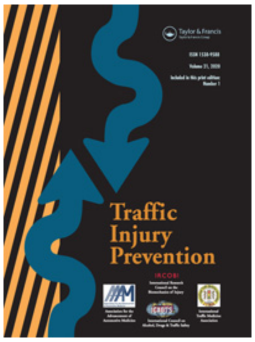

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Modeling head-on crash severity with drivers under the influence of alcohol or drugs (DUI) and non-DUI

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ABSTRACT

Objective: The objective of this research is to identify and compare contributing factors to head-on crashes with drivers under and not under the influence of alcohol or drugs.
Methods: The head-on crash data are collected from 2005 to 2013 in North Carolina from four aspects: vehicle, driver, roadway, and environmental characteristics. The final dataset includes 9,153 head-on crashes. A mixed logit model is developed to analyze the crash dataset involving drivers under and not under the influence of alcohol or drugs.
Results: According to the obtained results, factors such as rural roadways, adverse weather, curve road, and high speed limit are among the most significant contributing factors to both head-on crashes with DUI and non-DUI. In addition, the results of this research demonstrate that high speed limit is found to be better modeled as random-parameters at specific injury severity levels for head-on crashes with DUI. Besides the factors mentioned above, dark light condition, old drivers, pickups, and motorcycles also significantly affect the severity of head-on crashes with non-DUI.
Conclusions: The results of this study identify various factors that significantly affect the severity of head-on crashes with drivers under and not under the influence of alcohol or drugs. Also, the mixed logit model examines the heterogeneous effects and correlation in unobserved factors by allowing coefficients to be randomly distributed. The findings of this study call for more attention to head-on crashes and provide a reference for planners and engineers when developing and selecting countermeasures to reduce and/or mitigate head-on crashes.

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KEYWORDS
Head-on crashes; driving under influence; mixed logit model; contributing factors

Introduction

According to the National Highway Traffic Safety Administration, head-on crashes accounted for 2.3% of all crashes in 2015 U.S. statistics, but these crashes were responsible for 10.2% of all fatal crashes (NHTSA 2017). The probability of a fatal crash rises significantly after 0.05% blood alcohol concentration (BAC) and even more rapidly after 0.08% (Voas et al. 2012). Drivers with very high BACs (at or above 0.15%) have a very high risk of dying in a crash or getting severely injured (Peck et al. 2008). Alcohol-impaired-driving fatalities increased by 1.7% from 2015 to 2016 and accounted for 28% of 2016 overall fatalities (NHTSA 2017). Head-on crashes occur when the front-end of two vehicles hit each other in opposite directions, which lead to more severe injuries. To mitigate head-on crashes while also achieving a better understanding of head-on crashes associated with DUI and non-DUI, this study investigates and compares the contributing factors that significantly affect the injury severity of head-on crashes using a mixed logit model approach. The mixed logit model allows for heterogeneous effects and correlations in unobserved factors by allowing coefficients to be randomly distributed. With this feature, the mixed logit model is a more promising discrete choice model than the standard logit model.

This study investigates the head-on crashes that occurred in North Carolina between 2005 and 2013. The crash data are acquired from the North Carolina Highway Safety Information System (HSIS). The crash data files are linked and manipulated in SAS, containing the information about driver, vehicle, roadway, and environmental characteristics of each crash. Based on the comprehensive database and the mixed logit model, this study can provide more insights into the severity of head-on crashes with DUI and non-DUI.

This paper first presents a review of previous studies related to the crash severity analysis with different models. Then, the dataset collected from HSIS is described, including all the explanatory variables considered in the model. After that, the mixed logit model is developed along with the conduct of marginal effect analysis. Based on the modeling results, contributing factors that significantly impact the severity of head-on crashes with DUI and non-DUI are discussed in detail. Finally, conclusions and recommendations are made based on the findings of the study.

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Literature review

Crash severity analysis is of great importance in transportation safety and many studies have been conducted to investigate the contributing factors to the crashes (Dissanayake and Roy 2014). Head-on crashes are among the severest crash types due to the fact that they frequently result in more severe injuries and fatalities (Abdel-Aty 2003).

Early studies used linear models to analyze head-on crashes, such as negative binomial generalized linear model (Zhang and Ivan 2005). More recently, other researchers used non-linear models to conduct the analysis (Deng et al. 2006). For example, Hosseinpour et al. (2014) compared the contributing factors affecting the severity of head-on crashes among Poisson standard negative binomial, random-effect negative binomial, and hurdle Poisson model.

The mixed logit model allows for heterogeneous effects and correlation in unobserved factors (Train, 2009). It is also called the random coefficient logit model because this model allows coefficients to be randomly distributed. With this feature, the mixed logit model is a more promising discrete choice model than the standard logit model. Mixed logit model is a generalization of the multinomial structure with an error term that is independent and identically distributed (Ye and Lord 2014). The mixed logit model has been used by many researchers to conduct crash severity analysis (Liu and Fan 2019). By allowing parameters to differ across observations, the mixed logit model can provide more reliable parameter estimates (Weiss et al. 2014).

Alcohol or drugs can result in increased reaction time, decreased ability to estimate space and distance, increased feeling of self-confidence, and ultimately significantly decreased ability to safely operate a vehicle (Leporati et al. 2015). Velmurugan et al. (2013) developed a multinomial logit model by analyzing drunk and non-drunk drivers involved in road crashes on Indian highways. Chen et al. (2016) analyzed the risk factors affecting crash injury with DUI and non-DUI using an ordinal logistic regression.

Many studies have been conducted on head-on crashes (Hosseinpour et al. 2014). However, for the first time, this study attempts to investigate head-on crash severity by dividing the crash data into DUI and non-DUI related crashes. The major contribution of this study is to investigate the heterogeneous effects of the contributing factors of head-on crashes using a mixed logit model. Another contribution is to compare the contributing factors of head-on crashes with DUI and non-DUI.

Data description

In this study, the head-on crash data of North Carolina between 2005 and 2013 are provided by the Highway Safety Information System (HSIS) which is a multistate database created and maintained by the Federal Highway Administration (FHWA). The dataset contains various types of crash information on driver, roadway, vehicle, and environmental related characteristics. A total of 9,153 head-on crash records are collected in the dataset. Specifically, there are 1,179 DUI related crashes and 7,974 non-DUI related crashes available for this analysis. The severity of head-on crash refers to the most injured person involved in the crash who could be the driver or the occupant(s). The injury severity levels are divided into five categories, fatal injury crash (F), incapacitating injury crash (I), non-incapacitating injury crash (N), possible injury crash (P), and property damage only (PDO). Table 1 summarizes the descriptive statistics of each variable as well as the percentage of observed crash records under each severity level for DUI related crashes. As can be seen in the table, 16.03% of the collected head-on crashes with DUI are reported as fatal crashes, 13.91% are reported as incapacitating crashes, 37.83% are reported as non-incapacitating crashes, 20.02% are reported as possible injury crashes, and 12.21% are reported as property damage only crashes.

Table 2 summarizes the descriptive statistics of each variable as well as the percentage of observed crash records under each severity level for non-DUI related crashes. As can be seen in the table, 8.16% of the collected head-on crashes with non-DUI are reported as fatal crashes, 9.22% are reported as incapacitating crashes, 28.15% are reported as non-incapacitating crashes, 28.39% are reported as possible injury crashes, and 26.07% are reported as property damage only crashes. Dummy variables are created for each classification variable and the base is marked with an asterisk.

Methodology

Mixed logit model

The function determining injury severity of a mixed logit model is defined as a linear function that determines the specific injury severity level i for observation j as:

Table 1. Descriptive statistics of DUI related Head-on crash and explanatory variables.

			Injury Severity				
Variable	Description	No. of crashes	F[a]	I[b]	N[c]	P[d]	PDO[e]
Head-on crashes with DUI		1,179	16.03	13.91	37.83	20.02	12.21
Driver characteristics							
Age	Young(<25)	193	13.47%	11.40%	35.75%	24.35%	15.03%
	Mid-age(25-50)*	275	13.09%	15.64%	38.55%	21.82%	10.91%
	Old(>50)	711	17.86%	13.92%	38.12%	18.14%	11.95%

*Selected as the base of the categorical variable.
[a]F - fatal injury.
[b]I - incapacitating injury.
[c]N - non-incapacitating injury.
[d]P - possible injury.
[e]PDO - property damage only.

Table 2. Descriptive Statistics of non-DUI related head-on crash and explanatory variables.

Variable	Description	No. of crashes	Injury Severity				
			F[a]	I[b]	N[c]	P[d]	PDO[e]
Head-on crashes without DUI		7,974	8.16	9.22	28.15	28.39	26.07
Driver characteristics							
Age	Young(<25)	2564	6.94%	9.87%	29.49%	28.51%	25.20%
	Mid-age(25-50)*	3405	7.99%	9.37%	27.25%	27.64%	27.75%
	Old(>50)	2005	10.02%	8.13%	27.98%	29.53%	24.34%

Table 3. Results of the mixed logit model for DUI related crashes.

Variable	Description	F		I		N		P	
		Coef.	t-stats	Coef.	t-stats	Coef.	t-stats	Coef.	t-stats
Intercept		−1.4046	−3.90	−1.4865	−4.90	0.032	0.18	0.0207	0.11
Roadway characteristics									
Road_Class	Rural	0.7405	2.02	0.9982	3.65	–	–	–	–
Spd_Limit	30-50 mph	1.3875	3.24	0.9963	2.79	1.0521	4.07	0.4985	1.83
	>50mph	0.4312	0.31	1.5352	4.65	1.578	6.63	0.6738	2.68
	Std. dev.	3.6536	2.01	–	–	–	–	–	–

Note: No. of observations, 1,179; Log-likelihood at convergence, -1,703; Log-likelihood (constant-only), -1,898. PDO is set as the reference category.

$$U_{ij} = \beta_i X_{ij} + \varepsilon_{ij} \tag{1}$$

where X_{ij} is a vector of independent variables (driver, vehicle, roadway, and environmental characteristics), β_i is the vector of estimated parameters for variables X_{ij} influencing injury severity outcomes, and ε_{ij} is the error term representing unobservable impacts on severity outcomes. If ε_{ij} is assumed to follow a Gumbel (type 1) distribution, then the probability of individual j suffering injury severity i can be expressed as:

$$P_{ij}|\beta_i = \frac{\exp\left(\beta_i X_{ij}\right)}{\sum_{i=1}^{I}\exp\left(\beta_i X_{ij}\right)} \tag{2}$$

where I is the set of all injury severity levels (e.g., property damage only, possible injury, non-incapacitating injury, incapacitating injury, and fatal injury). To consider the randomly distributed parameters across individual drivers, a mixing distribution can further be expressed as (Train 2009):

$$P_{ij} = \int (P_{ij}|\beta_i) f(\beta|\varphi) d\beta \tag{3}$$

where $f(\beta|\varphi)$ is the probability density function (PDF) of the random vector β, and φ denotes a vector of parameters describing the PDF (e.g., the mean and variance of the normal distribution).

A simulation-based maximum likelihood method is used to estimate the model parameters by using SAS 9.3. Milton et al. (2008) verified that 200 Halton draws can provide an efficient estimation for the distribution of the random parameters. All the random parameters are set to be normally distributed in the mixed logit model. For the final model results, all the random parameters in the model are significant through a backward stepwise variable selection process.

Marginal effect

In order to evaluate the impacts of significant variables in the mixed logit model on driver injury outcome probabilities, marginal effect analysis is conducted. Since all independent variables are coded as dummy variables in this study, the marginal effects of all independent variables are calculated as follows:

$$E_{X_{ijk}}^{P_{ij}} = \frac{P_{ij}(X_{ijk} = 1) - P_{ij}(X_{ijk} = 0)}{P_{ij}(X_{ijk} = 0)} \tag{4}$$

The probabilities specific to each severity level for individual driver j, are calculated when the k th binary indicator variable, X_{ijk}, equals to 1 or 0, respectively. The marginal effect for each parameter is calculated by averaging the marginal effects over all observations.

Results

The model results for DUI and non-DUI related crashes are provided in Table 3 and Table 4. According to the model results, 7 indicator variables are found to have significant impacts on at least one of the severity levels of head-on crashes with DUI. Among them, high speed limit is found to have random effects across the crash data. The marginal effect of each independent variable is calculated and presented in Table 5. For head-on crashes with non-DUI, 15 indicator variables are found to have significant impacts on at least one of the severity levels. Among them, rural road, curve road, straight and grade road, adverse weather condition and dark light condition are found to have random impacts across the crash data. The marginal effect of each independent variable is calculated and presented in Table 6. A positive value of parameters and marginal effects indicates that the change of independent variable (from 0 to 1) would increase the probability of a given crash severity level. A negative value of parameters and marginal effects indicates that the change of independent variable (from 0 to 1) would decrease the probability of a given crash severity level.

Driver characteristics

Driver age is not a significant variable that affects the severity of head-on crashes with DUI. But for non-DUI crashes,

Table 4. Results of the mixed logit model for non-DUI related crashes.

		F		I		N		P	
Variable	Description	Coef.	t-stats	Coef.	t-stats	Coef.	t-stats	Coef.	t-stats
Intercept		−3.7596	−14.16	−2.6852	−14.84	−0.5832	−5.88	−0.0839	−1.59
Driver characteristics									
Age	Old	0.552	4.57	–	–	0.2377	2.29	0.1583	2.37
Vehicle characteristics									
Veh_Type	Pickup	–	–	−0.2854	−2.86	−0.1617	−1.67	−0.1596	−2.64
	Motorcycle	2.0471	5.51	1.302	4.22	1.1781	3.05	0.5579	1.91

Note: No. of observations, 7,974; Log-likelihood at convergence, -11,152; Log-likelihood (constant-only), -12,834. PDO is set as the reference category.

Table 5. Marginal effects of the mixed logit model for DUI related crashes.

		Marginal Effects				
Variable	Description	F	I	N	P	PDO
Roadway characteristics						
Road_Class	Rural	7.93%	4.02%	0.10%	−5.84%	−6.20%
Traff_Control	With Control	−7.93%	−4.01%	−0.10%	5.84%	6.20%
Spd_Limit	30-50 mph	9.78%	4.95%	0.12%	−7.20%	−7.64%
	>50 mph	14.55%	7.36%	0.18%	−10.72%	−11.37%
Environmental characteristics						
Weather	Adverse	−7.09%	−3.59%	−0.09%	5.23%	5.55%

Table 6. Marginal effects of the mixed logit model for non-DUI related crashes.

		Marginal Effects				
Variable	Description	F	I	N	P	PDO
Driver characteristics						
Age	Old	1.21%	1.05%	1.41%	−0.79%	−2.88%
Vehicle characteristics						
Veh_Type	Pickup	−0.98%	−0.85%	−1.14%	0.64%	2.33%
	Motorcycle	6.12%	5.30%	7.15%	−3.99%	−14.58%
Roadway characteristics						
Road_Class	Rural	4.93%	4.28%	5.77%	−3.22%	−11.76%

drivers over 50 years old are more likely to result in more severe crashes compared to middle-aged drivers. Abdel-Aty (2003) also concluded that older drivers have a higher probability of experiencing more severe injuries. The marginal effects obtained indicate that old drivers could increase the probability of fatal crashes, incapacitating injury crashes, and non-incapacitating injury crashes by 1.21%, 1.05%, and 1.41%, respectively. Enforcing the driver retesting (e.g., vision testing) could be a potential countermeasure.

Vehicle characteristics

The results indicate that vehicle type will not significantly impact the injury severity levels of head-on crashes with DUI. For non-DUI crashes, pickups tend to have lower levels of injury severity than passenger cars. As can be seen in Table 6, pickups can decrease the probability of fatal crashes, incapacitating injury crashes, and non-incapacitating injury crashes by 0.98%, 0.85%, and 1.14%, respectively. This is reasonable because pickups can absorb more collision energy during a head-on crash than passenger vehicles and hence reduce the potential risk of severe injury to the driver. Desapriya et al. (2005) also found that passenger vehicle drivers experienced greater injuries than pickup drivers in passenger vehicle and pickup collisions. Motorcycles are likely to have higher levels of injury severity than passenger cars. Motorcycles could increase the probability of fatal crashes, incapacitating injury crashes, and non-incapacitating injury crashes by 6.12%, 5.30%, and 7.15%, respectively.

Roadway characteristics

Head-on crashes that occurred on rural roadways are likely to have higher injury severity levels than those on urban roadways for both DUI and non-DUI crashes. It can be seen from Table 5 that the head-on crashes with DUI occurred on rural roadways could increase the probability of fatal and incapacitating injury by 7.93% and 4.02%, respectively. For non-DUI crashes, rural roadways could increase the probability of fatal and incapacitating injury crashes by 4.93% and 4.28%, respectively. Kweon and Kockelman (2003) also concluded that crashes occurred on urban interstate highways tend to be less severe. It is reasonable because drivers usually drive at a higher speed on rural roadways. In addition, there is better access control on urban roadways than that on rural roadways.

For non-DUI crashes, one-way roadways and divided two-way roadways will significantly decrease the levels of injury severity compared to undivided two-way roadways. According to Table 6, one-way roadways can lead to a decrease of fatal, incapacitating and non-incapacitating injury head-on crashes by 4.57%, 3.96%, and 5.35%, respectively. Two-way divided roadways can lead to a decrease of fatal, incapacitating and non-incapacitating injury head-on crashes by 1.60%, 1.39%, and 1.87%, respectively. Garrido et al. (2014) also found that motor-vehicle occupants traveling on one-way roads tend to suffer less severe injuries than those who travel on two-way undivided roads.

Head-on crashes that occurred on grade road segments and curved road segments tend to have higher levels of injury severity compared to straight and level road segments. The results also show that curved roadways have more impacts on the head-on crash injury severity levels than grade roadways. It can be seen from Table 5 that head-on crashes with DUI occurred on curved road segments could increase the probability of fatal crashes and incapacitating injury crashes by 6.56% and 3.32%, respectively. Head-on crashes with DUI that occurred on grade road segments could increase the probability of fatal crashes and incapacitating injury crashes by 5.45% and 2.76%, respectively. For head-on crashes with non-DUI, curved road segments could increase the probability of fatal crashes and incapacitating injury crashes by 3.14% and 2.72%, respectively. Head-on crashes with non-DUI that occurred on grade road segments could increase the probability of fatal crashes and incapacitating injury crashes by 1.79% and 1.55%, respectively. Duncan et al. (1998) also concluded that grade road would increase the crash injury severity. The reason is that drivers have limited sight distance when approaching grade or curve roadways. In addition, it is more difficult for drivers to brake sufficiently on grade or curve roadways than on the straight and level roadways. Hummer et al. (2010) examined curve collision characteristics and identified that providing an advance warning prior to the curve, enhanced curve delineation or pavement markings, installation of a shoulder, and centerline rumble strips could be potential countermeasures to curve collisions.

Roadway segments with traffic control can significantly decrease the probabilities of fatal, incapacitating, and non-incapacitating injury in both DUI and non-DUI head-on crashes. Traffic control can decrease the probability of fatal and incapacitating injury head-on crashes with DUI by 7.93% and 4.01%, respectively. For head-on crashes with non-DUI, traffic control can lead to a decrease of fatal and incapacitating injury by 1.46% and 1.26%, respectively. Chen et al. (2012) also found that the odds of fatalities doubled at no-control intersections than traffic light-controlled intersections.

Roadways with speed limit more than 35 mph can significantly increase the injury severity levels in both DUI and non-DUI head-on crashes. Malyshkina and Mannering (2008) examined the effect of speed limits on injury severity on non-interstate highways and found that higher speed limits could lead to higher injury severity. According to Table 5, speed limit between 30 mph and 50 mph can lead to an increase of fatal and incapacitating injury head-on crashes with DUI by 9.78% and 4.95%, respectively. Speed limit greater than 50 mph can lead to an increase of fatal and incapacitating injury head-on crashes with DUI by 14.55% and 7.36%, respectively. According to Table 6, speed limit between 30 mph and 50 mph can lead to an increase of fatal and incapacitating injury head-on crashes with non-DUI by 2.71% and 2.35%, respectively. Speed limit greater than 50 mph can lead to an increase of fatal and incapacitating injury head-on crashes with non-DUI by 5.10% and 4.43%, respectively.

Roadways with medians will significantly decrease the injury severity levels of head-on crashes with non-DUI. As one can see in Table 6, roadways with medians can lead to a decrease of fatal, incapacitating and non-incapacitating injury head-on crashes by 1.53%, 1.33%, and 1.79% respectively. Installation of median barriers and in-vehicle technology could significantly reduce the occurrence of head-on crashes.

Environmental characteristics

Adverse weather condition, such as rain and snow, is found to significantly decrease the injury severity of DUI and non-DUI head-on crashes. Edwards (1998) reported a similar result. This is reasonable because the vehicle speed is relatively lower under adverse weather conditions compared to clear weather, reducing the collision energy when a head-on crash occurs. According to Table 5, adverse weather condition could decrease the probability of fatal, incapacitating injury, and non-incapacitating injury in head-on crashes with DUI by 7.09%, 3.59%, and 0.09%, respectively. It can also be seen in Table 6 that adverse weather condition could decrease the probability of fatal, incapacitating injury, and non-incapacitating injury in head-on crashes with non-DUI by 3.75%, 3.25%, and 4.39%, respectively.

Light condition is a significant variable in head-on crashes with non-DUI. Dawn, dusk, and dark light condition tend to have higher injury severity levels of crashes compared to daylight condition. As one can see in Table 6, dawn and dusk light condition can increase the probability of fatal, incapacitating injury, and non-incapacitating injury of crashes by 1.1%, 0.96%, and 1.29%, respectively. Dark light condition can lead to an increase of fatal, incapacitating, and non-incapacitating injury of crashes by 0.61%, 0.53%, and 0.72%, respectively.

Discussion

In this study, the contributing factors that impact the injury severity in head-on crashes with DUI and non-DUI are examined. A comprehensive head-on crash dataset is generated from the North Carolina HSIS from 2005 to 2013, and a mixed logit model is developed to analyze the severity in head-on crashes with DUI and non-DUI separately. The mixed logit model examines the heterogeneous effects and correlation in unobserved factors by allowing coefficients to be randomly distributed. According to the modeling results, 7 indicator variables are found to have significant impacts on at least one of the severity levels of head-on crashes with DUI. Among them, high speed limit is found to have random impacts across the observations. For head-on crashes with non-DUI, 15 indicator variables are found to have significant impacts on at least one of the severity levels. Among them, rural road, curve road, straight and grade road, adverse weather condition and dark condition are found to have random effects across the observations. The contributing factors that increase the injury severity of head-on crashes are old drivers, motorcycles, rural roadways, speed limit between 30 mph and 50 mph, speed limit greater than 50 mph, curve roadways, grade roadways, and dark light condition. The contributing factors that decrease the injury severity levels of head-on crashes are pickups, one-way roadways, two-way divided roadways, traffic control, median, and adverse weather condition.

The findings of this study call for more attention to head-on crashes and provide a reference for planners and engineers when developing and selecting countermeasures that are associated with head-on crashes. For example, install centerline rumble strips on high volume roads which can have a potential for head-on crashes; provide additional delineation at sharp curves; lower the speed limit of roadways where head-on crashes occurred. Education and law enforcement are necessary for drivers under influence of alcohol or drugs to realize the potential risk to themselves and other drivers such as alcohol enforcement, speed enforcement, and safety belt enforcement. Advanced technologies such as in-vehicle sensors could be adopted to eliminate or minimize the severity in head-on crashes. The findings of this study can also be used to make policy decisions such as traffic fines for drivers driving under influence of alcohol or drugs.

It should be noted that the data used in this study are from 2005 to 2013. Temporal instability may exist within this period that is caused by the great recession (Mannering 2018). Thus, in the future study, the authors will try to explore the temporal instability of crash data and identify its impact on head-on crash severity. Also, in the future, the authors will consider heterogeneity in means and variances which is an extension of simple random parameters.

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References

Abdel-Aty M. 2003. Analysis of driver injury severity levels at multiple locations using ordered probit models. J Safety Res. 34(5):597–603. doi:10.1016/j.jsr.2003.05.009

Chen H, Cao L, Logan D. 2012. Analysis of risk factors affecting the severity of intersection crashes by logistic regression. Traffic Inj Prev. 13(3):300–307. doi:10.1080/15389588.2011.653841

Chen H, Chen Q, Chen L, Zhang G. 2016. Analysis of risk factors affecting driver injury and crash injury with drivers under the influence of alcohol (DUI) and non-DUI. Traffic Inj Prev. 17(8): 796–802. doi:10.1080/15389588.2016.1168924

Deng Z, Ivan J, Gårder P. 2006. Analysis of factors affecting the severity of head-on crashes. Transportation Research Record. 1953(1): 137–146. doi:10.1177/0361198106195300116

Desapriya E, Pike I, Kinney J. 2005. The risk of injury and vehicle damage severity in vehicle mismatched side impact crashes in British Columbia. IATSS Res. 29(2):60–66. doi:10.1016/S0386-1112(14)60134-5

Dissanayake S, Roy U. 2014. Crash severity analysis of single vehicle run-off-road crashes. JTTs. 04(01):1–10. doi:10.4236/jtts.2014.41001

Duncan C, Khattak A, Council F. 1998. Applying the ordered probit model to injury severity in truck-passenger car rear-end collisions. Transp Res Rec. 1635(1):63–71. doi:10.3141/1635-09

Edwards J. 1998. The relationship between road accident severity and recorded weather. J Safety Res. 29(4):249–262. doi:10.1016/S0022-4375(98)00051-6

Garrido R, Bastos A, de Almeida A, Elvas J. 2014. Prediction of road accident severity using the ordered probit model. Transp Res Rec. 3: 214–223. doi:10.1016/j.trpro.2014.10.107

Hosseinpour M, Yahaya A, Sadullah A. 2014. Exploring the effects of roadway characteristics on the frequency and severity of head-on crashes: case studies from Malaysian Federal Roads. Accid Analy Prev. 62:209–222. doi:10.1016/j.aap.2013.10.001

Hummer J, Rasdorf W, Findley D, Zegeer C, Sundstrom C. 2010. Curve collisions: road and collision characteristics and countermeasures. J Transp Saf Secur. 2(3):203–220. doi:10.1080/19439961003734880

Kweon Y, Kockelman K. 2003. Overall injury risk to different drivers: combining exposure, frequency, and severity models. Accid Anal Prev. 35(4):441–450. doi:10.1016/S0001-4575(02)00021-0

Leporati M, Salvo R, Pirro V, Salomone A. 2015. Driving under the influence of alcohol. A 5-year overview in Piedmont, Italy. J Forensic Leg Med. 34:104–108. doi:10.1016/j.jflm.2015.05.017

Liu P, Fan W. 2019. Modeling head-on crash severity on NCDOT freeways: a mixed logit model approach. Can J Civ Eng. 46(4):322–328. doi:10.1139/cjce-2018-0262

Malyshkina N, Mannering F. 2008. Effect of increases in speed limits on severities of injuries in accidents. Transp Res Rec. 2083(1): 122–127. doi:10.3141/2083-14

Mannering F. 2018. Temporal instability and the analysis of highway accident data. Anal Methods Accid Res. 17:1–13. doi:10.1016/j.amar.2017.10.002

Milton J, Shankar V, Mannering F. 2008. Highway accident severities and the mixed logit model: an exploratory empirical analysis. Accide Anal Prev. 40(1):260–266. doi:10.1016/j.aap.2007.06.006

NHTSA. 2017. Traffic Safety Facts 2015: A compilation of motor vehicle crash data from the fatality analysis reporting system and the general estimates system. Washington DC: U. S. Department of Transportation.

Peck R, Gebers M, Voas R, Romano E. 2008. The relationship between blood alcohol concentration (BAC), age, and crash risk. J Safety Res. 39(3):311–319. doi:10.1016/j.jsr.2008.02.030

Train K.E. 2009. Discrete choice methods with simulation. Cambridge: Cambridge University Press.

Velmurugan S, Padma S, Madhu E, Anuradha S, Gangopadhyay S. 2013. A study of factors influencing the severity of road crashes involving drunk drivers and non drunk drivers. Res Transport Econ. 38(1):78–83. doi:10.1016/j.retrec.2012.05.015

Voas R, Torres P, Romano E, Lacey J. 2012. Alcohol-related risk of driver fatalities: an update using 2007 data. J Stud Alcohol Drugs. 73(3):341–350. doi:10.15288/jsad.2012.73.341

Weiss H, Kaplan S, Prato C. 2014. Analysis of factors associated with injury severity in crashes involving young New Zealand drivers. Accid Anal Prev. 65:142–155. doi:10.1016/j.aap.2013.12.020

Ye F, Lord D. 2014. Comparing three commonly used crash severity models on sample size requirements: multinomial logit, ordered probit and mixed logit models. Anal Methods Accid Res. 1:72–85. doi:10.1016/j.amar.2013.03.001

Zhang C, Ivan J. 2005. Effects of geometric characteristics on head-on crash incidence on two-lane roads in Connecticut. Transport Res Rec. 1908(1):159–164. doi:10.1177/0361198105190800119