicle crashes, and some of these injuries may cause permanent disabilities. Highway crashes are predicted to become the fifth leading cause of fatalities worldwide unless immediate action is taken (WHO 2011). Hence, road traffic crashes place a high social and economic impact. Also, the report mentioned that the economic consequences of traffic crashes have been estimated to be between 1% and 3% of the respective gross national product (GNP) of the world's countries, which amounts to more than $500 billion. Reducing road injuries and fatalities will reduce peoples' suffering, cut work loss costs, cut healthcare costs, cut rehabilitation cost and unlock economic growth while freeing resources for more productive use.

Substantial progress in improving roadways, vehicle, and driver performance increased the overall level of road safety in U.S.A. over the last few decades. In 2011, AAA foundation reported the cost of motor vehicle crashes in U.S.A. is almost $ 164.2 billion per year (AAA 2012). In 2011, 32,885 fatalities and additional 2.24 million injuries were reported on U.S.A. roadways due to motor vehicle crashes (NHTSA 2012). Statistics from the 2008 Fatality Analysis Reporting System (FARS) illustrates that traffic fatalities in the U.S.A. due to ROR crashes represent about one-third of the total traffic fatalities. ROR crashes have become a major cause of serious injuries and fatalities in the U.S.A.

Each year ROR crashes cause serious injuries and fatalities in the world including the U.S.A. Data from Fatality Analysis Reporting System (FARS) illustrated that ROR crashes cause around 33% of fatalities in the U.S.A. in 2009 (FARS 2012). ROR crash usually involve running off the road onto the right or left shoulder and hitting a fixed object or a parked vehicle. ROR crashes also involve crossing into an opposite lane and colliding with an oncoming vehicle. Those crashes resulting in between two moving vehicles may be potentially more severe.

II. LITERATURE REVIEW

Logistic regression or relevant statistical methods are common in severity modeling. Several studies have adopted severity models to examine the association between crash characteristics and crash severity. Litao and Dissanayake (2009) examined the different factors affecting crash severity on gravel roads using binary logistic model. The study used 10-year crash database from the state of Kansas to identify the important factors that have effects towards the severity of gravel road crashes. Young and Liesman (2007) developed binary logistic model to estimate the relationship between wind speed and overturning truck crashes. The results showed that weather station data can be used as a predictor of overturning crashes. Therefore, this study motivate to development of operational rules for roadway sections where high risk overturning truck crashes in high wind conditions.

Dissanayake (2003) studied ROR crashes for young drivers using a sequential binary logistic regression model to identify the roadway, driver, environmental and vehicle related factors that affect the crash severity. The police reported crash data from the State of Kansas were used considering five different severity levels of crashes. The developed model showed that use of alcohol or drugs, ejection in the crash, gender, impact point of the vehicle, restraint device usage, urban/rural nature and grade/curve existence of the crash location, lighting condition, and speed were the most important factors affecting the severity of young driver single vehicle ROR crashes.

Lee and Mannering (1999) developed ROR crash severity using nested logistic model to investigate the effect of different observable characteristics. The crash characteristics such as time of accident, accident location, effects of pavement condition, weather, driver-related, and vehicle-related information to study crash severity were extracted from the Washington State crash database. Also, geometric factors such as lane, shoulders, median, intersections, and vertical or horizontal alignment and traffic data such as traffic volume, peak hour volume, legal speed limit, and truck volume as a percentage of Annual Average Daily Traffic (AADT) were gathered to study ROR crash severity. Roadside features such as guardrails, catch basins, slopes, tree groups, isolated trees, culverts, sign poles, ditches, fences, utility poles, miscellaneous fixed objects, luminaires, intersections, and bridges are gathered. Using all these data nested logistic model was developed and found that roadside features such as bridges, cut-type slopes, ditches, culverts, fences, tree groups, sign supports, utility poles, isolated trees were significantly affected the severity of ROR crashes.

Spainhour and Mishra (2008) developed binary logistic regression model to examine the association between human, roadway, vehicle, and environmental factors and fatal ROR crashes. Among different contributory factors, alcohol was the major one, followed by speed, inattention and fatigue/sleep. It was also found that overcorrection had a strong positive association with the presence of rumble strips, inclement weather, rural locations, incapacitated drivers, and running off the road to the left or straight and a strong negative association with male drivers, speeding, paved or curbed shoulders, wet or slippery roads, and larger vehicles. Fewer than 20 percent of fatal ROR crashes occurred where rumble strips were present.

Liu and Subramanian (2009) used fatal data from 1999 to 2007 to develop a logistic regression model for fatal single vehicle ROR crashes. The results showed that the most influential for fatal single vehicle ROR crashes were driver performance-related factors such as sleepy, followed by alcohol, roadway alignment with curve, speeding, passenger car, rural roadway, number of lanes, high-speed-limit-road, adverse weather and avoiding.

VIII. DATA

Crash data from 2007 to 2011 were obtained from the Kansas Department of Transportation (KDOT). This data set, KCARS database, is comprised of all police-reported crashes that occurred in Kansas, U.S.A. The police officers fill an accident report forms including contributory causes and send to KDOT within ten days of the investigation for any crash which occurs on a public roadway and which results in death or injury to any person or total property damage of $1,000 or more (KDOT 2013). More details of the recording each of the variables can be found from the KDOT accident reporting manual (KDOT 2013).

The KCARS is Access based database which consists of several tables describing each crash. The definition for ROR crashes in this study was the crashes where the vehicles leaving the roadway encroach upon the median, shoulders, or beyond and either overturns, collides with fixed objects or leads to head-on crashes with other vehicles; sideswipe with opposing vehicles; or crashes where the first harmful events occur off the roadway or median-off roadway in case of divided highway sections. The tables in the KCARS database were combined and queries were made to filter all ROR crashes in order to compare ROR crashes and non-ROR crashes. From the data, it has been found that ROR crashes were approximately to 18% that of total crashes for combined crash data from 2007 to

2011. For the same time period in Kansas injury ROR crashes were found to be approximately 24% of the total injury crashes and fatal ROR crashes were 54% to that of total fatal crashes. In contrast to ROR crashes, there are crashes in which vehicles remain on the road after the crashes and those are considered as non-ROR crashes.

IV. METHODOLOGY

Data were used to develop separate logistic regression models for ROR crashes and non-ROR crashes to identify variables expected to have an explanatory effect on crash severity. Using the coefficient of the explanatory variables, risk factors which increase crash severity could be determined. The dependent variable, crash severity is binary variable injured crash or not. The probability of person being injured with severity outcome is:

$$\Pi(x)_{ni} = P(U_{ni} \geq U_{ni'}), \quad \forall' \in I, \quad i' \neq i, \tag{1}$$

where:

- $\Pi(x)$: the probability of *x* injury category
- n: crash
- i: the injury severity of *n* crash (eg: fatal injury, injury, no injury)
- U_{ni}: a function determining injury severity outcome *i* of the *n* crash
- $U_{ni'}$: a function determining injury severity outcome i' of the n crash, and
- I: a set of I possible, mutually exclusive severity categories

The logistic regression analysis assumes a injury severity function has a linear-in-parameters form as:

$$U_{ni} = \beta_i x_n + \varepsilon_{ni} \tag{2}$$

where:

- β_i: a vector of estimable coefficients for injury severity *i* and x_i is a vector of variables for crash *n*
- ε_{ni}: a random component which has identically and independently distributed error terms

Then the logistic regression model is defined as follows (Long 1997):

$$\Pi(x)_{ni} = \frac{e^{\beta_i x_n}}{\sum_{\forall i' \in I} e^{\beta_{i'} x_n}}$$

The maximum likelihood method is then used to estimate the coefficients.

In some cases, logistic regression results may seem paradoxical, which means the model fits the data well, even though none of the independent variables has a statistically significant impact on predicting the dependent variable. This could happened due to the correlation of two or more independent variables. The model may not be accurate if both correlated variables were included or removed from the model. This is because the independent variables are collinear and the results show multicollinearity. In traffic safety analysis, the goal is to understand how various independent variables impact the dependent variable; hence, multicollinearity is a considerable problem. One problem is that even though the variable is important, model results show that it is not significant. The second problem is that confidence intervals on the model coefficients will be very wide. To help assess multicollinearity, the correlation matrix of the independent variables was investigated. If the element of correlation matrix has high value, model fit is affected by multicollinearity of the independent variable correspondent to that element. Also, each independent variable can be predicted from other independent variables. The model-fit statistic such as individual R^2 value and a variance inflation factor (VIF) are high for any of the independent variables, and model fit is affected by multicollinearity. In such cases, only one of those two variables was used for the development of the logistic regression model or relevant statistical methods.

IV. RESULTS

The total number of ROR crashes during the five year period (88,809) was lower than the total number of non-ROR during the same period (412,968). The developed crash severity models for ROR crashes and non-ROR crashes, including model fit statistics, is shown in Table 1. The statistical significance of individual coefficients was tested using the Wald Chi-Square statistic.

Variables such as driver being a male driver, holding a valid license, driver seat belt use, air bag deployment, alcohol involvement, travel on debris-filled road surfaces, posted speed limit, driver ejection, driver trapped, vehicle damage, and collision with an animal, collision with a vehicle, and vehicle backing/stopping, were significant at the 0.05 level in both models. Also, driver contributory causes such as failure to yield right-of-way, speeding, improper actions taken, driver conditions, and vehicle related conditions were significant in both models. The sign of the coefficient in most of these variables in the ROR model were similar to non-ROR model. The variables high posted speed limits, improper action taken, and vehicle backing/stopping in ROR model were positive but in non-ROR model those were negative. Being an older driver, driving during weekends, driving during dark, driving on dry surfaces, vehicle type, vehicle age, travel with passengers, involvement of non-collision overturn crashes, collision with a pedestrian, due to avoidance/evasive actions taken, inattention, attempt to turn or lane changing, and driver distraction were variables which were significant in ROR model but not in non-ROR model. Travel on straight levelled roadways, travel on straight unlevelled roadways, disregarding traffic sign or signals, attempting to avoidance actions or slow, and crashes due to turn or lane changing were the variables which were significant in non-ROR model but not in the ROR model.

The test of the intercept merely suggests whether an intercept should be included in the model. Interpretation of the intercept in a logistic regression model depends on how the independent variables were defined. The intercept represents the logistic of the probability of injury, if all of the characteristics are set to zero; consequently, the value of the intercept cannot be meaningfully interpreted. Negative coefficient estimates show the reduced probability of potential crash severity, while positive coefficient estimates show the increased probability of potential crash severity.

Variable 'seat belt use' in ROR model has a p-value less than 0.0000 and a likelihood ratio of -0.7035. That means, if the driver is belted, the crash severity is less. Seat belt-restrained drivers were less likely to involve in severe crashes. Effectiveness of seat belt restraint in reducing crash injuries is well known regardless of crash type.

Table 1 Injury Severity Models

Label	Parameters	ROR crashes		Non-ROR crashes	
		Coefficient	p	Coefficient	p
Intercept		-9.5264	<.0001*	-22.6339	0.8774
AGE	If driver is young (<30 years)	0.0204	0.4454	-0.1226	0.0027*
	If driver is old (>65 years)	0.3298	<.0001*	-0.0130	0.8406
GENDER	If driver is male=1, otherwise 0	-0.2317	<.0001*	-0.0754	0.0364*
VALID	If driver has valid license=1, otherwise 0	0.4931	<.0001*	0.5384	<.0001*
RETRIC	If restricted driver license=1, otherwise=0	0.0458	0.0735	-0.0588	0.1063
SEATB	If seat belt used=1, otherwise 0	-0.7035	<.0001*	-0.3024	<.0001*
AIRB	If air bag deployed=1, otherwise 0	0.9390	<.0001*	1.1340	<.0001*
ALOD	If alcohol or drug related=1, otherwise 0	0.5694	<.0001*	0.5120	0.0004*
DARK	If dark =1, otherwise 0	0.1692	0.0317*	0.0027	0.9567
WEEKE	If week ends=1, otherwise 0	0.1156	0.0003*	-0.0044	0.9195
CON	If concrete surface=1, otherwise 0	-0.1573	0.5612	0.3573	0.2912
GRAVEL	If gravel roads =1, otherwise 0	-0.2736	0.3141	0.1016	0.7710
DRY	If road surface is dry=1, otherwise 0	0.3765	<.0001*	-0.0521	0.3161
DEB	If road surface is debris=1, otherwise 0	-0.1723	0.0001*	-0.5532	<.0001*
STLE	If straight level=1, otherwise 0	0.0024	0.9429	0.2041	0.0031*
STNLE	If straight not level=1, otherwise 0	0.0599	0.1139	0.1928	0.0106*
LSPEED	If speed is less than 35 mph=1, otherwise 0	-0.3996	<.0001*	-0.6619	<.0001*
HSPEED	If speed is more than 60 mph=1, otherwise 0	0.6840	0.0243*	-0.1387	0.0009*
AUTO	If automobile =1, otherwise 0	-0.0574	0.0326*	-0.0454	0.2438
VAN	If van=1, otherwise 0	0.1432	0.0128*	0.0391	0.5768
TRUCK	If truck vehicle=1, otherwise 0	0.1824	0.0002*	0.1467	0.0764
NEW	If vehicle newer than 5 years =1, otherwise 0	-0.1297	<.0001*	0.0132	0.7248
OLD	If vehicle is older than 15 years=1, otherwise 0	0.1562	<.0001*	-0.1003	0.0735
EJECT	If eject =1, otherwise 0	3.3853	<.0001*	2.1795	<.0001*
TRAP	If trapped=1, otherwise 0	2.4988	<.0001*	4.8230	<.0001*
PASSEN	If with passengers =1, otherwise 0	0.4863	<.0001*	0.0475	0.2070
NODAM	If vehicle has not damage=1, otherwise 0	-0.7144	<.0001*	-1.1366	<.0001*
MDAM	If has minor damage=1, otherwise 0	-1.1681	<.0001*	-1.3972	<.0001*
FUNCT	If vehicle is functioning =1, otherwise 0	-1.1650	<.0001*	-1.1723	<.0001*
DISTRO	If vehicle is destroyed =1, otherwise 0	1.0396	<.0001*	1.0323	<.0001*
TURNCH	If turning or lane changing=1, otherwise 0	-0.3086	<.0001*	-0.0981	0.5080
STOPB	If stopped or backing=1, otherwise 0	-0.6185	<.0001*	0.3180	<.0001*
AVOILD	If avoidance or slow =1, otherwise 0	0.0114	0.7809	0.2645	0.0074*
OVERTN	If non-collision or overturned=1, otherwise 0	0.4095	<.0001*	0.2419	0.4013
PED	If collision with pedestrians=1, otherwise 0	4.3688	<.0001*	18.025	0.9022
CVEHI	If collision with a vehicle=1, otherwise 0	0.6124	<.0001*	1.8070	<.0001*
ANI	If collision with animal=1, otherwise 0	-1.4859	<.0001*	-0.9466	0.0006*
YEILD_C	If fail to yield right of way =1, otherwise 0	0.4946	<.0001*	0.3145	<.0001*
SIGNAL_C	If disregard traffic sign or signal=1, otherwise 0	0.1028	0.1185	0.5367	<.0001*
SPEED_C	If speeding =1, otherwise 0	0.2105	<.0001*	0.1255	0.0208*
AGGRE_C	If aggressive driving=1, otherwise 0	0.0432	0.5241	-0.0246	0.8948
TURN_C	If turning or lane changing=1, otherwise 0	-0.1801	0.0606	-0.4649	<.0001*
SLOW_C	If avoidance/ evasive or slow=1, otherwise 0	0.1887	0.0001*	0.1822	0.1778
ACT_C	If improper action=1, other 0	0.4565	<.0001*	-0.4299	0.0005*
DCON_C	If other driver conditions=1, otherwise 0	0.6361	<.0001*	0.6974	0.0076*
INATTN_C	If inattention=1, otherwise 0	0.1614	<.0001*	-0.0751	0.0916
DISTRA_C	If distraction=1, otherwise 0	0.1814	0.0034*	-0.0634	0.7253
ANIM_C	If crash due to animal=1, otherwise 0	-0.0782	0.2377	0.2054	0.1898
WEA_C	If crash due to weather factors=1, otherwise 0	-0.0063	0.8868	0.0940	0.3357
OBST_C	If vision obstruction=1, otherwise 0	-0.5960	0.7014	0.1278	0.3669
VEHI_C	If crash due to vehicle factors=1, otherwise 0	-0.1720	0.0284*	-1.1352	<.0001*
RD_C	If crash due to road factors=1, otherwise 0	0.0322	0.4427	0.1105	0.2031
AIC		56,339		21,602	
SC		56,347		22,036	
-2logL		56,337		21,496	
Likelihood Ratio		13,459	<.0001	5,322	<.0001
Score		11,980	<.0001	3,203	<.0001

* Significant at 95% confidence level

The positive coefficient of the airbag deployed variable indicates that crashes were severe, if the airbags were deployed. It may be because air bags only activate for serious head-on crashes but not for minor crashes. The coefficient of holding a valid license is positive indicating that those drivers were more likely to involve in severe crashes. This is not an expected result because generally drivers holding valid licenses can be taken proper precautions to reduce the severity when involved in crashes. Also, male drivers may able to take proper precautions to reduce the severe crashes compared to females. Alcohol impairment increased crash severity, as expected. Vehicle damage was a significant factor in which vehicle is destroyed; the probability of having a more severe crash will increase. If the road surface is debris-filled, people tend to drive carefully and slowly. Then decreased crash severities could be expected on debris-filled road surfaces. The posted-speed-limit of roadways was also a significant factor in which lower speed decreased crash severity. Conditions of ejection, and trapped at the time of crash, increased crash severity. Collisions with vehicles showed increased crash severity while collisions with animal showed decreased crash severity. Crashes were severe when failure to yield right-of-way, speeding, or other driver condition related factors as expected.

Increased crash severity could be expected when driving on high speeds. This may be because drivers may not able to take proper precautions to prevent crashes when driving high speeds. In non-ROR crash model variable 'high speed' has negative sign indicating decreased crash severity but this is not an expected result. Improver actions increased the crash severity when involved in ROR crashes. Interesting, non-ROR crash model showed that decreased crash severity when driver has taken an improper action.

According to the developed ROR severity model, older drivers were more likely to involve in severe ROR crashes. ROR crashes were severe when involving crashes while driving during dark, or during weekends. This may be because of higher speeds and limited enforcement during these times. The coefficients of age of the vehicle variable in ROR model showed that older vehicles were more likely to involve severe crashes while newer vehicles were less likely to involve severe crashes. More severe ROR crashes can be expected from non-collision over turn crashes or collision with pedestrian. ROR crashes due to avoidance/evasive action taken, or inattention showed increased severity as expected.

In non-ROR model the coefficients of 'travel on straight levelled roadways' and 'travel on straight unlevelled roadways' had positive signs as expected. On straight roadways, people tend to driver higher speeds and increased crash severity is possible. Also, disregarding traffic sign or signals, and due to turn or lane changing tend to more severity when involved in crashes.

V. SUMMARY AND CONCLUSIONS

This study investigated differences between ROR crashes and non-ROR crashes using Kansas crash data. Separate crash severity models were developed for ROR crashes and non-ROR crashes. Factors which associated with increased crash severity of ROR crashes and non-ROR crashes were identified. Some variables are significantly associated to crash risk of ROR crashes but not for crash risk of non-ROR crashes and vice versa. Travel on straight levelled roadways, travel on straight unlevelled roadways, disregarding traffic sign or signals, and due to turning or lane changing were the variables which were significant in non-ROR model but not in the ROR model. Variables such as being an older driver, driving during weekends, driving during dark, vehicle type, vehicle age, travel with passengers, involving non collision overturn crashes, collision with a pedestrian, due to avoidance/evasive actions taken, inattention, and road-related contributory causes were variables which were significant in ROR model but not in non-ROR model. This study adds detailed information about differences and similarities of ROR crashes and non-ROR crashes in the context of crash severity risk to the transportation safety literature.

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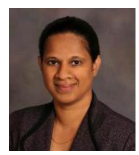

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