Journal of Positive School Psychology http://journalppw.com
2023, Vol. 7, No. 1, 1515-1526

Modeling Injury Outcomes Of Crashes Involving Driver And Pedestrian Victims

Mounir Belloumi[1] , Fedy Ouni[2]

[1]*Department of Business Administration, College of Administrative Sciences, Najran University,*
Email: mrbelloumi@nu.edu.sa
[2]*Higher Institute of Transport and Logistics of Sousse, University of Sousse, Tunisia*
Email: fedy.ouni@gmail.com

Abstract

Understanding the factors which influence the severity of accidents is crucial to preventing serious injuries. In this study, we aim at investigating the contribution of several variables concerning the severity of accidents on the driver and pedestrian. This will be achieved by means of Multinomial Logit models (MNL) using the data of 10000 subjects involved in serious accidents. The empirical results of Multinomial Logit models are of a great variety. The results of the first model of drivers show that drivers whose ages lie between 26 and 45 years are more likely than younger age groups to be fatally injured when they are involved in motor vehicle accidents. Male drivers are proven to experience higher severity levels than female drivers. Added to that, accidents occurring in rural areas increase the likelihood of serious injuries by 136.28 % but have no significant effect on other injury severity levels. Another finding of the study is that one-way streets increase the probability of fatal injury by 94.54%. For the second model which is the pedestrian, results suggest that the degree of injury severity of elderly pedestrians is higher than that of younger pedestrians. Another significant factor contributing to the injury severity model is darkness. Indeed, the risk of fatal injury increases by 110% at night as compared to day time. Another important factor is speed as pedestrians have been found to be seriously injured when they are involved in accidents caused by high-speed limit. Besides, the crashes involving pedestrian victims and which occur in rural areas or in a small town have a higher proportion of fatal injury with 61.22% and 67.91% respectively as compared to urban area. The factors identified in this research are expected to help developing potential countermeasures to reduce the severity and the number of single vehicle crashes.

Keywords: Accident severity; Driver injury severity; Pedestrian injury severity; Multinomial logit model; Logistic regression**.**

1. Introduction

Road safety is a broad topic that includes many aspects and factors such as road conditions, vehicles, the environment, and drivers. For example, the environment as a factor can be divided into two categories, namely the natural environment and the built environment. On the one hand, the natural environmental is characterized by the fact that is can be changed by human intervention such as geography and climate. The artificial environment on the other hand can be improved or reformed by human intention for the safety of road conditions. The term Collisions is considered as the result of complex correlations between several factors representing driver, vehicle, roadway infrastructure and environmental characteristics. Understanding how every factor contributes to the gravity of collision is not a simple task (Kouhpaenejad, 2010). Multivariate studies of the degree of severity of motor vehicle accidents have used different modeling approaches. Such approaches include:

Unordered response models (Savolainen and Ghosh, 2008; Schneider, 2009; Malyshkina and Mannering, 2010; Haleem and Abdel-Aty,2010; Wu et al.,2013; Eluru,2013) and Ordered response models (Jung et al., 2010; Quddus et al., 2010; Ferreira and Couto,2012; Jiang et al; 2013; Mergia et al., 2013; Yasmin and Eluru,2013). First of all, an attempt is made to provide the most recent studies on pedestrian crash severity. Lee and Abdel-Aty (2013) used ordered probit model to investigate severity of pedestrian injury at intersections in Florida. Their results suggested that injury severity of pedestrians rises with adverse weather and dark lighting, high vehicle speed, intersections without traffic control, and elderly pedestrian. Clifton et al, (2009) explored the impact of personal and environmental characteristics on the severity of injuries sustained by pedestrians involved in vehicle crashes using generalized ordered probit model. They took into account three severity classes which are: no injury, injury and fatal injury. Results of the modeling process show that women pedestrians involved in accidents are injured less frequently than male. Children however, have a serious likelihood of sustaining severe injuries while elderly pedestrians are more likely to be fatally injured. By means of an ordered logit model, Obeng and Rokonuzzaman (2013) investigated the severity of injuries of pedestrians who were involved in car accidents that occurred at signalized intersection in medium size towns. Among their important findings, it is noteworthy that factors such as vehicle type, pedestrian gender, traffic characteristics and speed limit significantly explain the degree of injury severity of pedestrian at signalized intersection. In large part, the majority of results of previous empirical studies are compatible. In a word, we deduce that the variables that are found to frequently increase the severity of accidents involving pedestrians are: elderly pedestrian, male pedestrian, pedestrian walking under the influence of alcohol, intoxicated driver, and darkness with or without lighting and excessive speed. In counterpart, variables that are more commonly found to reduce the severity of accidents in which pedestrians were involved are: elderly driver, day light condition, and wet or dump surface condition. Second of all, some empirical studies dealing with driver crash severity will be considered. Krull et al, (2000) used multinomial logit model to analyze the severity of injuries of drivers who were involved in a single-vehicle crash. Three years crash data from Michigan and Illinois were analyzed in order to investigate the effect of rollover while at the same time paying attention to roadway, vehicle, and driver factors. Results showed that the degree of drivers' injury-severity increases with failure to use a seatbelt. Bedard et al, (2002) applied a multivariate logistic regression analysis to determine the risk of death for drivers affected by factors including driver, crash, and vehicle. They found that the increase in the use of the safety belt and speed reduction play a major role in reducing the likelihood of sustaining severe injuries. Ulfarsson and Mannering (2004) explored the differences in injury severity among male and female drivers in single and two-vehicle accidents involving passenger cars, pickups, and sport-utility vehicles. This was done by using separate multivariate multinomial logit models. The results suggested that there are significant behavioral and physiological differences between male and female drivers. For both genders, drivers who did not use seat belts suffered more severe injuries. It has been shown in literature that young motorcyclists have a higher risk of being killed or severely injured (Leong et al, 2009). Moreover, it has been shown by Rifaat et al, (2011) that the number of victims involved in motorcycle accidents is significantly higher in younger group compared with other victims of road accidents in Singapore. The survey also showed that young riders have an increased risk in comparison with older riders. Isa et al, (2011) investigated the injury severity of accidents involving young motorcycle riders in Malaysia. They showed that there are many situations that led to a higher probability of serious and even fatal accidents. Male riders riding with a learner probationary license or without a license were studied. If they got involved in a crash that occurred during the wee hours or during dawn or dusk or in the dark (with and without street lighting), this led to serious consequences like being killed or severely injured (KSI) for those young motorcycle riders. Based on the reports on traffic accidents, the degree of severity of injuries is generally categorized as an ordered variable with multiple responses (such as the absence of injury, slight injury, serious injury and fatal). Thus, it is no wonder that the most frequent statistical formulation used to model the severity of injuries is the formulation of the ordered response models. The objective of our study is to identify driver, vehicle, road, environment, crash and temporal related factors which affect the severity of single vehicle crashes. These crashes studied are the ones affecting driver and pedestrian. Significant characteristics related to single vehicle crashes have been recognized and the factors influencing the severity of crashes are analyzed by developing multinomial logit models. Accordingly, multinomial logistic regression analysis is used to explore the association between explanatory variables and crash severity.

2. Data and methodology

2.1. data

It is worth mentioning that our data are drawn from The Stats19 accident injury database in Great Britain. The STATS19 data is the only national source to offer complete information on accident circumstances, vehicles implicated and resulting casualties. The statistics relate only to corporal accidents that occur in public roads and that are reported to the police. Accidents that occur on private roads or car parks are not included in these data. The focal point of our study is the identification of the multinomial response structure that is better suited to modeling pedestrian, and driver injury severity. Therefore, we engage a tow multinomial logit model using a comprehensive set of independents variables. These variables include: driver-related factors, environment-related factors, accident-related factors, vehicle related factors, roadway-related factors and temporal factors. Indeed, the choice of this type of model is suitable to the objective of our research since it enables us to know the measure of probability of the severity of an accident by means of studying the variation of each explanatory variable. The multinomial logit model is selected in this study for its increased flexibility in model specification

2.2. Methodology

In this study, the STATA statistical software package was used to estimate a multinomial logit model. This model was developed to identify the variables that are significantly influential on the injury severity crashes. The advantage of these models is that they allow calculating the likelihood that a victim will be involved in an accident. This calculation will allow us to know what are the major factors that determine the individual risk perception. The factors that aggravate the risk of individual injuries can also be determined. This model utilized the injury severity as a dependent variable and described the relationship between the injury severity and a set of explanatory variables. In this context, we assume the utility function approach:

$$U_{n_i} = \beta_i X_n + \varepsilon_{n_i} \quad (1)$$

Where X_n is vector of exogenous explanatory variables characterizing the nature of driver characteristics, vehicle characteristics, infrastructure and the environment for crashes n; β_i is a vector of coefficients to be estimated which present the marginal variation of the explanatory variables effect on the probability of exposure of individual i to an accident of gravity G. The MNL satisfies the hypothesis of

Independence of Irrelevant Alternatives IIA[1]. The multinomial logit model is used for a dependent variable with unordered categories. One category is chosen as the reference category. The slight injuries will be the reference modality (slight injuries are the category with the highest frequency of accidents). Each category is compared to the probability of reference category. For categories, i=2…..N, the probability of each category is given in equation (2):

$$P(Y=1)=\frac{\exp\left(\alpha_i+\sum_{J=1}^{N}\beta_{ij}X_{ij}\right)}{1+\sum_{j=2}^{N}\exp\left(\alpha_i+\sum_{J=1}^{N}\beta_{ij}X_{ij}\right)} \qquad (2)$$

For the reference category, the probability of the slight injuries is given in equation (3):

$$P(Y=3)=\frac{1}{1+\sum_{j=2}^{N}\exp\left(\alpha_i+\sum_{J=1}^{N}\beta_{ij}X_{ij}\right)} \qquad (3)$$

After reorganizing (2) and (3) the multinomial logit model can be written in equation (4):

$$\mathrm{Ln}\left[\frac{P(Y=i)}{P(Y=3)}\right]=\alpha_i+\sum_{J=1}^{N}\beta_{ij}X_{ij} \qquad (4)$$

Where i represent the number of injury categories; β_{ij}; X_{ij}: are vectors of the estimated parameters and independent variables respectively. We have previously noted that the coefficients from multinomial logit model can be difficult to interpret for the reason that they are relative to the base outcome. Another way to evaluate the effects of covariates is to examine the marginal effect of changing their values on the probability of observing an outcome. The maximum likelihood method is then employed to compute the associations by constructing the likelihood function.

$$l(\beta)=\prod_{i=1}^{n}\pi(x_i)^{y_i}\left(1-\pi(x_i)\right)^{1-y_i} \qquad (5)$$

Where y_i denotes the ith observed outcome, with the value of both 0 or 1 only, and i = 1, 2, 3, …, n, where n is the number of observations. The parameters are estimated by maximizing the log likelihood expression as:

$$LL(\beta)=\ln\left(l(\beta)\right)=\sum_{i=1}^{n}\left\{y_i\ln\left(\pi(x_i)\right)+\left(1-y_i\right)\ln\left(1-\pi(x_i)\right)\right\} \qquad (6)$$

It has been recognized that the estimated parameters of multinomial logit model analysis are not adequate to explore how changes in the explanatory variables affect the outcome likelihood. This is due to the fact that the marginal effect of a variable depends on all the parameters in the model (Kim et al ., 2007). Consequently, average direct pseudo elasticity is computed in order to estimate the impact of explanatory variables on the possible injury outcome. In our model, the majority of the variables are indicator in nature. Average direct-pseudo elasticity is estimated to measure the marginal effects of indicator variables when any particular indicator variable switches from 0 to 1 or reverse. For binary indicator variables, the direct-pseudo elasticity $E^{pn(i)}_{x_{nk}(i)}$ is shown in equation (7) (Kim et al ., 2010).

[1] This hypothesis reflects the fact that the ratio of two probabilities associated with particular two events is independent of other events

$$E_{x_{nk(i)}}^{p_{n(i)}} = \left[\frac{p_{ni(given\, x_{nk}=1)} - p_{ni(given\, x_{nk}=0)}}{p_{ni(given\, x_{nk}=0)}} \right] \quad (7)$$

Where $x_{nk}(i)$, the k-th independent variable related with injury severity i for accident n. It must be noted that the direct pseudo-elasticity $E_{x_{nk}(i)}^{pn(i)}$ is calculated for all injury category severity (i) and each accident n. For this reason the average direct pseudo-elasticity for each injury severity (i) is computed as the average over the complete sample of accidents (Kim et al., 2010).

3. Empirical results and discussions

The results of the estimated accident injury severity model for each category are presented in Table 1. The slight injury category is selected as a base case. It should be noted that the average direct pseudo elasticity reflects the influence of variables on the possibility of traffic accidents at a certain level of accident severity (Table 2). The coefficients presented in Table 1 indicate the effects of variables on the latent injury severity propensity of causality. A positive coefficient associated with a variable indicates that the variable contributes positively to a higher injury severity propensity. Drivers whose ages are between 26 and 45 years are more likely than younger age groups to be fatally injured when they are in motor-vehicle accidents. The risk is much greater in the case of young drivers who are less mature and who do not attach great importance to the dangers related to their lack of driving experience. As shown in Table 2, when the involved driver is a female, the probability of having a high severity crash is less. This can be explained by the fact that men move more at night and are more involved in different activities (parties, trips, sport...) than women are. Contrariwise, Abdel-Aty and Abdelwahab (2004) and Kockelman and Kweon (2002) found that when the involved driver is a male the chance of having a high severity crash is less. In other words, female drivers are more likely to be involved in high severity crashes in both rural and urban areas. In addition, men are more often employed as drivers or mechanics, particularly as truck drivers over long distances, often spending several days and nights in their vehicle. They are therefore more subjected to the risk of traffic accidents than women. There are several factors which explain the dangerous behavior of men: the role assigned to them in society, indifference about the usefulness of wearing seatbelts, lack of awareness of the consequences related to the excess of speed in urban areas or out of town and driving without concentration (under alcohol, drugs ...). In counterpart, women do not usually drive under the influence of alcohol and they are very concerned about not only their own security but also that of the passengers. In addition to the driver's behavior as a key factor of accidents, an additional factor which is an indirect one can be mentioned. The infrastructure also plays a role in the causes of accidents. As a matter of fact, the original cause of accidents is not speed but rather the road environment that can allow or "encourage" the driver to be less cautious as the speed increases. Roadway characteristics affect the driver injury severity levels in a rather complex way. The road type variable is divided into four categories namely: One way street, dual carriageway, single carriageway and slip roads. As shown in Table 2, the dual carriageway increases the probability of fatal injury (56.52%) while at the same time it decreases the probability of slight injuries (16.58%). Added to that, the one-way street increases the probability of fatal injury (94.54%). Accidents from other types of junctions might appear but they also result in the decrease of the likelihood of accident fatality. As also shown in Table, males account for about 57.46% of pedestrian involvements in traffic accidents as compared to female pedestrians (52.54%). Among pedestrian gender, it is found that females have a lower propensity to sustain severe injuries (3.51% for fatal injuries). This is due to higher mobility of the male population. In Kuwait for example, more than 80% of pedestrian victims are males (Koushki et al., 2001). On the other side, Waylen and Mckenna (2002) and Obeng and Rokonuzzaman (2000) have demonstrated that more females than male are involved in vehicle-pedestrian crashes. As a point of fact, there are many explanations for this judgment in the traffic safety literature. Probably it is that females move more than men and this increases the likelihood of severe injuries (Ross and Hayes, 1988). Elderly Pedestrians over the age of 45 are more likely to suffer a fatal injury than the younger age groups. The highest relative involvement of the pedestrian casualties by age groups in fatal injuries was for the age groups (56-65), (36-45), (46-55), (26-35) respectively as shown in Table 2 and figure 1.

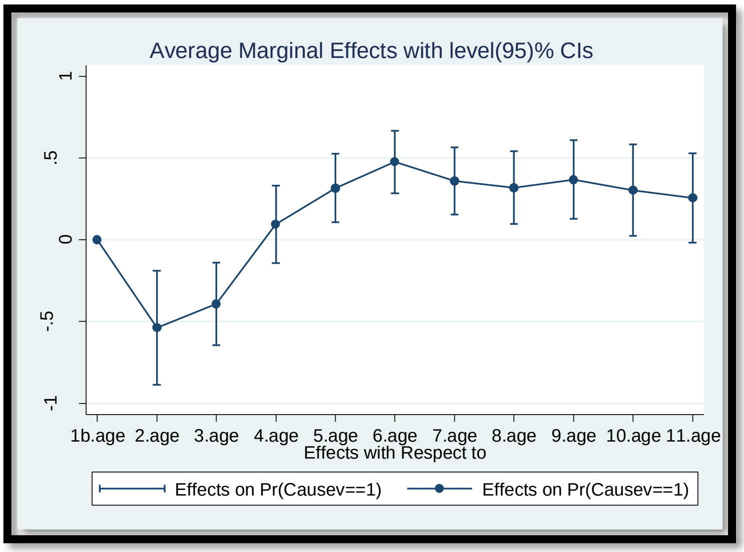

Figure 1: The adjusted predicted probability of pedestrian age in accident fatality

In general, the crash risk of elderly pedestrians is higher due to their reduced physical and cognitive abilities. The higher injury severity of elderly pedestrians can also be explained by the fact that they are less able to withstand collision. This is mainly due to their frailty. Accordingly, even a minor crash can result in severe injuries to elderly pedestrians. The Darkness - no lighting is also a significant factor in the injury severity model and the risk of fatal injury increases by 110% at night by comparison to day time and this is due to many reasons. First of all, Rifaat et al. (2011) explain this by the fact that during night, traffic flows are lighter which engenders higher traffic speed. Due to insufficient time left for driver to react, a pedestrian is more likely to be severely injured if a crash occurs during night. Second, reduced visibility of pedestrians during night might be a contributing factor to fatal and serious injuries (Lee and Abdel-Aty, 2005; Mohamed et al., 2013). Indeed, pedestrians have been found to be seriously injured when they are involved in accident with high-speed limit. As a matter of fact, the speed limit increases the probability of serious injuries by about 42.62%. It is worth mentioning that our results are also consistent with the vast majority of studies that have found an increased risk of serious injuries associated with high-speed limit (Belloumi and Ouni, 2019; Ouni and Belloumi, 2018). Added to that, the crashes that occur in rural areas and in a small-town affecting pedestrian victims have a higher proportion of fatal injury (61.22% and 67.91%) respectively. It seems that crash severity is less important in urban areas compared to rural ones. Possible reasons include higher intersection density (shorter straight road sections), higher urban traffic and possibly enforcement at night when compared to rural areas

4. Conclusion

As has been demonstrated above, identifying factors that increase or decrease the risk of accident severity is one of the fundamental tasks necessary in order to enhance road safety.

Accordingly, the goal of this study is to analyze driver, pedestrian and passenger crashes severity that occurred in Great Britain. This was made feasible by using the STATS 19 databases in order to identify influential factors that can affect the severity of causalities resulting of an accident. In order to do so, independent variables were classified into six groups which are: driver, accident, roadway, vehicle, environmental and temporal related factors. The level of crash severity is the dependent variable. To further examine the impact of various exogenous factors, average direct pseudo elasticity effects were considered for both injury-severity components. The results of the study are as follows. Firstly, for drivers' model, drivers whose ages are between 26 and 45 years are more likely than younger age groups to be fatally injured when they are in motor vehicle accidents. Added to that, male drivers are proven to experience higher severity levels than female drivers. Another finding is that accidents occurring in rural areas increase the likelihood of serious injuries by 136.28 % but have no significant effect on the other injury severity levels. One-way streets increase the probability of fatal injury which reaches 94.54%. Secondly for pedestrian model, results suggest that the severity of injuries of elderly pedestrians is higher compared to younger pedestrians. Darkness - no lighting is also a significant factor in the injury severity model and the risk of fatal injury increases by 110% at night compared to day time. In addition, pedestrians have been found to be seriously injured when they were involved in accidents with high-speed limit. Another interesting finding is that the crashes that occur in rural areas and in a small-town affecting pedestrian victims have a higher proportion of fatal injury (61.22%) and (67.91%) respectively compared to urban areas.

Acknowledgments

The authors are thankful to the Deanship of Scientific Research at Najran University for funding this work through grant research code (NU/RG/SEHRC/11/1).

References

1. Abdel-Aty, M., & Abdelwahab, H. (2004). Modeling rear-end collisions including the role of driver's visibility and light truck vehicles using a nested logit structure. Accident Analysis & Prevention, 36(3), 447-456.
2. Bedard, M., Guyatt, G. H., Stones, M. J., & Hirdes, J. P. (2002). The independent contribution of driver, crash, and vehicle characteristics to driver fatalities. Accident Analysis & Prevention, 34(6), 717-727.
3. Belloumi, M., & Ouni, F. (2019). Factors affecting the severity of motor vehicle traffic crashes in Tunisia. SAE International journal of transportation safety, 7(2), 99-128.
4. Clifton, K. J., Burnier, C. V., & Akar, G. (2009). Severity of injury resulting from pedestrian–vehicle crashes: What can we learn from examining the built environment?. Transportation research part D: transport and environment, 14(6), 425-436.
5. Ferreira, S., & Couto, A. (2012). Categorical modeling to evaluate road safety at the planning level. Journal of Transportation Safety & Security, 4(4), 308-322.
6. Haleem, K., & Abdel-Aty, M. (2010). Examining traffic crash injury severity at unsignalized intersections. Journal of safety research, 41(4), 347-357.
7. Isa, M. H. M., Jawi, Z. M., Sarani, R., & Wong, S. V. (2011). Injury severity analysis of accidents involving young motorcycle riders in Malaysia. Journal of the Eastern Asia Society for Transportation Studies, 9, 1997-2010.
8. Jiang, X., Huang, B., Yan, X., Zaretzki, R. L., & Richards, S. (2013). Two-vehicle injury severity models based on integration of pavement management and traffic engineering factors. Traffic injury prevention, 14(5), 544-553.
9. Jung, S., Qin, X., & Noyce, D. A. (2010). Rainfall effect on single-

vehicle crash severities using polychotomous response models. Accident Analysis & Prevention, 42(1), 213-224.
10. Kim, D. G., Lee, Y., Washington, S., & Choi, K. (2007). Modeling crash outcome probabilities at rural intersections: Application of hierarchical binomial logistic models. Accident Analysis & Prevention, 39(1), 125-134.
11. Kim, J. K., Ulfarsson, G. F., Shankar, V. N., & Mannering, F. L. (2010). A note on modeling pedestrian-injury severity in motor-vehicle crashes with the mixed logit model. Accident Analysis & Prevention, 42(6), 1751-1758.
12. Kockelman, K. M., & Kweon, Y. J. (2002). Driver injury severity: an application of ordered probit models. Accident Analysis & Prevention, 34(3), 313-321.
13. Kouhpaenejad, A. (2010). Statistical modeling and analysis of injury severity sustained by occupants of passenger vehicles involved in crashes with large trucks (Doctoral dissertation, University of Nevada, Las Vegas).
14. Koushki, P., Al-Saleh, O., Yaseen, S., & Ali, M. (2001). On Fatal and Injurious Pedestrian Accidents. In Transportation Research Board 80th Annual Meeting.
15. Krull, K. A., Khattak, A. J., & Council, F. M. (2000). Injury effects of rollovers and events sequence in single-vehicle crashes. Transportation Research Record, 1717(1), 46-54.
16. Lee, C., & Abdel-Aty, M. (2005). Comprehensive analysis of vehicle–pedestrian crashes at intersections in Florida. Accident Analysis & Prevention, 37(4), 775-786.
17. Leong, Q. M., Tsung Shyen, K. G., Appasamy, V., & Chiu, M. T. (2009). Young adults and riding position: factors that affect mortality among inpatient adult motorcycle casualties: a major trauma center experience. World journal of surgery, 33(4), 870-873.
18. Malyshkina, N. V., & Mannering, F. L. (2010). Zero-state Markov switching count-data models: An empirical assessment. Accident Analysis & Prevention, 42(1), 122-130.
19. Mergia, W. Y., Eustace, D., Chimba, D., & Qumsiyeh, M. (2013). Exploring factors contributing to injury severity at freeway merging and diverging locations in Ohio. Accident Analysis & Prevention, 55, 202-210.
20. Obeng, K., & Rokonuzzaman, M. (2013). Pedestrian injury severity in automobile crashes.
21. Ouni, F., & Belloumi, M. (2018). Spatio-temporal pattern of vulnerable road user’s collisions hot spots and related risk factors for injury severity in Tunisia. Transportation research part F: traffic psychology and behaviour, 56, 477-495.
22. Quddus, M. A., Wang, C., & Ison, S. G. (2010). Road traffic congestion and crash severity: econometric analysis using ordered response models. © American Society of Civil Engineers.
23. Rifaat, S. M., Tay, R., & De Barros, A. (2011). Effect of street pattern on the severity of crashes involving vulnerable road users. Accident Analysis & Prevention, 43(1), 276-283.
24. Savolainen, P., & Ghosh, I. (2008). Examination of factors affecting driver injury severity in Michigan's single-vehicle–deer crashes. Transportation Research Record, 2078(1), 17-25.
25. Schneider, W. H., Savolainen, P. T., & Zimmerman, K. (2009). Driver injury severity resulting from single-vehicle crashes along horizontal curves on rural two-lane highways. Transportation Research Record, 2102(1), 85-92.
26. Ulfarsson, G. F., & Mannering, F. L. (2004). Differences in male and female injury severities in sport-utility vehicle,

minivan, pickup and passenger car accidents. Accident Analysis & Prevention, 36(2), 135-147.

27. Waylen, A., & McKenna, F. (2002). Cradle Attitudes-Grave Consequences-The Development of Gender Differences in Risky Attitudes and Behaviour in Road Use.
28. Wu, Z., Sharma, A., Mannering, F. L., & Wang, S. (2013). Safety impacts of signal-warning flashers and speed control at high-speed signalized intersections. Accident Analysis & Prevention, 54, 90-98.
29. Yasmin, S., & Eluru, N. (2013). Evaluating alternate discrete outcome frameworks for modeling crash injury severity. Accident Analysis & Prevention, 59, 506-521.

Table 1: Maximum likelihood estimation results of multinomial logit models

Explanatory variables	Driver		Pedestrian	
	Fatal accident	Serious injuries	Fatal accident	Serious
Causality related factor				
Gender causality				
Male (ref)				
Female	-0.22(-2.97)***	-0.52(-2.67)***	2.02 (3.2)***	
Age band of causality				
-0 - 5(ref)				
-6 - 10			-0.7(-0.11)	
-11 -15			-0.53(-0.42)	
-16-20				
-21 -25			0.43(2.88)***	
-26 - 35	0.47 (3.02)***		0.68(1.12)	
-36 - 45	0.33 (2.05)**		0.52(3.56)***	
-46 - 55			0.46(2.9)***	
-56 - 65			0.57(3.19)***	
-66 – 75			0.58(2.77)***	0.64(2.84)***
-Over 75			0.58(2.9)***	0.84(4.04)***
Home area type				
-Urban area(ref)				
-Small town			1.04 (2.4)**	
-Rural		1.43(2.95)***	0.98 (2.27)**	
Roadway related factors				
Road type				
-Roundabout(ref)				
-One way street	1.71(4.25)***		1.06 (2.43)**	
-Dual carriageway	0.73(1.89)*	-1.46(-1.80)*		
-Single carriageway		-1.40(-1.80)*		
Slip road				
Speed limit	-0.14(-9.15)***		-0.08(-0.05)	
Weather conditions				
-Fine no high winds(ref)				
-Unknown	1.63(2.27)**			
Light conditions				
-Daylight (ref category)				
-Darkness - no lighting			2.007(2.07)**	
Skidding and overturning				
-Skidded(ref)				
-Skidded and overturned	0.71(3.60)***		0.67(3.34)***	
Hit object in carriageway				
Previous accident (ref)				
Parked vehicle	0.58(2.04)**			
Road works				-0.85(-1.93)*
Open door of vehicle	1.29(2.11)**		1.21(1.62)*	
Point of impact				
Did not impact (ref)				
Front				
Back	-0.19(-1.65)*			
Offside	-0.26(-1.81)*		-	
Nearside			-0.24(-1.66)*	
Vehicle maneuver				
Reversing(ref)				
Slowing or stopping	-0.55(-1.85)*			
moving vehicle - offside			0.67(1.7)*	
Going ahead right-hand bend	-0.75(-1.85)*			
Vehicle related factors				
Age of vehicle	-0.02(-2.84)***		-0.02(-0.17)	0.02(2.39)**
Vehicle propulsion code				
Petrol (ref category)				
Heavy oil			051(5.72)***	

Gas/Bi-fuel				2.04(1.65)*
Day of week				
Sunday (ref)				
Monday	0.43(3.32)***			
Tuesday	0.48(3.72)***			
Wednesday	0.53(4.15)***		0.48(3.61)***	
Thursday	0.76(5.14)***			
Friday	0.5(3.92)***			
Saturday	0.3(2.27)**			
Alternative specific	3.38(4.83)***	-2.17(-1.67)*	1.84(2.64)***	
-Log likelihood at convergence - Log likelihood intercept only - Log likelihood full model - Number of observations	-3747.9695 -4182.265 -3747.969 5000		-4507.7473 -4865.990 -4507.747 5000	

Table 2 : Average direct pseudo elasticity of explanatory variables

	DRIVER			PEDESTRIAN		
	Fatal	Serious	Slight	Fatal	Serious	Slight
Gender of causality						
Female	3.51%	-15.28%	2.52%	-10.77%	-40.49%	11.75%
Age band of causality						
6 – 10	-53.77%	-5.47%	16.24%			
11 - 15	-39.09%	-9.49%	13.89%			
21 - 25	9.44%	-12.24%	-11.57%			
26 - 35	31.61%	-14.24%	-21.20%	25.58%	14.31%	-22.04%
36 - 45	36%	-3.88%	-16.43%	18.16%	20.23%	-15.34%
46 - 55	31.98%	-1.25%	-14.86%			
56 - 65	36.9%	6.16%	-20.12%			
66 - 75	30.36%	36.13%	-27.93%			
Over 75	25.61%	51.46%	-32.97%			
Home area type						
Small town	67.91%	-66.86%	-36.95%			
Rural	61.22%	-33.85%	-37.11%	-19.63%	136.38	-7.35%
Road type						
One way street	64.67%	-68.92%	-41.85%	94.54%	-	-76.92%
Dual carriageway				56.52%	-	-16.58%
Single carriageway				41.13%	-	-4.01%
Speed limit	-187.86	42.62%	78.69%			
Light conditions						
Darkness - no lighting	110.51%	-150.42%	-90.25%			
Unknown				64.80%	-	-98.51%
Skidding and overturning						
Skidded and overturned	50.09%	-69.88%	-17.42%	33.67%	-11.03%	-38.13%
Hit object in carriageway						
Road works	10.54%	-76.05%	9.42%			
Parked vehicle				28.63%	-20.93%	-29.89%
Open door of vehicle	61.83%	16.79%	-59.59%	50.56%	28.62%	-79.37%
Point of impact (impact)						
Front	-26.93%	-1.28%	15.99%			
Back	-40.62%	2.49%	21.01%	-10.81%	19.81%	8.37%
Offside	-28.02%	12.14%	12.62%	-15.66%	35.34%	10.94%
Nearside	-16.09%	5.01%	8.56%			
Vehicle maneuver						
Moving vehicle offside	39.25%	26.34%	-28.46%			
Slowing or stopping				-33.76%	107.05	21.36%
Going ahead right-hand bend				-42.47%	4.38%	32.72%
Vehicle propulsion						
Heavy oil	35.67%	-17.83%	-15.44%			
Gas/Bi-fuel	60.22%	82.58%	-122.39%			
Age of vehicle	-10.76%	2.60%	0.46%	-4.54%	1.71%	3.46%
Day of week						
Monday				24.45%	16.65%	-19.15%
Tuesday				29.07%	-23.11%	-19.41%
Wednesday	24.57%	-0.77%	-13.08%			
Thursday				39.69%	-50.55%	-27.82%
Friday				30.60%	-32.80%	-20.07%
Saturday				19.05%	-20.02%	-11.30%