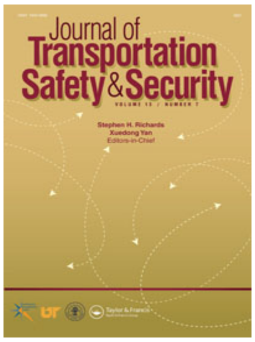

Taylor & Francis
Taylor & Francis Group

Journal of Transportation Safety & Security

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/utss20

Analysis of head-on crash injury severity using a partial proportional odds model

Pengfei Liu & Wei (David) Fan

To cite this article: Pengfei Liu & Wei (David) Fan (2021) Analysis of head-on crash injury severity using a partial proportional odds model, Journal of Transportation Safety & Security, 13:7, 714-734, DOI: 10.1080/19439962.2019.1667933

To link to this article: https://doi.org/10.1080/19439962.2019.1667933

JOURNAL OF TRANSPORTATION SAFETY & SECURITY
2021, VOL. 13, NO. 7, 714–734
https://doi.org/10.1080/19439962.2019.1667933

Taylor & Francis
Taylor & Francis Group

Check for updates

Analysis of head-on crash injury severity using a partial proportional odds model

Pengfei Liu[a] and Wei (David) Fan[b]

[a]Department of Civil and Environmental Engineering, University of North Carolina at Charlotte, Charlotte, North Carolina, USA; [b]USDOT Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE) Professor, Department of Civil and Environmental Engineering, University of North Carolina at Charlotte, Charlotte, North Carolina, USA

ABSTRACT
Head-on crashes are one of the most severe crash types and always result in injuries or fatalities. To prevent and mitigate head-on crashes, factors that significantly affect the injury severity of head-on crashes must be identified before appropriate countermeasures can be explored. To bridge the gap between ordered and unordered response modeling, in this research, a partial proportional odds model is developed to analyze the factors that influence the injury severity of head-on crashes. The analyses are performed based on the data collected from Highway Safety Information System (HSIS) from 2005 to 2013 in North Carolina. The results of this research demonstrate that there are 14 factors that have significant effects on the injury severity of head-on crashes. Among them, the roadway with speed limit over 50 mph is found to increase the fatal crash most. Appropriate countermeasures are recommended according to the influencing factors that are identified. The model performance is also compared with ordered logit model and multinomial logit model. The partial proportional odds model can provide adequate fit without potential loss of prediction accuracy.

KEYWORDS
head-on crashes; severity analysis; partial proportional odds model; ordered logit model; multinomial logit model

1. Introduction

Head-on crash is a crash type where the two front ends of vehicles hit each other in opposite directions. Due to the way that the vehicles collide with each other, head-on crashes often result in fatal injuries, severe property damage, and economic and social costs. According to the U.S. Statistics, in 2015, head-on crashes were only 2.3% of all crashes, yet accounted for 10.2% of all fatal crashes (NHTSA, 2017). Unlike other crash types, vehicles involved in head-on crashes are traveling toward each other at the time of the collision, which increases force sustained by both drivers. To prevent

CONTACT Wei (David) Fan wfan7@uncc.edu USDOT Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE) Professor, Department of Civil and Environmental Engineering, University of North Carolina at Charlotte, EPIC Building, Room 3261, 9201 University City Boulevard, Charlotte, NC 28223-0001, USA.
Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/utss.

and mitigate head-on crashes, the factors that significantly affect the injury severity of head-on crashes must be identified before appropriate countermeasures can be explored.

The aim of this research is to investigate the potential risk factors that contribute to the injury severity of head-on crashes. Crash injury severity analysis has the distinct advantage of including and examining potential driver-related contributing factors and individual crash characteristics, which generally are not available in crash frequency analysis. Although a significant number of studies have been conducted for crash injury severity analysis and reported in the literature, few studies have focused on the analysis of head-on crash injury severity. In addition, only ordered or unordered response models were used in these studies to conduct the head-on crash analysis. To bridge the gap between ordered and unordered response models, a partial proportional odds model is developed which allows certain independent variables to ignore the proportional odds assumption, while others retain the assumption. A large and comprehensive database is developed based on head-on crash data from 2005 to 2013 for the entire state of North Carolina. This database contains records of 9,153 head-on crashes and more than 100 attributes for each crash record, including information about the drivers, vehicles, characteristics of the crashes, roadway conditions, and environmental conditions. Based on such a comprehensive database, a partial proportional odds model is developed, which can provide more accurate results regarding the risk factors associated with head-on crashes and their influence on the levels of injury severity of the crashes.

The paper is organized as follows. Section 2 conducts a literature review on previous studies related to crash injury severity analysis and introduces the concept of the partial proportional odds model. Section 3 presents the methodological framework for the partial proportional odds model, the multinomial logit model, and the ordered logit model. Section 4 explains the available data related to head-on crashes and the variables considered in the analysis of the injury severity of the crashes. Section 5 summarizes the modeling results in detail and the model performances are also compared. Finally, section 6 concludes this paper and recommendations are made based on the findings of this research.

2. Literature review

Several research studies have been conducted to investigate the factors that influence the injury severity of crashes. Some studies focused on crashes involving head-on crashes (Zhang & Ivan, 2005; Gårder, 2006; Deng, Ivan, & Gårder, 2006; Hosseinpour, Yahaya, & Sadullah, 2014; Ma, Hao, Pan, & Xiang, 2018; Ma, Hao, Pan, et al., 2018; Ma, Yang, Zhou, Feng, & Yuan, 2019), but most of them investigated the injury severity of other crashes. In addition, some studies focused on certain types of crashes, such as rear-end crashes or rollover crashes (Khattak, 2001, Kweon & Kockelman, 2003), and some others focused on certain locations where the crashes occurred (Dissanayake & Roy, 2014).

Zhang and Ivan (2005) evaluated the effects of roadway geometric features on the incidence of head-on crashes on two-lane rural roads in Connecticut using negative binomial generalized linear models. Variables found to influence the incidence of head-on crashes significantly were speed limit, sum of absolute change rate of horizontal curvature, maximum degree of horizontal curve, and sum of absolute change rate of vertical curvature. Gårder (2006) used an ordered probit model for looking at the simultaneous influence of different variables on the injury severity of head-on crashes. The results showed that higher speed limits lead to a higher percentage of crashes involving fatal injuries or incapacitating injuries. Deng et al. (2006) conducted an analysis of the statistical association between head-on crash injury severity and potential causal factors, such as the geometric characteristics of the road segment, weather conditions, road surface conditions, and time of occurrence. It was found that a wet roadway surface and narrow road segments were significantly related to more severe head-on crashes. Hosseinpour et al. (2014) examined the factors affecting both the frequency and injury severity of head-on crashes by developing a random-effect generalized ordered probit model. With regard to the crash injury severity, the results showed that horizontal curvature, paved shoulder width, terrain type, and side friction were associated with more severe crashes.

In terms of methodologies, previous studies have used various modeling methods to analyze the injury severity of crashes, which include the ordered probit model (Gårder, 2006; Deng et al., 2006; Ma & Kockelman, 2006), nested logit model (Lee & Mannering, 1999), multinomial logit model, Heteroskedastic ordered probit model, Bayesian ordered probit model (Xie, Zhang, & Liang, 2009), mixed logit model (Chen & Chen, 2011; Liu & Fan, 2019), random parameter ordered probit model (Chen, Song, & Ma, 2019), partial proportional odds model (Sasidharan & Menéndez, 2014), hybrid finite mixture model (Ma, Wang, Yan, & Weng, 2016), and machine learning classification methods (Ahmadi, Jahangiri, Berardi, & Machiani, 2018). Yasmin and Eluru (2013) compared ordered response and unordered response discrete choice models for driver injury severity.

The ordered logit or ordered probit models are commonly used to modeling crash injury severity because crash injury severity levels are inherently related to each other. The ordered response models can capture the association between different injury severity levels. These models have to adhere to the proportional odds (PO) assumption. The PO assumption forces the estimated coefficient of an independent variable to remain constant for all injury severity levels. In other words, a change in an independent variable can only increase or decrease the probabilities of all severity levels by the same scale. However, the truth is some variables may increase the probability of one injury severity level while decreasing the probability in another injury severity level (Savolainen & Mannering, 2007). Even if the variable increases or decreases the probability of all the injury severity levels, the scope of impact on different injury severity levels may vary. The multinomial logit model relaxes the PO assumption for all independent variables when predicting crash injury severity levels. It allows all independent variables to affect each crash injury severity level differently (Chang & Mannering, 1999; Lee & Mannering, 2002; Ulfarsson & Mannering, 2004). The defect of this model is that it neglects the ordered crash injury severity levels which are an inherent characteristic of crash injury severity.

To address the limitation in both ordered and unordered response models, a partial proportional odds model is developed to conduct the crash injury severity analysis. This model considers the ordinal response levels in crash injury severity. Also, it relaxes the PO assumption for some variables allowing them to affect each severity level differently (Hedeker, Berbaum, & Mermelstein, 2006). Wang and Abdel-Aty (2008) examined left-turn crash injury severity using a partial proportional odds model. The results showed that the proposed model outperformed the ordered logit model in terms of model fit. Mooradian, Ivan, Ravishanker, and Hu (2013) modeled driver and passenger injury severity by comparing a partial proportional odds model with both the ordinal and multinomial response models. The data source was the Connecticut Department of Transportation crash database which contains crash records on state-maintained roads. Different types of crash were considered based on similarities of contributing factors to the crash including angle collision, rear-end collision, head-on collision, etc. The authors concluded that the partial proportional odds model performs best among the three models. Pour-Rouholamin and Zhou (2016) developed a partial proportional odds model to analysis driver injury severity in wrong-way driving crashes. The estimation results showed that driver age and condition, seatbelt use, time of day, airbag status, type of setting, surface condition, lighting condition, and type of crash have significant impact on the injury severity of Wrong-way driving crashes. Wang and Prato (2019) focused on mitigating factors associated with the injury severity of truck crashes on mountain expressways using a partial proportional odds model. Countermeasures for mitigating the injury severity level of truck crashes on mountain expressways were concluded.

The objective of this study is to evaluate the effects of various roadway geometric design, the environment and traffic characteristics on the injury severity of head-on collisions. As noted above, a partial proportional odds model is developed to conduct the analysis. And the performance of the model is also compared with the multinomial logit model and the ordered logit model.

3. Methodology

The SAS 9.4 is used to develop the three models in this study. The multinomial logit model uses the MDC procedure and has a case alternative data structure. The ordered logit model and the partial proportional odds model use the LOGISTIC procedure.

3.1. Proportional odds assumption

The proportional odds assumption, also known as parallel lines assumption, forces the effect of an independent variable to keep constant over all crash injury severity levels. This implies that the distances between different crash injury severity levels are the same. The Brant test is conducted for all the independent variables to check if the data satisfies the proportional odds assumption. The Brant test uses a series of Wald Chi-square tests for all independent variables comparing different crash injury severity levels. The independent variables that failed the Brant test can reject the assumption and be relaxed through a partial proportional odds model. These variables will have different coefficients for each crash injury severity level.

3.2. Ordered logit model

The ordered logit model has a vital assumption that the data meets the proportional odds assumption (Wang & Abdel-Aty, 2008). Let Y_i denote the crash injury severity level in crash i, Y_i^* the latent crash injury severity measure, X the matrix of independent variables, j the crash injury severity level, and J the number of severity levels.

The latent injury severity measure Y_i^* can be estimated as follows:

$$Y_i^* = X_i\beta + \varepsilon \tag{1}$$

where β is the coefficients for X, ε is the independently distributed error term

The probability of crash injury severity level j for a given crash i can be specified as

$$P(Y_i > j) = \frac{\exp(\alpha_j + \beta x_i)}{1 + \exp(\alpha_j + \beta x_i)}, \ j = 1, \ 2, \ \ldots, \ J - 1 \tag{2}$$

where α_j is the intercept for j th cumulative logit.

It should be noted that β is constant for all crash injury severity levels.

3.3. Partial proportional odds model

The partial proportional odds model allows certain independent variables to affect each crash injury severity level differently, while other independent variables adhere to the proportional odds assumption. The probability of crash injury severity level j for a given crash i can be specified as (Williams, 2006):

$$P(Y_i > j) = \frac{\exp(\alpha_j + \beta_j x_i)}{1 + \exp(\alpha_j + \beta_j x_i)}, \ j = 1, \ 2, \ \ldots, \ J - 1 \tag{3}$$

For the independent variables being relaxed from the proportional odds assumption, β_j are free to differ for different injury severity levels. For other independent variables, β_j remain constant no matter which injury severity level j is.

3.4. Multinomial logit model

The multinomial logit model is used when the dependent variable has three or more values. The multinomial logit model is derived under the assumption that the unobserved factors are uncorrelated over the alternatives or outcomes, also known as the independence from irrelevant alternatives (IIA) assumption. This assumption is the most notable limitation of the multinomial logit model since it is very likely that the unobserved factors are shared by some outcomes. This limitation can be relaxed by the mixed logit model (Chen, Chen, & Ma, 2018).

The probability of crash injury severity level j for a given crash i can be specified as (Ye & Lord, 2014)

$$P(Y_i > j) = \frac{\exp(\beta_j x_i)}{\sum_{j=1}^{J} \exp(\beta_j x_i)} \tag{4}$$

The multinomial logit model completely ignores the inherent ordinal characteristic of different injury severity levels. The estimated coefficients are different for all injury severity levels.

3.5. Model comparison

The partial proportional odds model and the other two models can be fit using the same dataset. A performance assessment can be conducted based on the model outcomes. Three different criteria, log-likelihood of the full model (LL_{full}), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) are proposed to conduct the comparison. The AIC and BIC are two measures to evaluate the quality of different statistical models. By including a penalty term for the number of predictors along with the log-likelihood value of the model, AIC and BIC consider both the goodness of model fit and complexity of the model. Smaller values of AIC and BIC indicate a better model fit. The AIC and BIC are formulated as follows (Posada & Buckley, 2004):

$$AIC = 2m - 2LL_{full} \tag{5}$$

$$BIC = mln(N) - 2LL_{full} \tag{6}$$

where m is the number of parameters estimated in the model, N is the number of observations.

3.6. Elasticity analysis

In order to evaluate the impacts of significant variables in the partial proportional odds model on crash injury severity probabilities, elasticity analysis is conducted (Ma et al., 2016; Ma, Yang, et al., 2019; Pour-Rouholamin & Zhou, 2016; Xiong et al., 2019). Since all independent variables are coded as dummy variables in this study, the pseudo-elasticities of all independent variables are calculated as follows:

$$E^{P_{ij}}_{X_{ijk}} = \frac{P_{ij}(X_{ijk} = 1) - P_{ij}(X_{ijk} = 0)}{P_{ij}(X_{ijk} = 0)} \tag{7}$$

The probabilities specific to each injury severity level i for individual driver j, are calculated when the k^{th} binary indicator variable, X_{ijk}, equals to 1 or 0, respectively. The elasticity for each parameter is calculated by averaging the simulation-based elasticities over all observations.

4. Data description

For this research, crash data from 2005-2013 are requested and downloaded from the Highway Safety Information System (HSIS) in North Carolina. Based on the accident types, all the head-on crashes are then extracted. The end result is that 9,153 head-on crash records are extracted and used in the analysis of the injury severity of head-on crashes.

Table 1. Descriptive statistics of head-on crash severity outcomes and explanatory variables.

Variable	Description	No. of crashes	Injury Severity (%) F[a]	I[b]	N[c]	P[d]	PDO[e]
Head-on crashes		9,153	9.18	9.82	29.4	27.31	24.29
Driver characteristics							
Age	Young(<25)	2,839	7.54	10.43	30.36	27.86	23.81
	Mid-age(25–50)*	4,116	9.69	10.16	29.13	26	25.02
	Old(>50)	2,198	10.33	8.42	28.66	29.07	23.52
Gender	Male	5,795	10.32	10.37	29.53	26.3	23.49
	Female*	3,358	7.21	8.87	29.18	29.06	25.67
Alc_Drug	No drink or drugs*	7,974	8.16	9.22	28.15	28.39	26.07
	Drink or drugs	1,179	16.03	13.91	37.83	20.02	12.21
Vehicle characteristics							
Veh_Type	Pickup	3,484	9.5	9.07	28.3	27.18	25.95
	Truck/Trailer	160	12.5	10.63	28.75	22.5	25.63
	Motorcycle	241	23.24	21.16	31.12	16.6	7.88
	Passenger Car*	5,221	8.26	9.83	30.03	27.98	23.9
	Other	47	4.26	4.26	34.04	34.04	23.4
Roadway characteristics							
Road_Class	Rural	5,637	13.04	13.8	32.45	23.58	17.14
	Urban*	3,516	2.99	3.44	24.52	33.3	35.75
Road_Conf	Two-way Undivided*	7,391	10.24	11.19	30.63	25.76	22.18
	Two-way Divided	1,658	4.95	4.04	24.49	33.84	32.69
	One-way	104	0.96	4.81	20.19	33.65	40.38
Median	No Median*	7,313	10.08	11.09	30.85	25.98	22
	With Median	1,840	5.6	4.78	23.64	32.61	33.37
Traff_Control	No Control*	2,733	10.39	9.04	29.35	25.94	25.28
	With Control	6,420	8.66	10.16	29.42	27.9	23.86
Spd_Limit	>=50 mph	4,515	14.55	13.55	31.67	23.23	16.99
	30-50 mph	2,363	5.76	7.91	29.58	29.58	27.17
	<=30 mph*	2,275	2.07	4.4	24.7	33.05	35.78
Road_Align	Curve	2,334	13.24	15.25	33.42	22.96	15.12
	Straight and level*	5,274	7	7.38	27.49	29.29	28.84
	Straight and grade	1,545	10.49	9.97	29.84	27.12	22.59
AADT	>= 13,000 veh/day	3,226	5.18	5.52	25.48	31.09	32.73
	< 13,000 veh/day*	5,927	11.35	12.16	31.53	25.26	19.69
Environmental characteristics							
Weather	Adverse	1,421	5.07	8.02	27.59	28.15	31.18
	Clear*	7,732	9.93	10.15	29.73	27.16	23.02
Ligt_Cond	Dawn/Dusk	435	10.11	11.72	28.05	24.37	25.75
	Dark	2,731	9.85	10.11	30.68	27.21	22.15
	Daylight*	5,987	8.8	9.55	28.91	27.58	25.15

*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.

The dependent variable for the developed models is the injury severity of head-on crashes. The severity of a head-on crash is defined as the most severe injury level resulted from the crash. Five different severity levels for crashes are considered in the model representing fatal injury crash (F), incapacitating injury crash (I), non-incapacitating injury crash (N), possible injury crash (P), and property damage only (PDO). Table 1 shows the descriptive statistics of each variable as well as the percentage of observed crash records under each severity level. The independent variables include the roadway, environmental, vehicle and driver's characteristics. As can be seen in the table, 9.18% of the collected head-on crashes are reported as fatal crashes, 9.82% are reported as incapacitating crashes, 29.4% are reported as non-incapacitating crashes, 27.31% are reported as possible injury crashes, and 24.29% are reported as property damage only crashes.

The percentage of male drivers being involved in fatal head-on crashes is 10.32%, which is higher than the percentage in female drivers (7.21%). Male drivers seem to have a higher likelihood of being involved with fatal injury in head-on crashes. This is in line with the finding by Ahmadi et al. (2018). For the speed limit variable, compared to speed limit 30–50 mph and less than 30 mph, speed limit higher than 50 mph have a higher probability to result in fatal crashes (14.55% vs. 5.76% vs. 2.07%), incapacitating injury crashes (13.55% vs. 7.91% vs. 4.4%), and non-incapacitating injury crashes (31.67% vs. 29.58% vs. 24.7%). Dummy variables are created for each classification variable and the base is marked with an asterisk in Table 1.

5. Results and analysis

This section includes a comparison between the partial proportional odds model, the multinomial logit model, and the ordered logit model using criteria like log-likelihood value, AIC, and BIC is also present. The elasticities of the partial proportional odds models for different crash severity levels are also calculated and present in this section.

5.1. Visual test

To decide whether the variable adheres to the proportional odds assumption, the empirical cumulative logit function can be plotted. If the plots of the empirical cumulative logits look approximately parallel, the proportional odds assumption is appropriate for this variable (Derr, 2013). For an independent variable x, the empirical cumulative logits are calculated as

$$\log \frac{P(Y \leq j)}{P(Y > j)} \tag{8}$$

Figure 1 indicates that variable ‘curve’ is more likely to adhere to the proportional odds assumption, and variable ‘old’ seems to reject the assumption.

Another way to assess proportionality is to compare the mean value of the independent variable within each severity level to the model-expected value of$X|Y = j$, given that the proportional odds assumption holds for the model. If the model-expected value curve closely follows the mean curve, the independent variable is likely to adhere to the proportional odds

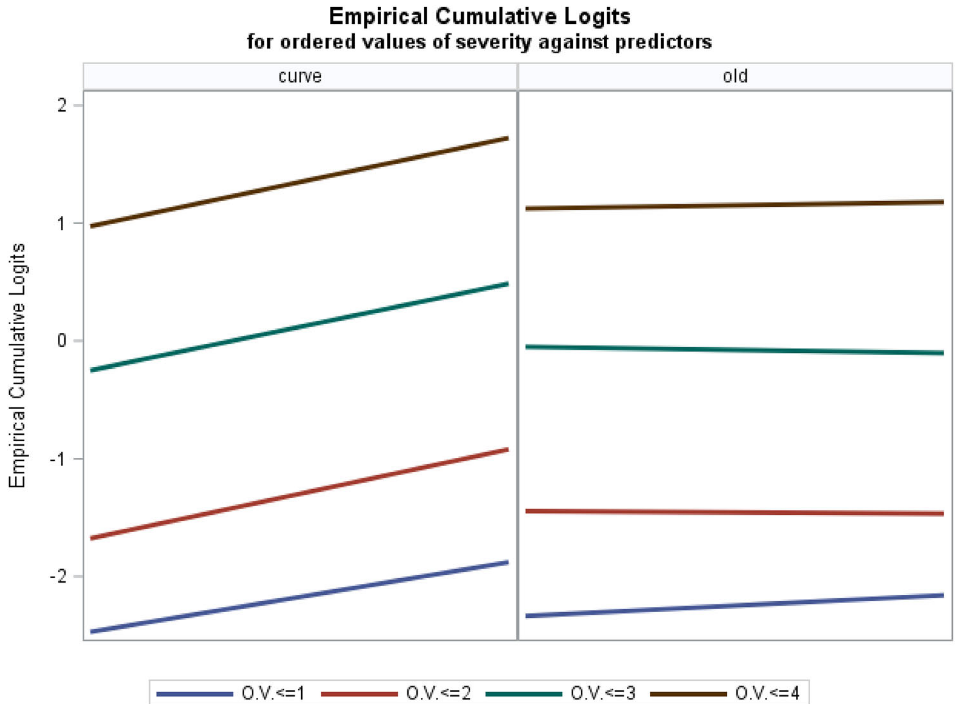

Figure 1. Empirical cumulative logits plots for variable 'curve' and 'old'.

assumption. Figure 2 shows an example of this plot using the same variables plotted above. The plots for variable 'curve' show no profound departure from proportionality, while the plots for 'old' show an inconsistency obviously. In other words, 'curve' has a proportional odds structure and 'old' has a general structure. As a result, the partial proportional odds model is more appropriate to use compared to the proportional odds model.

5.2. Brant test

Brant test is performed to check the parallel regression assumption for the partial proportional odds model. The null hypothesis for the Brant test is that each variable has only one coefficient for all crash severity levels. Table 2 shows the results of the Brant test. The insignificant variables (with p-value greater than 0.05) suggest that the proportional odds assumption is reasonable for those variables. The significant variables (marked with *) indicate the null hypothesis should be rejected and a partial proportional odds model is preferred. These variables will have different coefficients for different crash severity levels in the partial proportional odds model.

It can be seen from the results that independent variables such as drink or drugs, rural road, traffic control, old drivers, speed limit 30-50 mph,

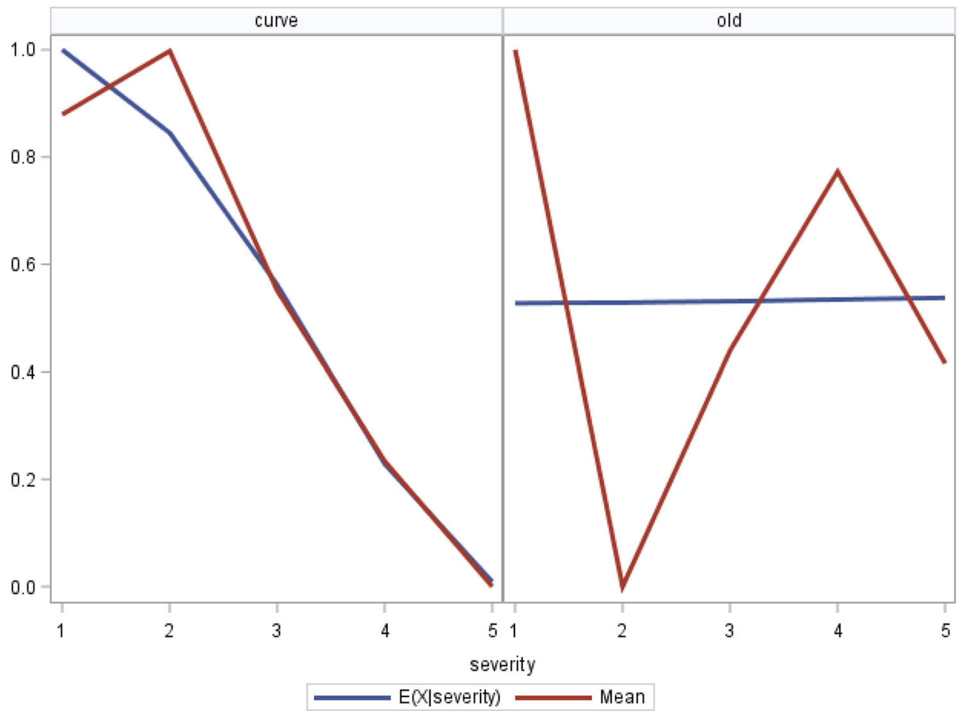

Figure 2. Assessing proportionality of 'curve' and 'old' using mean value.

Table 2. Results of the Brant test for all independent variables.

	Linear Hypotheses Testing Results	
Variables	Wald Chi-Square	*P*-value
Drink or Drugs	9.6832	0.0215*
Rural	22.6635	<.0001*
Adverse	4.6681	0.1978
Straight and Grade	2.7178	0.4372
Curve	1.7842	0.6184
One-way	3.2098	0.3604
Two-way Divided	10.3924	0.0155*
With Traffic Control	22.2129	<.0001*
Old (>50)	11.3559	0.0099*
Speed Limit 30–50mph	10.2054	0.0169*
Speed Limit >=50mph	30.4092	<.0001*
With Median	4.0449	0.2567
Pickup	11.9012	0.0077*
Motorcycle	0.4032	0.9396

*Fail the parallel regression assumption.

speed limit >50 mph, and pickups failed the proportional odds assumption and will be relaxed to have different coefficients for different crash severity levels. Independent variables such as adverse weather, straight and grade road, curve road, one-way road, roadway with median, and motorcycle adhere to the proportional odds assumption and will have only one coefficient across all crash severity levels.

5.3. Partial proportional odds model

According to the Brant test results, a partial proportional odds model is developed for head-on crash severity. Table 3 summarizes the results of the developed partial proportional odds model. First, a stepwise selection process is conducted and all insignificant independent variables are removed from the proportional odds model. Then according to the results of the Brant test, the proportional odds assumption is relaxed for certain independent variables. Finally, the appropriate partial proportional odds model is developed to estimate the parameters for selected variables.

The interpretation of the estimated coefficients should be cautious for those variables that violate the proportional odds assumption. The sign of the coefficients does not always determine the direction of the effect (Washington, Karlaftis, & Mannering, 2010). So, the elasticities of the partial proportional odds model are calculated and presented in Table 4 to better interpret the model results.

The predictors that meet the proportional odds assumption (motorcycle, one-way, curve, straight and grade, roadway with median, and adverse weather) have the same coefficient values across all crash severity levels. The positive coefficient values of the independent variables indicate that the existence of such variables could increase the likelihood of higher crash severity levels and vice versa. For example, compared to passenger vehicle, motorcycle could suffer more severe head-on crash instead of property damage only. Compared to two way non-divided roadway, one-way roadway tends to result in less severe head-on crashes. Garrido, Bastos, de

Table 3. Estimation results for the partial proportional odds model.

Variable	Description	F Coef.	I Coef.	N Coef.	P Coef.
Intercept		−4.0432***	−2.8695***	−0.8418***	0.4819***
Driver characteristics					
Alc_Drug	Drink or Drugs	0.6687***	0.6152***	0.8617***	0.8526***
Age	Old (>50)	0.2719***	0.0809	0.0564	0.1555***
Vehicle characteristics					
Veh_Type	Pickup	0.1001	−0.0411	−0.1351***	−0.1976***
	Motorcycle	0.922***			
Roadway characteristics					
Road_Class	Rural	0.8445***	1.0201***	0.6731***	0.5464***
Road_Conf	One-way	−0.7243***			
	Two-way Divided	−0.1948	−0.3213***	−0.2407***	−0.0494
Traff_Control	With Control	−0.5451***	−0.4289***	−0.2991***	−0.1208*
Spd_Limit	30-50 mph	0.895***	0.664***	0.4524***	0.3651***
	>50mph	1.509***	1.081***	0.7128***	0.6180***
Road_Align	Curve	0.4509***			
	Straight and Grade	0.2820***			
Median	With Median	−0.1762***			
Environmental characteristics					
Weather	Adverse	−0.4977***			

Note: No. of observations, 9,153; Log-likelihood at convergence, −12887; Log-likelihood (constant-only), −13777. PDO is set as the reference category.
***Significant at the 99% confidence level. *Significant at the 95% confidence level.

Table 4. Elasticity analysis of the partial proportional odds model.

	Elasticities for Different Crash Severity levels (%)				
Variables	F	I	N	P	PDO
Drink or Drugs	27.67	21.02	14.72	13.68	−51.54
Rural	44.97	72.80	22.13	7.60	−37.70
Adverse	−10.40	−10.40	−10.40	−10.40	47.39
Straight and Grade	5.40	5.40	5.40	5.40	−20.50
Curve	8.52	8.52	8.52	8.52	−30.87
One-way	−16.57	−16.57	−16.57	−16.57	72.15
Two-way Divided	−10.98	−21.56	−14.98	2.95	8.16
With Traffic Control	−33.06	−24.82	−14.39	2.31	15.45
Old (>50)	17.70	−2.77	−5.12	4.76	−10.32
Speed Limit 30–50mph	76.19	39.85	13.18	3.71	−28.01
Speed Limit >=50mph	163.78	71.94	18.98	8.22	−41.67
With Median	−3.52	−3.52	−3.52	−3.52	15.07
Pickup	−27.00	−10.27	−0.38	5.70	14.90
Motorcycle	14.38	14.38	14.38	14.38	−54.51

Almeida, and Elvas (2014) also found that motor-vehicle occupants traveling at one-way roads tend to suffer less severe injuries than those who travel at two-way roads.

Compared to a straight and level road segment, steep road segment and curved road segment are more likely to result in more severe head-on crashes. Crashes that occur at a curved road segment are more severe than the straight and grade road alignment conditions according to the results in Table 3. It also can be seen from Table 4 that head-on crashes occurred at curved road segment could increase the probability of fatal crashes by 8.52%, which is higher than the impact of straight and grade road segment on the same severity level. Duncan, Khattak, and Council (1998) also found that grade road would increase the crash injury severity. This is because drivers have limited sight distance when approaching the road segments with a grade or a curve. In addition, it is difficult for the driver to brake sufficiently at a grade or a curve. Hummer, Rasdorf, Findley, Zegeer, and Sundstrom (2010) examined curve collision characteristics and identified some potential countermeasures for curve collisions, e.g., including providing an advance warning prior to the curve, enhanced curve delineation or pavement markings, installation of a shoulder, and centerline rumble strips. Roadways with median will significantly decrease the likelihood of a higher crash severity level compared to property damage only crashes. Install centerline rumble strips on high volume roads could decrease the probability of head-on crash.

Table 3 indicates that the severity level of head-on crashes tends to decrease when there is adverse weather condition such as rain and snow. Edwards (1998) reported a similar result. This is to be expected because drivers usually drive slower in adverse weather than they do when the weather is clear. From Table 4, one can see that crashes occurred in adverse weather condition could decrease the probability of fatal crashes by 10.40%.

With respect to drink or drugs driving, head-on crashes are expected to significantly increase crash severity. From Table 4, one can see that drink or drug driving will increase the probability of fatal crashes, incapacitating injury crashes, and non-incapacitating injury crashes by 27.67%, 21.02%, and 14.72%. Reducing the legal blood alcohol concentration limit for driving, supplementing enforcement by public education campaigns, and increasing punishment could be countermeasures to reduce the severity of drink or drugs driving. Head-on crashes occurred in rural areas tend to have more severe injury levels than those in urban areas. It can be seen from Table 4, the head-on crashes occurred in a rural area could increase the probability of fatal crashes, incapacitating injury crashes, and non-incapacitating injury crashes by 44.97%, 72.80%, and 22.13%, respectively. Ma and Kockelman (2006) also found crashes occurred on urban interstate highway tend to be less severe. These observations are reasonable because drivers usually drive at a higher speed on a rural roadway. In addition, urban interstate highways have better access control and usually are safer than other types of roadways.

Table 3 indicates that the head-on crashes occurred at roadway segments with traffic control tend to be less severe. Chen, Cao, and Logan (2012) also found that the odds of fatalities at no-control intersections were twice as high as traffic light-controlled intersections. It can be seen from Table 4 that traffic control can reduce the probability of fatal crashes, incapacitating injury crashes, and non-incapacitating injury crashes by 33.06%, 24.82%, and 14.39%, respectively. For drivers over 50 years old, there is a significant increase in fatal crashes. Abdel-Aty (2003) also concluded that older drivers have a higher probability of more severe injuries. The elasticity analysis in Table 4 also shows that old driver will increase the probability of fatal head-on crashes by 17.70%.

Head-on crashes occurred on the roadway with speed limit of more than 30 tend to have more severe injuries compared with roadway speed limit less than 30 mph. Malyshkina and Mannering (2008) examined the effect of speed limits on injury severity on non-interstate highways, and the results showed that higher speed limits were associated with higher injury severity. From the table of elasticity analysis, one can see that roadways with speed limit greater than 30 mph could lead to a lower probability of no injury crashes but a higher probability of possible injury crashes, non-incapacitating injury crashes, incapacitating injury crashes, and fatal crashes. Especially for a roadway with speed limit over 50 mph, the probability of fatal head-on crashes could increase by 163.78%. Increase speed enforcement and lower the speed limit where head-on crashes occurred could be countermeasures to reduce the probability of head-on crashes. Pickups can reduce the probability of fatal crashes, incapacitating injury crashes, and non-incapacitating crashes. Desapriya, Ian, and Kinney (2005) also found that passenger vehicle drivers experienced greater injuries than pickup drivers in passenger vehicle and pickup collisions.

5.4. Ordered logit model

This section presents the results of the ordered logit model developed in this study. For each independent variable, there is only one estimated coefficient across all crash severity levels. The results are shown in Table 5. Only significant independent variables with a 95% confidence level are included in the table. In ordered logit model, a positive coefficient value indicates that the existence of certain independent variable could increase the probability of more severe head-on crash compared to property damage only. A negative coefficient indicates that the existence of certain independent variable could decrease the probability of more severe head-on crash. According to the ordered logit model, independent variables that will increase crash severity include drink or drugs driving, old driver, motorcycle, rural roads, speed limit 30-50 mph, speed limit >50 mph, curve roadway, and straight and grade roadway.

Compared to the results of the partial proportional odds model, the independent variables that adhere to the proportional odds assumption have similarly estimated coefficients with the ordered logit model. For example, the estimation of adverse weather is -0.4977 in the partial

Table 5. Results of the ordered logit model.

Variables	Description	Coef.
Intercept1		0.4965***
Intercept2		−0.8544***
Intercept3		−2.4204***
Intercept4		−3.3297***
Driver characteristics		
Alc_Drug	Drink or Drugs	0.7588***
Age	Old (>50)	0.1144*
Vehicle characteristics		
Veh_Type	Pickup	−0.1284***
	Motorcycle	0.8946***
Roadway characteristics		
Road_Class	Rural	0.6555***
Road_Conf	One-way	−0.6937***
	Two-way Divided	−0.1637***
Traff_Control	With Control	−0.2606***
Spd_Limit	30–50 mph	0.4169***
	>50mph	0.7608***
Road_Align	Curve	0.4338***
	Straight and Grade	0.2720***
Median	With Median	−0.1824***
Environmental characteristics		
Weather	Adverse	−0.5125***

Note: No. of observations, 9,153; Log-likelihood at convergence, −12980; Log-likelihood (constant-only), −13777. PDO is set as the reference category.
***Significant at the 99% confidence level. *Significant at the 95% confidence level.

proportional odds model and -0.5125 in the ordered logit model. But for the independent variables that violate the proportional odds assumption, the estimated coefficients in the ordered logit model will either overestimate or underestimate the effect of certain variables. For example, the estimated coefficient for speed limit >50 mph is 0.7608 in the ordered logit model. The results in the partial proportional odds model indicate that this coefficient value underestimates the effect of speed limit >50 mph on fatal crash (1.509) and incapacitating injury crash (1.081), and overestimates the effect of the same on non-incapacitating injury crash (0.7128) and possible injury crash (0.6180).

5.5. Multinomial logit model

The multinomial logit model holds an assumption of the independence of irrelevant alternatives (IIA), which means a person's choice between two alternative outcomes is unaffected by what other choices are available. The IIA assumption is tested using the Hausman and McFadden (HM) test and the Small and Hsiao (SH) test (Train, 2003). The results of both tests suggested that the IIA assumption is not violated. Therefore, the multinomial logit model is developed and the results are shown in Table 6. Only the independent variables that significantly impact the head-on crash on at least one of the severity levels with 95% confidence level are included in the model.

Table 6. Results of the multinomial logit model.

Variables	Description	F Coef.	I Coef.	N Coef.	P Coef.
Intercept		−3.1377***	−2.4953***	−0.3961***	−0.1138***
Driver characteristics					
Alc_Drug	Drink or Drugs	1.394***	1.1398***	1.0235***	0.3863***
Age	Young (<25)	−0.192*	–	–	–
	Old (>50)	0.2171*	–	–	–
Vehicle characteristics					
Veh_Type	Pickup	–	−0.269***	−0.1993***	−0.1183*
	Motorcycle	1.4271***	1.135***	0.5833***	–
Roadway characteristics					
Road_Class	Rural	1.266***	1.4448***	0.5888***	0.258***
Road_Conf	One-way	−2.3076*	–	−0.5456*	–
	Two-way Divided	−0.4716***	−0.632***	−0.1711*	–
Traff_Control	With Control	−0.6297***	−0.3476***	−0.2066***	–
Spd_Limit	30–50 mph	1.2091***	0.7243***	0.4399***	0.1501*
	>50 mph	1.9944***	1.0606***	0.6139***	0.2401***
Road_Align	Curve	0.7482***	0.7589***	0.4851***	0.2522***
	Straight and Grade	0.4858***	0.3311***	0.1859***	–
Median	With Median	–	–	−0.2271***	–
Environmental characteristics					
Weather	Adverse	−1.1474***	−0.7037***	−0.4916***	−0.3287***

Note: No. of observations, 9,153; Log-likelihood at convergence, −12880; Log-likelihood (constant-only), −14731. PDO is set as the reference category.
***Significant at the 99% confidence level. *Significant at the 95% confidence level. – indicates that the coefficient is statistically insignificant.

Table 7. Model performances of the PPO, OL, and MNL models.

Model	Criterion		
	Log-likelihood	AIC	BIC
PPO	−12887	25859	26158
OL	−12980	25997	**26125**
MNL	−**12880**	**25856**	26198

5.6. Model comparison

The model performances of the three developed models are compared using log-likelihood of the full models along with AIC and BIC. These parameters are calculated and presented in Table 7. A lower log-likelihood indicates a better model fit, given the same sample and dependent variable. As can be seen in Table 7, the MNL model has the best model fit among the three models. A well fitness for the given database does not translate to an effective model. Over fitting by increasing unnecessary parameters can lead to poor predictions with other database. The PPO model performs approximately as effective as the MNL model with less degree of freedom. The PPO model can avoid excessive variance inflation and potential loss in prediction accuracy. The ordered logit model has the lowest BIC due to the lowest degree of freedom among the three models since BIC penalizes free parameters more strongly. The degree of freedom for the ordered logit model is 18, compared to 42 and 48 for the PPO and MNL model, respectively.

6. Conclusions and recommendations

In this study, the factors that influence the severity of head-on crashes are investigated. A comprehensive set of head-on crash data is collected in North Carolina from 2005 to 2013. The crashes are categorized into five different levels based on injury severity, which are fatal crash, incapacitating injury crash, non-incapacitating injury crash, possible injury crash, and property damage only. The partial proportional odds model is developed and the elasticities are also calculated. Based on the Brant test, eight variables (i.e., drink or drugs driving, rural road, old drivers, two-way divided road, traffic control, speed limit 30-50 mph, speed limit >50 mph, and pick-ups) are found to violate the parallel regression assumption, thus are relaxed in the partial proportional odds model. These variables will have different coefficients for different crash severity levels. The PPO model results show that there are 14 variables that have significant impacts on the severity of head-on crashes. Variables that could significantly increase the probability of more severe head-on crashes include drink or drugs driving, old drivers, rural roads, curve roads, straight and grade roads, speed limit 30-50 mph, speed limit >50 mph, and motorcycle. Head-on crashes occurred on the roadway with speed limit over 50 mph would increase the severity of injuries most. To mitigate and prevent such crashes, traffic signs and pavement markings should be implemented in locations with a history of head-on crashes.

The partial proportional odds model is compared with the other two commonly used models, the ordered logit model and the multinomial logit model. The ordered logit model holds the proportional odds assumption, also known as parallel lines assumption, which forces the effect of an independent variable to keep constant over all crash severity levels. This assumption is too restrictive such that it may underestimate the different influence of a certain variable on different crash severity level. The multinomial logit model, however, does not account for the hierarchical nature of the dataset. It adds unnecessary variance to the model even these parameters are not significantly different between different severity levels. The partial proportional odds model takes a parsimonious approach by considering the ordinal nature of the crash outcomes and allowing the predictors that violate the proportional odds assumption to vary between different crash severity levels.

The model performances are also compared between the PPO, OL, and MNL model using the log-likelihood at convergence, AIC, and BIC. The comparison results indicate that the PPO model performs approximately as effective as the MNL model. Over fitting by increasing unnecessary parameters is avoided in the PPO model without potential loss of prediction accuracy. Overall, the results of this study can help traffic engineers better understand the factors that influence the severity of head-on crashes and develop the most effective countermeasures for preventing and mitigating head-on crashes.

The three models developed in this study are all fixed-parameter models which restrict the parameters to be the same value across all observations. In future study, a random effect or random parameter model can be taken into account that allows the parameters follow a distributional assumption across the observation population. Also, model validation can be conducted to make sure the model estimations are reliable.

The authors want to express their deepest gratitude to the financial support by the United States Department of Transportation, University Transportation Center through the Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE) at The University of North Carolina at Charlotte (Grant Number: 69A3551747133).

ORCID

Wei (David) Fan http://orcid.org/0000-0001-9815-710X

References

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

Ahmadi, A., Jahangiri, A., Berardi, V., & Machiani, S. G. (2018). Crash severity analysis of rear-end crashes in California using statistical and machine learning classification methods. *Journal of Transportation Safety & Security*, 1–25. doi:10.1080/19439962.2018.1505793

Chang, L. Y., & Mannering, F. (1999). Analysis of injury severity and vehicle occupancy in truck-and non-truck-involved accidents. *Accident Analysis & Prevention*, *31*(5), 579–592. doi:10.1016/S0001-4575(99)00014-7

Chen, F., & Chen, S. (2011). Injury severities of truck drivers in single-and multi-vehicle accidents on rural highways. *Accident Analysis & Prevention*, *43*(5), 1677–1688. doi:10.1016/j.aap.2011.03.026

Chen, F., Chen, S., & Ma, X. (2018). Analysis of hourly crash likelihood using unbalanced panel data mixed logit model and real-time driving environmental big data. *Journal of Safety Research*, *65*, 153–159. doi:10.1016/j.jsr.2018.02.010

Chen, F., Song, M., & Ma, X. (2019). Investigation on the injury severity of drivers in rear-end collisions between cars using a random parameters bivariate ordered probit model. *International Journal of Environmental Research and Public Health*, *16*(14), 2632.

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

Deng, Z., Ivan, J., & Gårder, P. (2006). Analysis of factors affecting the severity of head-on crashes: Two-lane rural highways in Connecticut. *Transportation Research Record: Journal of the Transportation Research Board*, *1953*(1), 137–146. doi:10.3141/1953-16

Derr, B. (2013). Ordinal response modeling with the LOGISTIC procedure. In *SAS Global Forum* (pp. 1–20). Cary, NC: SAS Institute, Inc.

Desapriya, E., Ian, P. I. K. E., & Kinney, J. (2005). The risk of injury and vehicle damage severity in vehicle mismatched side impact crashes in British Columbia. *IATSS Research*, *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. *Journal of Transportation Technologies*, *4*(1), 1. doi:10.4236/jtts.2014.41001

Duncan, C. S., Khattak, A. J., & Council, F. M. (1998). Applying the ordered probit model to injury severity in truck-passenger car rear-end collisions. *Transportation Research Record: Journal of the Transportation Research Board*, *1635*(1), 63–71. doi:10.3141/1635-09

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

Gårder, P. (2006). Segment characteristics and severity of head-on crashes on two-lane rural highways in Maine. *Accident Analysis & Prevention*, *38*(4), 652–661. doi:10.1016/j.aap.2005.12.009

Garrido, R., Bastos, A., de Almeida, A., & Elvas, J. P. (2014). Prediction of road accident severity using the ordered probit model. *Transportation Research Procedia*, *3*, 214–223. doi:10.1016/j.trpro.2014.10.107

Hedeker, D., Berbaum, M., & Mermelstein, R. (2006). SAS code for "Location-scale models for multilevel ordinal data: Between-and within-subjects variance modeling. *Journal of Probability and Statistical Science*, *4*, 1–20.

Hosseinpour, M., Yahaya, A. S., & Sadullah, A. F. (2014). Exploring the effects of roadway characteristics on the frequency and severity of head-on crashes: Case studies from Malaysian federal roads. *Accident Analysis & Prevention*, *62*, 209–222. doi:10.1016/j.aap.2013.10.001

Hummer, J. E., Rasdorf, W., Findley, D. J., Zegeer, C. V., & Sundstrom, C. A. (2010). Curve collisions: Road and collision characteristics and countermeasures. *Journal of Transportation Safety & Security*, *2*(3), 203–220. doi:10.1080/19439961003734880

Khattak, A. (2001). Injury severity in multivehicle rear-end crashes. *Transportation Research Record: Journal of the Transportation Research Board*, *1746*(1), 59–68. doi:10.3141/1746-08

Kweon, Y. J., & Kockelman, K. M. (2003). Overall injury risk to different drivers: Combining exposure, frequency, and severity models. *Accident Analysis & Prevention*, *35*(4), 441–450. doi:10.1016/S0001-4575(02)00021-0

Lee, J., & Mannering, F. (1999). Analysis of roadside accident frequency and severity and roadside safety management. Final Research Report. Research Project T9903, Task 97. Report Number WA-RD 475.1

Lee, J., & Mannering, F. (2002). Impact of roadside features on the frequency and severity of run-off-roadway accidents: An empirical analysis. *Accident Analysis & Prevention*, *34*(2), 149–161. doi:10.1016/S0001-4575(01)00009-4

Liu, P., & Fan, W. (2019). Modeling head-on crash severity on NCDOT freeways: A mixed logit model approach. *Canadian Journal of Civil Engineering*, *46*(4), 322–328. doi:10.1139/cjce-2018-0262

Ma, C., Hao, W., Pan, F., & Xiang, W. (2018). Road screening and distribution route multi-objective robust optimization for hazardous materials based on neural network and genetic algorithm. *PLoS One*, *13*(6), e0198931. doi:10.1371/journal.pone.0198931

Ma, C., Hao, W., Xiang, W., & Yan, W. (2018). The impact of aggressive driving behavior on driver-injury severity at highway-rail grade crossings accidents. *Journal of Advanced Transportation*, *2018*, 1. doi:10.1155/2018/9841498

Ma, C., Yang, D., Zhou, J., Feng, Z., & Yuan, Q. (2019). Risk riding behaviors of urban e-bikes: A literature review. *International Journal of Environmental Research and Public Health*, *16*(13), 2308.

Ma, J., & Kockelman, K. (2006). Crash frequency and severity modeling using clustered data from Washington State. In Proceedings of *2006 IEEE Intelligent Transportation Systems Conference*, 1621-1626. Toronto, Ontario, Canada. September 17-20, 2006.

Ma, L., Wang, G., Yan, X., & Weng, J. (2016). A hybrid finite mixture model for exploring heterogeneous ordering patterns of driver injury severity. *Accident Analysis & Prevention*, *89*, 62–73. doi:10.1016/j.aap.2016.01.004

Ma, L., Xiong, H., Wang, Z., & Xie, K. (2019). Impact of weather conditions on middle school students' commute mode choices: Empirical findings from Beijing, China. *Transportation Research Part D: Transport and Environment*, *68*, 39–51. doi:10.1016/j.trd.2018.05.008

Malyshkina, N., & Mannering, F. (2008). Effect of increases in speed limits on severities of injuries in accidents. *Transportation Research Record: Journal of the Transportation Research Board*, *2083*(1), 122–127. doi:10.3141/2083-14

Mooradian, J., Ivan, J. N., Ravishanker, N., & Hu, S. (2013). Analysis of driver and passenger crash injury severity using partial proportional odds models. *Accident Analysis & Prevention*, *58*, 53–58. doi:10.1016/j.aap.2013.04.022

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.

Posada, D., & Buckley, T. R. (2004). Model selection and model averaging in phylogenetics: Advantages of Akaike information criterion and Bayesian approaches over likelihood ratio tests. *Systematic Biology*, *53*(5), 793–808. doi:10.1080/10635150490522304

Pour-Rouholamin, M., & Zhou, H. (2016). Analysis of driver injury severity in wrong-way driving crashes on controlled-access highways. *Accident Analysis & Prevention*, *94*, 80–88. doi:10.1016/j.aap.2016.05.022

Sasidharan, L., & Menéndez, M. (2014). Partial proportional odds model—An alternate choice for analyzing pedestrian crash injury severities. *Accident Analysis & Prevention*, *72*, 330–340. doi:10.1016/j.aap.2014.07.025

Savolainen, P., & Mannering, F. (2007). Probabilistic models of motorcyclists' injury severities in single-and multi-vehicle crashes. *Accident Analysis & Prevention*, *39*(5), 955–963. doi:10.1016/j.aap.2006.12.016

Train, K. E. (2003). *Discrete choice methods with simulation*. Cambridge: Cambridge University Press.

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. doi:10.1016/S0001-4575(02)00135-5

Wang, X., & Abdel-Aty, M. (2008). Analysis of left-turn crash injury severity by conflicting pattern using partial proportional odds models. *Accident Analysis & Prevention*, *40*(5), 1674–1682. doi:10.1016/j.aap.2008.06.001

Wang, Y., & Prato, C. G. (2019). Determinants of injury severity for truck crashes on mountain expressways in China: A case-study with a partial proportional odds model. *Safety Science*, *117*, 100–107. doi:10.1016/j.ssci.2019.04.011

Washington, S. P., Karlaftis, M. G., & Mannering, F. (2010). *Statistical and econometric methods for transportation data analysis*. New York: Chapman and Hall/CRC.

Williams, R. (2006). Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *The Stata Journal: Promoting Communications on Statistics and Stata*, *6*(1), 58. doi:10.1177/1536867X0600600104

Xie, Y., Zhang, Y., & Liang, F. (2009). Crash injury severity analysis using Bayesian ordered probit models. *Journal of Transportation Engineering ASCE*, *135*(1), 18–25. doi:10.1061/(ASCE)0733-947X(2009)135:1(18)

Xiong, H., Ma, L., Wei, C., Yan, X., Srinivasan, S., & Chen, J. (2019). Exploring behavioral heterogeneities of elementary school students' commute mode choices through the urban travel big data of Beijing, China. *IEEE Access*, *7*, 22235–22245. doi:10.1109/ACCESS.2019.2897890

Yasmin, S., & Eluru, N. (2013). Evaluating alternate discrete outcome frameworks for modeling crash injury severity. *Accident Analysis & Prevention*, *59*, 506–521. doi:10.1016/j.aap.2013.06.040

Ye, F., & Lord, D. (2014). Comparing three commonly used crash severity models on sample size requirements: Multinomial logit, ordered probit, and mixed logit. *Analytic Methods in Accident Research*, *1*, 72–85. doi:10.1016/j.amar.2013.03.001

Zhang, C., & Ivan, J. N. (2005). Effects of geometric characteristics on head-on crash incidence on two-lane roads in Connecticut. *Transportation Research Record: Journal of the Transportation Research Board*, *1908*(1), 159–164. doi:10.3141/1908-19