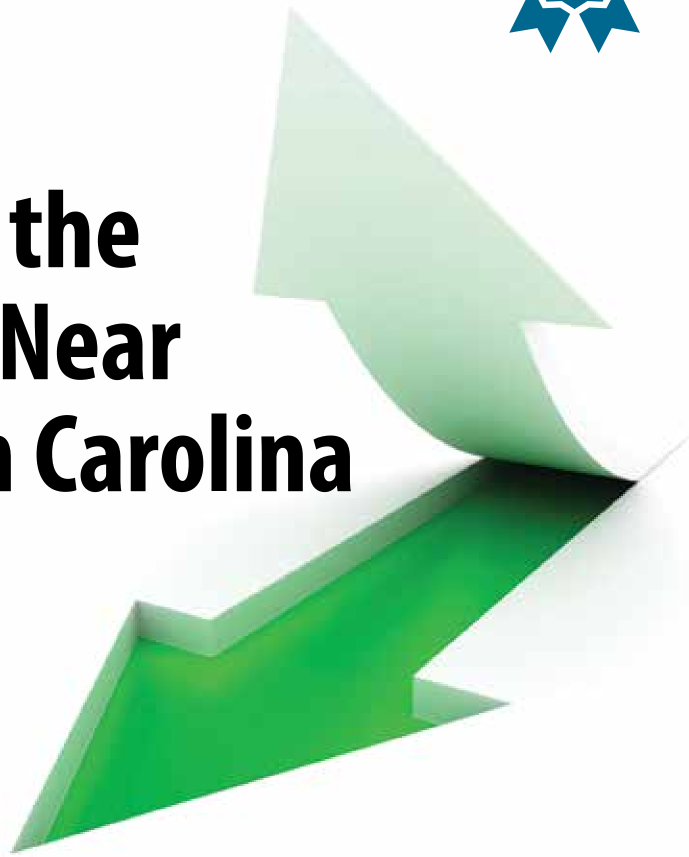

Factors Influencing the Severity of Crashes Near Exit Ramps in North Carolina

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Exit ramps play an essential role in diverting traffic from a non-interrupted traffic flow facility to another non-interrupted or interrupted traffic flow facility. To access exit ramps, motorists need to perform maneuvers such as lane change, lane merge, and/or lane diverge at lower speeds. The extent and frequency of these maneuvers vary by ramp configuration, traffic composition, horizontal alignment, crossroad ramp terminal control, and the design speed differential of the two connecting facilities.[1] Therefore, traversing through a ramp presents a driver with complex conditions and multiple decision points. Besides, these maneuvers create a speed differential as diverging traffic moves at a relatively slower speed than the mainline traffic. This situation may increase the probability of crash occurrence and even exacerbate crash injury severity.[2, 3]

HSIS First Place Safety Data Award

This is the first place winning paper of the Federal Highway Administration's (FHWA) 2020 Excellence in Highway Safety Data Award, which is designed to encourage university students to use Highway Safety Information System (HSIS) data to investigate a topic that advances highway safety and to develop a paper to document the original research. The HSIS Highway Safety Data Awards Program is jointly administered by FHWA and ITE.

A substantial proportion of total freeway crashes occur on and near ramps.[4] For instance, about a fifth of all interstate crashes occur at interchanges, although such locations constitute less than 5 percent of total freeway mileage.[3,4] McCartt et al.[3] suggested that about half of all ramp-related crashes occurred when at-fault drivers were in the process of exiting interstates. Compared to entrance ramps, exit ramps were found to experience more severe crashes.[3, 5] Therefore, crashes on exit ramps have been a significant freeway safety issue.[2]

Several studies analyzed the likelihood, types, and severity of crashes near exit ramps.[3-10] Qu et al.[7] found frequent lane-changing maneuvers and merging activities as the main reason for the differences in crash risk across the different lane types near exit ramps. Among the crashes that occur at freeway diverge areas, rear-end and angle crashes were more likely to result in severe outcomes than sideswipe crashes.[10] Lee and Abdel-Aty[4] suggested using advisory speed signs as a countermeasure to potentially reduce the likelihood of crashes on exit ramps.

Most of the existing studies evaluated the safety of freeway exit ramps by considering crash frequency, crash type, and crash severity. However, these studies did not consider the effect of heterogeneity in crashes while identifying factors influencing the severity of crashes near exit ramps. Moreover, previous studies on the severity of crashes near exit ramps assumed that the effect of factors on different severity levels does not vary. This study, therefore, evaluated the severity of crashes near freeway exits using latent class clustering analysis (LCCA) and partial proportional odds (PPO) model in an effort to account for the limitations of previous studies on the severity of crashes near exit ramps.

Study Area and Data

This study focused on crashes that occurred near freeway exit ramps in North Carolina from 2013 to 2017. The crash data were requested from the Highway Safety Information System (HSIS). One piece of information essential for this study was the crash location in relation to the exit ramps categorized as the entry of the exit ramps, the ramp terminal with the crossroad, and the ramp proper. This study focused on crashes that occurred at the entry of exit ramps only. About 4,157 crashes that occurred at the entry of exit ramps were retrieved and processed for analysis. After removing crashes with missing information in the target variables, 3,541 crashes were available for analysis. In summary, out of 3,541 crashes, about 1 percent resulted in fatalities (K crashes) and incapacitating injuries (A crashes). About 5 percent of the crashes led to non-incapacitating injuries (B crashes), nearly 20 percent of crashes caused possible injuries (C crashes), and approximately 75 percent of the crashes were property damage only (PDO).

Data Variables

The variables included in the analysis were selected based on existing literature.[1-12] Table 1 shows the variables included in this study and their corresponding categories. All categories of the variables are self-explanatory except for crash severity, alcohol use, older drivers, crash type, and time of day. Although crash severity had five levels, the study recategorized crash severity into three groups: KAB crashes (i.e., fatal, incapacitating, and non-incapacitating crashes), C crashes (possible injury crashes), and PDO. Older drivers included those aged 65 years and above. The alcohol use variable was categorized into a group that at least one driver involved in a crash had the blood alcohol concentration (BAC) > 0 percent (i.e., *Yes*) and a group that no driver in the crash had the BAC > 0 percent (i.e., *No*). The crash type variable included single-vehicle, rear-end, sideswipe, and angle crashes. Head-on crashes were removed from the analysis since their crash mechanisms are significantly different from other crash types. The time of day was categorized into morning peak hours (6 a.m.–10 a.m.), evening peak hours (3 p.m.–7 p.m.), and off-peak hours (10 a.m.–3 p.m. and 7 p.m.–6 a.m.).

Descriptive Statistics

Table 1 shows the frequency distribution of crashes according to the severity of crashes and explanatory variables. The distribution shows that more KAB and C crashes involved intoxicated drivers. The percentage of KAB crashes was higher when older drivers were involved. Crashes involving trucks had a higher percentage of KAB and C crashes. Single-vehicle crashes involved more KAB crashes than all other crash types. Conversely, angle crashes had the highest percentage of C crashes than other crash types.

Nighttime was associated with more KAB and C crashes than daylight. More KAB crashes occurred during adverse weather conditions. Morning peak hours had a lower percentage of C crashes than off-peak and evening peak hours. Weekends experienced more C and KAB crashes than weekdays. The proportion of KAB and C crashes in urban areas was higher than in rural areas. Mountainous terrain had a higher percentage of KAB and C crashes than rolling and flat terrain. Freeway segments with AADT< 50,000 vehicles per day (vpd) had a higher proportion of C crashes than segments with AADT ≥ 50,000 vpd.

Methodology

A two-step approach was used to evaluate factors that influence the severity of crashes near exit ramps. First, crashes were grouped into clusters using LCCA to reduce heterogeneity in the data. Therefore, crash clusters were defined as groups of crashes with similar characteristics. Second, the PPO model was fit to each cluster. The PPO model accounts for the natural ranking between severity categories: KAB, C, and PDO. Also, the PPO model relaxes the proportional odds (PO) assumption that the effect of variables is the same across severity

Table 1. Descriptive Statistics of the Crashes Near Exit Ramps

Variable	Levels	PDO crashes		C crashes		KAB crashes		Total
		Count	%	Count	%	Count	%	
Alcohol	No	2,469	72	642	19	342	10	3,453
	Yes	61	69	20	23	7	8	88
Older driver involved	No	1,480	72	387	19	176	9	2,043
	Yes	1,050	70	275	18	173	12	1,498
Teen driver involved	No	1,974	71	529	19	258	9	2,761
	Yes	556	71	133	17	91	12	780
Truck involved	No	2,360	72	611	19	319	10	3,290
	Yes	170	68	51	20	30	12	251
Crash type	Single-vehicle	704	68	203	20	127	12	1,034
	Angle	144	66	54	25	20	9	218
	Rear-end	1,189	70	343	20	173	10	1,705
	Sideswipe	493	84	62	11	29	5	584
Light condition	Daylight	1,975	73	493	18	248	9	2,716
	Nighttime	555	67	169	20	101	12	825
Weather	Clear	2,137	71	570	19	285	10	2,992
	Adverse	393	72	92	17	64	12	549
Time of day	Off-peak hours	1,721	72	473	20	197	8	2,391
	Morning peak hours	341	73	69	15	59	13	469
	Evening peak hours	468	69	120	18	93	14	681
Day	Weekday	1,978	72	512	19	262	10	2,752
	Weekend	552	70	150	19	87	11	789
Area type	Rural	110	77	21	15	12	8	143
	Urban	2,420	71	641	19	337	10	3,398
Horizontal alignment	Straight	1,887	72	470	18	271	10	2,628
	Curve	643	70	192	21	78	9	913
Terrain	Flat	181	74	48	20	16	7	245
	Rolling	2,220	72	569	18	308	10	3,097
	Mountainous	129	65	45	23	25	13	199
Speed limit (mph)	< 55	1,091	70	315	20	156	10	1,562
	≥ 55	1,439	73	347	18	193	10	1,979
Shoulder width (ft)	< 4	376	70	115	22	43	8	534
	4 – 10	1,332	72	339	18	191	10	1,862
	>10	822	72	208	18	115	10	1,145
AADT (vpd)	< 50,000	949	72	255	19	118	9	1,322
	≥ 50,000	1,581	71	407	18	231	10	2,219

levels.[13] The PPO model assumes that only a subset of variables in the model violates the PO assumption. Given the imbalanced distribution of KAB, C, and PDO crashes within the dataset, the PPO model was fit using the bootstrap resampling method.

Latent Class Clustering Analysis

LCCA assumes that data originates from a model of mixed probability distributions, and there is a latent variable separating the data into homogeneous and mutually exclusive subgroups.[14] In general, LCCA estimates an observation's probability to be allocated to a homogeneous group.[15] The Bayes rule was applied to calculate the probability of crash belonging to latent class k (posterior membership probability):

$$P_{x_k|y_l} = \frac{P_{x_k} P_{y_l|x_k}}{P_{y_l}} \qquad (1)$$

where

Y_l is one of the L $(1 \leq l \leq L)$ observed variables,

X is a latent variable,

k (k =1,2,…..K) is a latent class,

P_{y_l} is the probability of obtaining response variable Y_l,

P_{x_k} is the prior probability of being in cluster k,

$P_{y_l|x_k}$ is the conditional probability that a crash has response pattern Y_l $(y_1,\ldots.y_l)$, given it is in the k class of latent variable X.

The optimum number of clusters in LCCA was selected using measures indicating the accuracy improvements in the model for assigning crashes to clusters.[16] The accuracy measures used include Bayesian Information Criteria (BIC), Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC), and entropy-based measures. The number of clusters associated with low AIC, BIC, CAIC, and the entropy criterion value greater than 0.9 was considered to have the most relevant results.[17]

Partial Proportional Odds Model

The PPO model was derived by defining an unobserved latent variable U as a linear function for each crash such that:

$$U = \beta X + \varepsilon \qquad (2)$$

where X is a vector of independent variables determining a discrete ordering for each crash, β is a vector of estimable parameters, and ε is the random disturbance term. Using Equation 3, the observed severity level y for each observation was defined as:

$$
\begin{array}{lll}
y_1 = 1\ (\text{PDO}) & \text{if } U \le \mu_1 & \\
y_2 = 2\ (\text{C}) & \text{if } \mu_1 < U \le \mu_2 & \\
y_3 = 3\ (\text{KAB}) & \text{if } \mu_2 < U & (3)
\end{array}
$$

where μ_1, μ_2, and μ_3 are estimable thresholds that define y_1, y_2, and y_3. The probability of a crash severity level in the PPO model was calculated as:

$$P(y_i > j) = \frac{exp(X_{pi}\beta_p + X_{qi}\beta_q - \mu_j)}{1 + exp(X_{pi}\beta_p + X_{qi}\beta_q - \mu_j)} \qquad j = 1,..\ J-1 \qquad (4)$$

where

β_p is a vector of parameter estimates that do not violate the PO assumption,

β_q is a vector of parameter estimates that violate the PO assumption,

X_{pi} and X_{qi} are vectors of independent variables that violate and do not violate the PO assumption, respectively. Other variables were defined in Equation 2 for the ith crash with severity j from J severity levels.

A graphical test proposed by Harrel was used to identify variables violating proportional assumption (if any).[18] Results of the PPO model were interpreted using the odds ratio (OR), calculated as the exponential of the estimated mean β. An OR of 1.0 indicates that the variable has no effect on crash severity. An OR > 1.0 and OR < 1.0 indicates a 100(OR – 1) percent increase and a 100(OR – 1) percent decrease in the odds of severe outcomes, respectively.

Bootstrap Resampling

The bootstrap resampling method was applied to resolve the imbalance problem caused by a higher percentage of PDO crashes than C and KAB crashes. The bootstrap method estimates the coefficients and standard errors by repeatedly and randomly sampling subsets of data from the original dataset to reduce bias that can be caused by imbalanced data in parameter and standard errors of the model's estimates.[19] Although the conventional bootstrapping approach involves drawing a sample randomly and evenly with replacement, this study divided the sample into three datasets (KAB, C, and PDO crashes) and applied the method on each subset. Then, n samples (where n is the number of PDO crashes) were randomly drawn from all groups in each bootstrap replication. The samples were then joined into a single dataset with a balanced number of crash severity levels. The procedure of drawing samples of n was repeated 1000 times, and the estimates of variables in each repetition were recorded. The number of repetitions (i.e., 1,000) was arbitrarily selected as the optimum number to enable measuring of the model performance while balancing the computation time.

Results

Crash Clusters

Crashes near exit ramps were clustered using variables listed in Table 1. The maximum number of possible clusters investigated was seven, assuming that the sample size (3,541 crashes) was not expected to have more than seven clusters. As shown in Figure 1, the performance measures (BIC, AIC, and CAIC) were slightly decreasing from three clusters to seven clusters indicating the insignificant change in the information criteria when more than two clusters were considered. The entropy was highest (0.94) when data were subdivided into two clusters. Therefore, crashes near exit ramps were divided into two clusters.

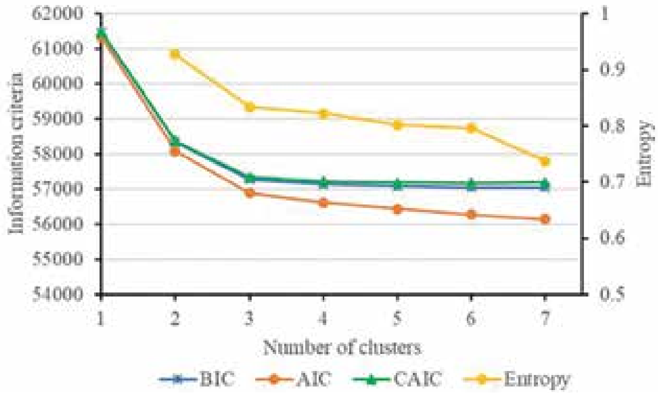

Figure 1. Determination of the Optimum Number of Crash Clusters

Figure 2 illustrates the distribution of variables in the two clusters. *Cluster A* was defined as "single-vehicle crashes or crashes involving older drivers" because approximately 95 percent and 99 percent of the crashes in this cluster involved a single vehicle and older drivers, respectively. *Cluster B* was defined as "multi-vehicle crashes" as about 99 percent of the crashes in this cluster involved at least two vehicles.

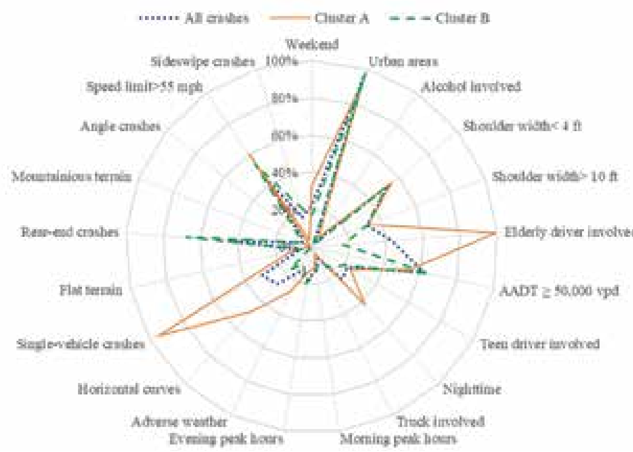

Figure 2. Distribution of the Variables in All Crashes and Cluster A and B

Factors Associated with Severity of Crashes

Table 2 presents the results of the PPO model fitted to *all crashes*, *Clusters A* and *B*. The table shows the estimates of the PPO model variables when comparing C crashes with PDO crashes (Threshold 1) and when comparing KAB crashes with C crashes (Threshold 2). The estimates of variables that violated the PO assumption were different for Threshold 1 and Threshold 2. This indicated that a variable had a different effect on the risk of crash severity levels. Variables that followed the PO assumption had the same effect between different levels of crash severity. Figure 3 shows the ORs of significant variables of the PPO models.

All Crashes

The following variables were significant at the 95 percent CI in the model fitted to all crashes: truck involvement, light condition, weather condition, time of day, day of the week, area type, horizontal alignment, terrain, shoulder width, and AADT. Crashes involving trucks had a 37 percent higher risk of C crashes than crashes not involving trucks. Adverse weather was associated with a 59 percent and 125 percent increased risk of C crashes and KAB crashes, respectively. Urban areas had a 54 percent and 26 percent higher risk of C crashes and KAB crashes, respectively. Mountainous terrain had a 39 percent higher risk of C and KAB

Table 2. Results of the PPO models

Var.	Levels	All crashes						Cluster A						Cluster B					
		Threshold 1 Est.			Threshold 2 Est.			Threshold1 Est.			Threshold 2 Est.			Threshold 1 Est.			Threshold 2 Est.		
		Mn	95% CI		Mn	95% CI		Mn	95% CI		Mn	95% CI		Mn	95% CI		Mn	95% CI	
			2.5	97.5		2.5	97.5		2.5	97.5		2.5	97.5		2.5	97.5		2.5	97.5
Alcohol[b]	No*																		
	Yes	0.21	-0.15	0.57	0.21	-0.15	0.57	**0.52**	**0.10**	**0.95**	**0.73**	**0.27**	**1.18**	**1.32**	**0.63**	**2.01**	**1.32**	**0.63**	**2.01**
Teen driver inv.[b]	No*																		
	Yes	0.04	-0.11	0.20	0.04	-0.11	0.20	0.00	-0.19	0.19	0.00	-0.19	0.19	-0.12	-0.31	0.07	-0.12	-0.31	0.07
Truck inv.[c]	No*																		
	Yes	0.31	0.06	0.57	0.31	0.06	**0.57**	-0.18	-0.59	0.24	-0.18	-0.59	0.24	**-0.73**	**-0.97**	**-0.49**	**-1.11**	**-1.42**	**-0.80**
Light cond.[a]	Daylight*																		
	Nighttime	-0.34	-0.51	-0.18	-0.65	-0.85	**-0.45**	**0.41**	**0.23**	**0.60**	**0.41**	**0.23**	**0.60**	-0.06	-0.31	0.18	-0.06	-0.31	0.18
Weath.[a,b]	Clear*																		
	Adverse	0.46	0.24	0.69	0.81	0.49	**1.13**	**0.70**	**0.48**	**0.93**	**1.23**	**0.94**	**1.53**	0.27	-0.02	0.55	**0.75**	**0.21**	**1.29**
Time of day	Off-PH*																		
	Morn. PH	0.54	0.35	0.72	0.54	0.35	**0.72**	0.28	-0.04	0.60	-0.32	-0.68	0.03	**0.38**	**0.17**	**0.59**	**0.38**	**0.17**	**0.59**
	Even. PH	0.45	0.27	0.62	0.45	0.27	**0.62**	0.11	-0.20	0.42	0.01	-0.31	0.33	**0.55**	**0.38**	**0.72**	**0.55**	**0.38**	**0.72**
Day of the week	Weekday*																		
	Weekend	0.17	0.02	0.32	0.17	0.02	**0.32**	-0.05	-0.24	0.14	-0.05	-0.24	0.14	-0.03	-0.24	0.18	-0.03	-0.24	0.18
Area type[a]	Rural*																		
	Urban	**0.43**	**0.13**	**0.73**	0.23	-0.09	0.56	**0.44**	**0.12**	**0.76**	**0.44**	**0.12**	**0.76**	0.32	-0.17	0.81	0.32	-0.17	0.81
HZ align.	Straight*																		
	Curve	0.31	0.16	0.46	0.31	0.16	**0.46**	-0.16	-0.34	0.01	-0.16	-0.34	0.01	0.12	-0.07	0.31	0.12	-0.07	0.31
Terrain[b]	Rolling*																		
	Flat	-0.19	-0.47	0.08	-0.19	-0.47	0.08	**0.44**	**0.11**	**0.77**	**0.62**	**0.24**	**1.01**	-0.08	-0.46	0.31	-0.28	-0.71	0.16
	Mount.	0.33	0.07	0.59	0.33	0.07	**0.59**	-0.08	-0.53	0.36	**-0.52**	**-0.91**	-0.13	-0.15	-0.48	0.18	0.41	-0.17	0.99
Speed limit (mph)	< 55*																		
	≥ 55	0.08	-0.07	0.23	0.08	-0.07	0.23	-0.03	-0.21	0.15	-0.03	-0.21	0.15	-0.09	-0.27	0.10	-0.09	-0.27	0.10
Shoulder width (ft)	4 – 10*																		
	< 4	-0.33	-0.54	-0.11	-0.33	-0.54	**-0.11**	0.05	-0.28	0.39	**0.42**	**0.09**	**0.75**	0.02	-0.20	0.25	0.02	-0.20	0.25
	> 10	-0.13	-0.29	0.02	-0.13	-0.29	0.02	0.00	-0.22	0.21	0.16	-0.06	0.38	-0.08	-0.27	0.11	-0.08	-0.27	0.11
AADT	< 50,000*																		
	≥ 50,000	-0.37	-0.54	-0.21	-0.37	-0.54	**-0.21**	-0.14	-0.33	0.05	-0.14	-0.33	0.05	-0.05	-0.24	0.14	**0.38**	**0.11**	**0.64**
Constant		0.27	-0.07	0.60	1.47	1.13	1.81	-0.58	-0.95	-0.21	0.77	0.40	1.14	1.06	0.54	1.58	2.29	1.77	2.82

*Note: a,b,c variables that violated proportional odds assumption in all crashes, cluster A, cluster B, respectively; * base category, Mn means mean, CI means confidence interval, inv. means involved, HZ means horizontal, PH means peak hours, cond. means condition, align. means alignment, Morn. means morning, Even. means evening, weath. means weather, Bold numbers show significant values at the 95% CI.*

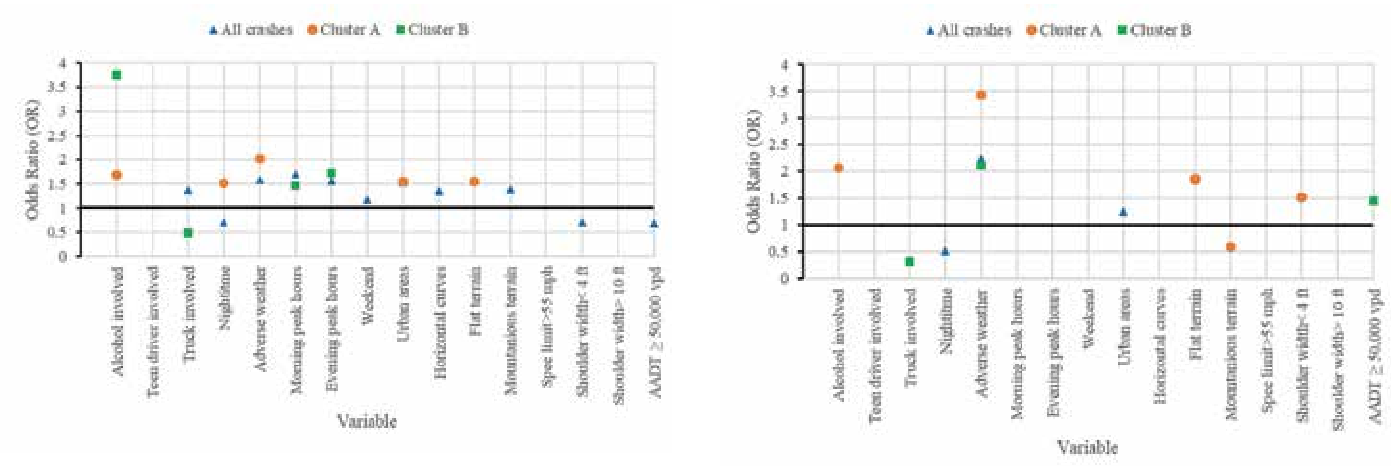

Figure 3: Odds Ratios of the Significant Variables in (a) Threshold 1 and (b) Threshold 2 of the PPO models

crashes than rolling terrain. The results could be related to Wang et al.[2] findings that up- and down-grades increase the risk of severe crashes near diverge areas. Results indicated that nighttime, shoulder width < 4 ft, and AADT ≥ 50,000 vpd were associated with the decreased risk of C and KAB crashes. Nighttime was associated with the decreased risk of C crashes and KAB crashes by 29 percent and 48 percent, respectively. Mainline segments near exit ramps with AADT ≥ 50,000 had a 31 percent lower risk of C and KAB crashes than segments with AADT< 50,000 vpd.

Cluster A: Crashes Involving Single Vehicles or Older Drivers

Variables significant at the 95 percent CI in the model fitted to *Cluster A* include alcohol use, light condition, weather conditions, area type, terrain, and shoulder width. The effect of alcohol on the crash severity varied across severity levels. The risk of C and KAB crashes was 69 percent and 107 percent higher when an intoxicated driver was involved, respectively. Nighttime was associated with a 51 percent higher risk of C and KAB crashes than daylight. The risk of C crashes was 102 percent higher during adverse weather conditions than during clear weather conditions. Similarly, the risk of KAB crashes was 243 percent higher during adverse weather conditions.

Urban areas were associated with a 55 percent higher risk of C and KAB crashes than rural areas. Compared to crashes that occurred on a rolling terrain, crashes on flat terrain had a 55 percent and 86 percent higher likelihood of being C and KAB crashes, respectively. Mountainous terrain showed a 41 percent lower risk of KAB crashes than rolling terrain. The high risk of C and KAB crashes on flat terrain could be associated with higher driving speeds on flat terrains. Since the roadway grade in mountainous terrain is steeper than that of rolling terrain, reduced vehicle speed could serve as a reason for the lower risk of KAB crashes on mountainous terrain. Segments with shoulder width less than 4 ft had a 52 percent higher likelihood of KAB crashes than segments with 4-10-foot shoulders.

Cluster B: Multi-vehicle Crashes

Variables significant at the 95 percent CI in the model fitted to *Cluster B* include alcohol use, truck involvement, weather condition, time of day, and AADT. Results indicated that the risk of C and KAB crashes was 274 percent higher when the crash involved an intoxicated driver. The effect of truck involvement varied across the severity levels. The risk of C and KAB crashes was 52 percent and 67 percent lower when a truck was involved in a crash. Similar counterintuitive results were observed in the study on crash severity near diverge areas in Florida.[2] The risk of KAB crashes was 111 percent higher during adverse weather. Morning peak hours had a 46 percent higher risk of C crashes than off-peak hours. Similarly, evening peak hours had a 73 percent higher risk of C crashes than off-peak hours. Segments with AADT ≥ 50,000 vpd had a 46 percent higher risk of KAB crashes than segments with AADT < 50,000 vpd.

Comparison of Results Across All Crashes, Clusters A and B

The following significant variables had different coefficient signs across the three crash datasets: truck involvement, lighting condition, terrain, shoulder width, and AADT. The risk of C and KAB crashes when a truck was involved was higher for *all crashes* and lower for *Cluster B*. Overall, crashes involving trucks are expected to be severe, considering their size. The reason for crashes in *Cluster B* involving trucks to be less severe is not apparent and seeks an in-depth investigation.

When considering *all crashes*, nighttime was associated with a lower likelihood of C and KAB crashes. Conversely, nighttime crashes in *Cluster A* were more likely to be C or KAB crashes. The lower severity of nighttime crashes in *all crashes* dataset may be due to drivers' cautiousness during nighttime. However, as expected, nighttime crashes in *Cluster A* were severe, possibly due to diminished vision of older drivers. The provision of lighting near exit ramps may improve safety, particularly for older drivers.

Compared to rolling terrain, mountainous terrain significantly influenced the likelihood of C and KAB crashes in *all crashes* and PDO crashes in *Cluster A* crashes. Compared to mountainous terrain, rolling terrain provides a good preview of the roadway to make last-minute maneuvers, if necessary, and avoid imminent collisions. Nevertheless, crashes in *Cluster A* occurring in mountainous terrain may be less likely to be severe considering the defensive nature of older drivers.

Narrow shoulders were associated with a lower likelihood of C and KAB crashes in the *all crash* dataset and a higher likelihood of KAB crashes in the *Cluster A* crashes. Wider shoulders provide more clearance for drivers to take corrective actions after making an errant maneuver and avoid running off the roadway and encountering a harmful roadside object or embankment. Thus, it is expected that crashes in *Cluster A* at locations with narrower shoulders to be severe. The opposite observation made in *all crashes* indicates that crashes in *Cluster B* might neutralize the effect of shoulder width on crashes in *Cluster A* when analyzing the entire dataset. While higher AADT was associated with a reduced likelihood of C and KAB crashes in *all crashes*, it was associated with an increased risk of KAB crashes in *Cluster B*. The aggressive driving behavior of other (not older) drivers may explain the high severity of crashes at locations with high traffic volumes.

For all the three datasets used in the study, crashes under inclement weather conditions were more likely to be severe. The impact of inclement weather was at the highest in *Cluster A*. Adverse weather conditions are associated with reduced sight distance and friction between the tire and the roadway surface. Considering this situation and older drivers having a longer reaction time, the likelihood of severe crashes in *Cluster A* may increase. A majority of significant variables influenced crash severity in the *all crashes* and either of the clusters except for alcohol involvement. Results indicated that the risk of C and KAB crashes was 274 percent higher when the crash involved an intoxicated driver.

Conclusions

Freeway exit ramps have been long considered crash-prone locations. The objective of this study was to investigate factors influencing the severity of crashes near exit ramps. Also, the study aimed to show factors that affect specific crash categories near exit ramps that cannot be identified by analyzing all crashes in one model.

Resources

Please go to https://bit.ly/3ImaDyC to watch a video and learn more about HSIS, HSIS data, and the Excellence in Highway Safety Data Award.

The analysis was based on crashes that occurred near exit ramps in North Carolina from 2013 to 2017. The crash analysis was performed using LCCA and PPO model. The LCCA divided crashes into homogeneous subgroups, and the PPO model identified variables with significant influence on crash severity. Also, a bootstrap resampling approach was used when fitting the PPO model to account for the imbalance of data in different crash severity levels.

The study identified two crash clusters: single-vehicle crashes or those involving older drivers (*Cluster A*) and multi-vehicle crashes (*Cluster B*). The variables with significant influence on all crashes near exit ramps include: truck involvement, light condition, weather condition, time of day, day of the week, area type, horizontal alignment, terrain, shoulder width, and AADT. The variables that significantly affected the severity of crashes in *Cluster A* include alcohol use, light condition, weather conditions, area type, terrain, and shoulder width. The variables that significantly influenced the severity of crashes in *Cluster B* include alcohol, truck involvement, weather condition, time of day, and AADT.

In addition to identifying factors influencing the severity of crashes near exit ramps, the results showed that categorizing the crashes near exit ramps into homogenous groups helps identify patterns that would not have been identified by only analyzing the entire dataset. With specific attributes leading to different crash severities, homogenous groups enhance the process of identifying measures for mitigating severe crashes near exit ramps by focusing on specific contributing variables in crash clusters. The study results and methodology could potentially be used by agencies when devising methods and policies to reduce the severity of crashes near exit ramps. Some of the potential countermeasures may include provision of sufficient lighting, advance warning messages to drivers during inclement weather conditions, and adequate shoulder width to the extent possible. **itej**

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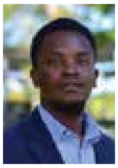

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