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Roadway classifications and the accident injury severities of heavy-vehicle drivers

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ABSTRACT

Previous heavy-vehicle (a truck with a gross vehicle weight rating greater than 10,000 pounds) injury severity studies have disaggregated data by factors such as urban/rural and time-of-day, yet a focus on contributing factors by roadway classification is lacking. Taking this into consideration, the current study aims to extend traditional heavy-vehicle driver injury severity analyses, through the application of a mixed logit modeling framework, by determining statistically significant injury severity contributing factors by roadway classification. In the course of identifying statistically significant injury severity factors, a parameter transferability test is conducted to determine if roadway classifications need to be considered separately for safety analyses. Empirical results show that roadway classifications need be modeled separately with a high level of confidence, as the estimated parameters are statistically different by classification based on corresponding chi-square statistics and degrees of freedom. The majority of significant contributing factors are exclusive to a specific road classification, however, two factors were found to impact injury severity regardless of classification while some factors were significant for two classifications. Findings from this study can prompt future work to focus on injury severity, as well as other safety measures, by roadway classification and/or other subpopulations within crash datasets.

1. Introduction

The economic impact of heavy-vehicle crashes, where a heavy-vehicle is a truck with a gross vehicle weight rating of greater than 10,000 pounds, is widely known. For instance, in 2011, heavy-vehicle crashes resulted in a total of $87 billion nationwide (Federal Motor Carrier Safety Administration, 2013). Furthermore, no injury crashes, crashes involving injuries, and fatal crashes amounted to $16 billion, $32 billion, and $39 billion, respectively (Federal Motor Carrier Safety Administration, 2013). In addition, the cost of crashes due to delay and other associated consequences totaled $28 billion (Blincoe et al., 2015). Therefore, any decrease in heavy-vehicle crashes can lead to a substantial reduction in societal costs.

More specifically, at the State level, Idaho experienced a 5.6% increase in heavy-vehicle crashes from 2010 to 2013 (Idaho Office of Highway Safety, 2014). In 2014, 65.2% of all heavy-vehicle crashes in Idaho resulted in no injury, 33.4% involved an injury, and 1.4% were fatal (Idaho Office of Highway Safety, 2014). That being said, heavy-vehicle crashes happened most often on local roads (e.g., major collectors) accounting for 50% of all heavy-vehicle crashes (Idaho Office of Highway

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Safety, 2014), while 50% of no injury crashes also took place on local roads (e.g., major collectors). In addition, 68% of all fatalities occurred on U.S. and State highways (e.g., principal arterials) and 28% of injury crashes happened on interstates (Idaho Office of Highway Safety, 2014). As seen from these statistics, there is a clear need to better understand the effect of roadway classification and the associated contributing factors (observed and unobserved) on heavy-vehicle driver injury severity.

When fitting injury severity models, roadway classification is typically modeled as an indicator variable (e.g., a factor that may influence an injury severity outcome), yet studies that extend such an analysis to focus on injury severities by roadway classification are scarce. As such, disaggregating heavy-vehicle crashes by roadway classification can provide additional insights to assist transportation engineers, planners, and agencies in mitigating these types of crashes and their coinciding costs. On account of such, the present study will use seven years of Idaho crash data to investigate heavy-vehicle crashes by roadway classification through a heavy-vehicle driver injury severity analysis on four types of roadway classifications, namely, principal arterials, major collectors, interstates, and other principal arterials.

To the best of the authors' knowledge, this is the first attempt at analyzing heavy-vehicle driver injury severity by roadway classification. Suitably, this study aims to fill the gap in literature regarding heavy-vehicle driver injury severity analysis by roadway classification. In addition to identifying contributing factors, the current study extends the literature by providing results from a parameter transferability test that determines if road classifications need to analyzed separately (see Section 5).

2. Related work

The mixed logit model is a common approach to injury severity analyses and has been used in recent efforts to investigate injury severity (Anastasopoulos and Mannering, 2011; Kim et al., 2010, 2013; Milton et al., 2008; Moore et al., 2011; Yasmin and Eluru, 2013). Still, injury severity analysis regarding drivers of heavy-vehicles (a truck with a gross vehicle weight rating greater than 10,000 pounds) is less documented. Islam and Hernandez (2013a) used the mixed logit approach to identify injury severity contributing factors for any crash involving a heavy-vehicle in Texas without disaggregating the crash data into subpopulations (e.g., roadway classification, age, urban/rural, etc.). Khorashadi et al. (2005), however, investigated heavy-vehicle injury severity by rural and urban area crashes utilizing a fixed-parameter logit model and found that urban and rural areas need to be modeled separately through a transferability test. More, Pahukula et al. (2015) separated heavy-vehicle crashes by time-of-day to fit several mixed logit models and discovered that parameter estimates are statistically different by time-of-day. Cerwick et al. (2014) expanded the heavy-vehicle injury severity analysis by introducing a latent class logit model and comparing its estimates to that of the mixed logit model. The authors based their evaluation on overall model fit, inferences based on marginal effects, and predicted crash severity outcome probabilities. The authors discovered that the mixed logit model better predicted injury severity outcomes for their crash data.

As seen above, the literature regarding heavy-vehicle injury severity analyses is acutely limited. Subsequently, the current study seeks to expand the literature on heavy-vehicle driver injury severity analysis by identifying contributing factors by roadway classification through the application of a mixed logit modeling framework. Previous works have used age, gender, rural, urban, and alcohol consumption as subpopulations, therefore the present study analyzes heavy-vehicle driver injury severity utilizing roadway classifications as subpopulations.

3. Empirical setting

Data used for analysis consisted of police-reported crash data obtained from Idaho for years 2007 to 2013. Each year was filtered by unit type and seat type to represent only the drivers of heavy-vehicles (a truck with a gross vehicle weight rating greater than 10,000 pounds). The data was then combined to create a dataset that included all seven years and used to determine the four roadway classifications with the largest number of heavy-vehicle crashes. The result was a dataset for each road classification of interest: principal arterials, major collectors, interstates, and other principal arterials. Each observation in the crash data represents the maximum injury severity for the heavy-vehicle driver.

Pertaining to injury severity, Idaho categorizes injury severities into five distinct classifications: no injury, possible injury, incapacitating injury, non-incapacitating injury, and fatal injury. However, to ensure that each injury severity had an adequate percentage of crashes for analysis, injury severities were grouped together to create three distinct severity types: no injury, minor injury (possible injury and non-incapacitating injury), and major injury (incapacitating injury and fatal injury). Table 1 shows the driver injury severity split after grouping severities and the total observations for each road classification[1].

Several variables were found to be significant in contributing to the outcome probabilities of the three injury severities. Variable descriptions and summary statistics for each road classification are shown in Tables 2 to 4.

[1] The injury severity split on other principal arterials did not allow a model to be fit (e.g., greater than 96% of the observations were no injury crashes). It was later determined that other principal arterials was a classification used by the Idaho Department of Transportation in which any uncertain classification was classified as. For this reason, contributing factors to heavy-vehicle driver injury severity could not be identified for this roadway classification.

Table 1
Heavy-Vehicle Driver Injury Severity by Road Classification.

Road Classification	Injury Severity	Observations	Percent
Principal Arterials	No Injury	1334	85.29%
	Minor Injury (Non-Incapacitating Injuries and Possible Injuries)	197	12.60%
	Major Injury (Incapacitating Injuries and Fatalities)	33	2.11%
	Total Observations	1564	
Major Collectors	No Injury	916	86.58%
	Minor Injury (Non-Incapacitating Injuries and Possible Injuries)	117	11.06%
	Major Injury (Incapacitating Injuries and Fatalities)	25	2.36%
	Total Observations	1058	
Interstates	No Injury	1402	87.13%
	Minor Injury (Non-Incapacitating Injuries and Possible Injuries)	174	10.81%
	Major Injury (Incapacitating Injuries and Fatalities)	33	2.05%
	Total Observations	1609	

Table 2
Variable Descriptions and Summary Statistics for Principal Arterials.

Variable Description	Mean	Standard Deviation
Time of Day (1 if Between 10:00 PM and 5:00AM, 0 Otherwise)	0.164	0.371
Vertical Geometrics (1 if Grade, 0 Otherwise)	0.282	0.450
Weather (1 if Cloudy, 0 Otherwise)	0.260	0.439
Speed Limit (1 if Between 55 mi/h and 65 mi/h, 0 Otherwise)	0.607	0.489
Crash Location (1 if On Right Shoulder, 0 Otherwise)	0.128	0.334
Point of Impact (1 if Rear Bumper, 0 Otherwise)	0.171	0.376
Protective Device (1 if Seatbelt and Non-Activated Air Bag, 0 Otherwise	0.090	0.286
Horizontal Geometrics (1 if Straight, 0 Otherwise)	0.735	0.442
Traffic Control Device (1 if No Traffic Control Device, 0 Otherwise)	0.701	0.458
Crash Location (1 if On Roadway, 0 Otherwise)	0.786	0.410
Age (1 if Driver Between 35 and 45 Years, 0 Otherwise)	0.222	0.416
Surface Condition (1 if Wet, 0 Otherwise)	0.107	0.309
Time of Week (1 if Weekend, 0 Otherwise)	0.159	0.366
Age (1 if Driver Younger Than 35 Years, 0 Otherwise)	0.254	0.435
Protective Device (1 if Shoulder and Lap Belt, 0 Otherwise)	0.721	0.449
Horizontal Geometrics (1 if Curved, 0 Otherwise)	0.263	0.441

Table 3
Variable Descriptions and Summary Statistics for Major Collectors.

Variable Description	Mean	Standard Deviation
Horizontal Geometrics (1 if Curve, 0 Otherwise)	0.216	0.412
Heavy Vehicle Type (1 if Tractor 2-Trailer, 0 Otherwise)	0.109	0.311
Contributing Circumstances (1 of No Contributing Circumstances, 0 Otherwise)	0.479	0.500
Point of Impact (1 if Rear Bumper, 0 Otherwise)	0.121	0.326
Time of Year (1 if Winter, 0 Otherwise)	0.256	0.437
City Limits (1 if Crash Occurred Within City Limits, 0 Otherwise)	0.146	0.353
Location of Impact (1 if Curb Line/Off Surface, 0 Otherwise)	0.266	0.442
Protective Device (1 if No Protective Device, 0 Otherwise)	0.123	0.328
Vertical Geometrics (1 if Grade, 0 Otherwise)	0.209	0.407
Time of Day (1 if Between 10:00 PM and 5:00AM, 0 Otherwise)	0.086	0.280
Location (1 if Crash Occurred Within 1 Mile of An Intersection, 0 Otherwise)	0.338	0.473
Harmful Event (1 if Overturn, 0 Otherwise)	0.160	0.366
Age (1 if Driver Greater Than 50 Years, 0 Otherwise)	0.353	0.478
Speed Limit (1 if Greater Than 55 mi/h, 0 Otherwise)	0.173	0.378
Weather (1 if Cloudy, 0 Otherwise)	0.233	0.423

4. Methodology

In an attempt to better understand heavy-vehicle (a truck with a gross vehicle weight rating greater than 10,000 pounds) driver injury severity factors, the authors aim to disaggregate the crash data by roadway classification. As mentioned previously, past works have disaggregated data into rural and urban crashes, time-of-day crashes, crashes by age, and crashes by gender, yet analyses by road classification are limited. With different road classifications having varying speed limits, traffic volumes, among other factors, the current study seeks to determine if parameters are statistically different by roadway classification (e.g., heavy-vehicle driver injury severity factors are contingent on roadway classification). As such, a comprehensive dataset provided by Idaho will be used to determine if classifications need to be modeled independently.

Table 4
Variable Descriptions and Summary Statistics for Interstates.

Variable Description	Mean	Standard Deviation
Horizontal Geometrics (1 if Curve, 0 Otherwise)	0.233	0.423
Weather (1 if Snow, 0 Otherwise)	0.161	0.368
Heavy Vehicle Type (1 if Tractor 1-Trailer, 0 Otherwise)	0.691	0.462
Protective Device (1 if Shoulder and Lap Belt, 0 Otherwise)	0.759	0.427
Crash Location (1 if On Roadway, 0 Otherwise)	0.764	0.425
Contributing Circumstances (1 if Speeding Contributed to Crash, 0 Otherwise)	0.158	0.365
Location (1 if Crash Occurred Within 1 Mile of On/Off Ramp, 0 Otherwise)	0.737	0.440
Weather (1 if Cloudy, 0 Otherwise)	0.272	0.445
Protective Device (1 if Seatbelt and Non-Activated Air Bag, 0 Otherwise)	0.117	0.321
Age (1 if Driver is Less Than 30 Years, 0 Otherwise)	0.152	0.359
Harmful Event (1 if Sideswipe in Same Direction, 0 Otherwise)	0.236	0.424
Location of Impact (1 if Center Lane or Median, 0 Otherwise)	0.124	0.330
Surface Conditions (1 if Dry, 0 Otherwise)	0.516	0.500
Contributing Circumstances (1 if No Contributing Circumstances, 0 Otherwise)	0.464	0.499
Age (1 if Driver Greater Than 50 Years, 0 Otherwise)	0.375	0.484
Vertical Geometrics (1 if Level, 0 Otherwise)	0.643	0.479

Crash datasets, however, naturally do not include each and every factor that contributes to the outcome probability of a distinct injury severity (i.e., specific attributes regarding driver behavior, environmental aspects, characteristics of the roadway, etc.) and, as a result, can lead to biased estimates and inaccurate inferences. For example, seatbelts are known to save lives, yet they are capable of causing an injury based on several unseen factors (e.g., speed at the point of impact, physiology of the driver) (Mannering et al., 2016). Likewise, crash data will often indicate if the crash occurred on a grade, but characteristics such as the percent grade and direction of travel (up/down grade) are often unknown. Variation within a known factor can also result in unobserved heterogeneity, such as gender, posted speed limits, and weather conditions (see Mannering et al. (2016) for further discussion) . Due to such variation, to properly overcome the limitations of the crash data and resulting unobserved heterogeneity, this analysis is conducted through a discrete outcome modeling technique that identifies contributing factors based on statistical significance, the mixed logit model.

4.1. Mixed logit model

The first step was to validate the data by generating a two-thirds random sample from the complete dataset. To ensure proper proportioning, the choice variable (injury severity) was selected for strata. A mixed logit model was then estimated using the two-thirds sample (the holistic model) and compared to the same model using the remaining one-third of data. It was determined that the coefficients decreased relative to the population size, hence demonstrating a valid dataset.

The econometric modeling approach allows heavy-vehicle driver injury severity outcomes to be modeled as a discrete choice, therefore allowing inference regarding the outcome probabilities of each injury severity to be made. With such inference, the estimated parameters of the mixed logit model provide statistical significance of key factors that increase or decrease the outcome probability for each of the injury severity outcomes considered[2].

With that in mind, models such as the ordered logit model and ordered probit model are capable of modeling crash severity, yet limitations of these exist (Geedipally et al., 2011; Savolainen and Mannering, 2007). Due to such limitations, the mixed logit model is an improved method for investigating injury severities and offers a framework to better the parameter estimations (Gkritza and Mannering, 2008; Islam and Hernandez, 2013a,b; Islam et al., 2014; Morgan and Mannering, 2011; Pahukula et al., 2015).

The mixed logit model begins with a linear-in-parameters function, where each function represents an injury severity of a crash and is represented as:

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

where U_{in} is a linear-in-parameters function for injury severity i and heavy-vehicle crash n; i represents injury severities of no injury, minor injury, and major injury; $\boldsymbol{X_{in}}$ represents the vector of explanatory variables that lead to injury severity i of heavy-vehicle crash n; $\boldsymbol{\beta_i}$ represents the vector of estimated parameters for injury severity i; and, ε_{in} is the error term that attempts to capture the unobserved factors within the model (Washington et al., 2011). However, ε_{in} is unable to capture all the unobserved factors. As previously stated, crash data is often missing key variables (i.e., variables not on the data collection forms, therefore not collected) and has variation across the available variables that results in unobserved heterogeneity, and if disregarded, will result is biased estimates and inaccurate inferences (Mannering et al., 2016). Therefore, the mixed

[2] For this work, the authors have elected not to use a base case scenario. When using a base case scenario, the significant indicators in the non-base case scenario are interpreted relative to the base case scenario (Alvarez and Nagler, 1998). However, the authors want to infer directly on the injury severity outcome and not relative to a base case severity. In other words, the significant indicators for each severity function in this work are interpreted in terms of that severity and not relative to a base case severity.

logit model attempts to capture this heterogeneity by allowing parameters to vary across observations. In addition, if estimated parameters (including constants) are found to be random, the independence from irrelevant alternatives (IIA) property is eliminated. In other words, unobserved factors are accounted for if estimated parameters are found to be random, so grouping the injury severities into three categories is permitted (Geedipally et al., 2011). The mixed logit model is then formulated as follows (McFadden and Train, 2000; Washington et al., 2011):

$$P_n(i|\varphi) = \int \frac{e^{(\boldsymbol{\beta_i X_{in}})}}{\sum_{\forall I} e^{(\boldsymbol{\beta_i X_{in}})}} k(\beta_i|\varphi) d\beta_i \tag{2}$$

where $P_n(i|\varphi)$ is the weighted outcome probability of injury severity i conditional on $k(\beta_i|\varphi)$. $k(\beta_i|\varphi)$ is the density function of $\boldsymbol{\beta_i}$ conditional on the distribution parameter φ, where the distribution of $\boldsymbol{\beta_i}$ is specified by the analyst. The density function allows the parameters to vary and is regularly specified to be normally distributed, yet several distributions are tested for statistical significance. All other variables have the same definition as the traditional multinomial logit model (Washington et al., 2011).

Lastly, to determine the effect of a change in an indicator variable on the probability of injury severity i, marginal effects for an indicator variable are computed (Greene, 2012a):

$$M_{\boldsymbol{X_{ink}}}^{P_n(i)} = \Pr[P_n(i) = 1|\mathbf{X}_{(X_{ink})}, X_{ink} = 1] - \Pr[P_n(i) = 1|\mathbf{X}_{(X_{ink})}, X_{ink} = 0] \tag{3}$$

where $\mathbf{X}_{(X_{ink})}$ represents the means of all other variables (variables are held constant) while indicator variable X_{ink} changes from zero to one.

4.2. Model significance and model separation

To determine if the log-likelihood of the mixed logit model is of more statistical significance than the fixed-parameter log-likelihood, a log-likelihood ratio test is conducted for each road classification model. To do this, the following equation is used (Washington et al., 2011):

$$\chi^2 = -2[LL(\beta_{MNL}) - LL(\beta_{MXL})] \tag{4}$$

where $LL(\beta_{MNL})$ is the log-likelihood at convergence for the model with fixed parameters; $LL(\beta_{MXL})$ is the log-likelihood at convergence for the model with random parameters; and, χ^2 is a chi-square statistic with degrees of freedom for χ^2 equal to the number of random parameters in β_{MXL}.

With regard to the validation of separating the mixed logit models by roadway classification, two tests were conducted. The first is a log-likelihood ratio test between the holistic model and the models for each roadway classification (Washington et al., 2011):

$$\chi^2 = -2[LL(\beta_{TOT}) - LL(\beta_{PA}) - LL(\beta_{MACOL}) - LL(\beta_{INT})] \tag{5}$$

where $LL(\beta_{TOT})$ is the log-likelihood at convergence for the holistic model (model with the two-thirds dataset); $LL(\beta_{PA})$ is the log-likelihood at convergence for the principal arterial model; $LL(\beta_{MACOL})$ is the log-likelihood at convergence for the major collector model; and, $LL(\beta_{INT})$ is the log-likelihood at convergence for the interstate model.

The final step in confirming if road classifications are to be modeled separately was to conduct a parameter transferability test. In regard to the transferability test, the assumption of equal variances created convergence problems within the constants due to large amounts of heterogeneity and generated highly erroneous constant estimates and log-likelihood values (Greene, 2012b). To avoid such bias, the heteroscedastic extreme value multinomial logit model was used to conduct the separation test (Greene, 2012b). Using the log-likelihood values obtained from the heteroscedastic extreme value multinomial logit model, the following log-likelihood ratio test is applied (Washington et al., 2011):

$$\chi^2 = -2[LL(\beta_{X_{1_{X_2}}}) - LL(\beta_{X_1})] \tag{6}$$

where $LL(\beta_{X_1})$ is the log-likelihood at convergence for model X_1 and $LL(\beta_{X_{1_{X_2}}})$ is the log-likelihood at convergence for model X_1 using the data from model X_2. For example, the best fit mixed logit model for principal arterials provides beta (β) and constant estimates (model X_1). The beta (β) values are then fixed and the constants are given starting values based on the estimates from model X_1, then the same principal arterial model is ran using the data from major collectors (model X_2) and this output is $LL(\beta_{X_{1_{X_2}}})$.

5. Model estimation results

It was determined through Eq. (4) that each mixed logit model log-likelihood was of more significance than that of the fixed-parameter log-likelihood. With 5 degrees of freedom and a chi-square statistic of 12.97, the mixed logit log-likelihood is of more significance with 98% confidence for principal arterials; parameter estimates and marginal effects for the best fit

Table 5
Heavy-Vehicle Driver Injury Severity Model Results for Principal Arterials.

Variable	Coefficient	*t*-statistic	Marginal Effects		
			No Injury	Minor Injury	Major Injury
No Injury					
Constant	3.21	3.11			
Time of Day (1 if Between 10:00 PM and 5:00AM, 0 Otherwise)	−0.68	−1.45	−0.0060	0.0050	0.0010
Weather (1 if Cloudy, 0 Otherwise)	−1.04	−1.88	−0.0139	0.0118	0.0021
Crash Location (1 if Right Shoulder, 0 Otherwise)	0.46	0.82	0.0048	−0.0040	−0.0008
Point of Impact (1 if Rear Bumper, 0 Otherwise)	−1.52	−2.34	−0.0145	0.0119	0.0026
Protective Device (1 if Seatbelt and Non-Activated Air Bag, 0 Otherwise)	2.08	1.93	0.0057	−0.0039	−0.0018
Vertical Geometrics (1 if Grade, 0 Otherwise)	1.05	0.97	−0.0207	0.0160	0.0047
Standard Deviation of Parameter, Normally Distributed	*4.61*	*2.11*			
Speed Limit (1 if Between 55 mi/h and 65 mi/h, 0 Otherwise)	0.28	0.33	−0.0448	0.0357	0.0091
Standard Deviation of Parameter, Normally Distributed	*3.23*	*1.88*			
Minor Injury					
Constant	2.24	2.32			
Horizontal Geometrics (1 if Straight, 0 Otherwise)	−1.43	−2.21	0.3683	−0.3432	−0.0251
Age (1 if Driver is Between 35 and 45 Years, 0 Otherwise)	−0.90	−1.65	0.0060	−0.0070	0.0009
Surface Condition (1 if Wet, 0 Otherwise)	−1.09	−1.65	0.0036	−0.0042	0.0006
Traffic Control Device (1 if No Control Device, 0 Otherwise)	0.21	0.38	−0.0352	0.0353	−0.0002
Standard Deviation of Parameter, Normally Distributed	*2.12*	*2.00*			
Crash Location (1 if On Roadway, 0 Otherwise)	−4.35	−2.63	0.0559	−0.0607	0.0049
Standard Deviation of Parameter, Normally Distributed	*2.57*	*1.89*			
Major Injury					
Time of Week (1 if Weekend, 0 Otherwise)	2.59	2.63	−0.0072	−0.0040	0.0112
Age (1 if Driver is Less Than 35 Years, 0 Otherwise)	−2.38	−1.95	0.0014	0.0011	−0.0026
Protective Device (1 if Lap and Shoulder Belt, 0 Otherwise)	−2.68	−3.18	0.0085	0.0061	−0.0146
Horizontal Geometrics (1 if Curved, 0 Otherwise)	1.57	1.84	−0.0040	−0.0033	0.0073
Crash Location (1 if On Roadway, 0 Otherwise)	−5.94	−2.08	0.0066	0.0034	−0.0100
Standard Deviation of Parameter, Normally Distributed	*2.96*	*1.75*			
Model Statistics					
Number of Observations	1,564				
Log-Likelihood at Zero	−747.67				
Log-Likelihood at Convergence	−647.78				
McFadden Pseudo R-Squared	0.14				

*Major Injury (fatality and incapacitating injury), Minor Injury (non-incapacitating injury and possible injury).

principal arterial model are shown in Table 5. The major collector model log-likelihood, with a chi-square statistic of 9.66 and 2 degrees of freedom, is more significant than the fixed-parameter log-likelihood with over 99% confidence; best fit model estimations and marginal effects for the major collector model are displayed in Table 6. To finish, a chi-square statistic of 25.65 and 6 degrees of freedom indicate that the interstate injury severity mixed logit log-likelihood has a higher statistical significance than the fixed-parameter log-likelihood with well over 99% confidence; Table 7 presents the parameter estimates and marginal effects for the best fit interstate model.

As for the results regarding model separation, applying Eq. (5) results in a chi-square statistic of 1,083.57 with degrees of freedom being the total number of estimated parameters in the three road classification models (Washington et al., 2011). Therefore, with a chi-square statistic of 1,083.57 and 49 degrees of freedom, Eq. (5) suggests that road classifications need be modeled separately with well over 99% confidence. Turning to the parameter transferability test, chi-square statistics and degrees of freedom[3] are shown in Table 8. Each chi-square statistic and its corresponding degrees of freedom further illustrate, with well over 99% confidence, that road classifications need be modeled separately for safety analyses.

6. Discussion

6.1. Mixed logit model

A total of 50 indicator variables were found to be significant throughout the three road classification models, with just two variables being significant in each model. The two variables found to be significant for all three road classification models were cloudy weather conditions and horizontal curves. Cloudy weather conditions decrease the outcome probability of

[3] The degrees of freedom for this log-likelihood ratio test is equal to the number of variables in model X_1 using the data from model X_2. If a model X_1 variable is not present in the data of model X_2, then it is removed for the parameter transferability test. The only variables used are variables that are present in both datasets and the remaining number of variables after removing any that are not in both datasets is the degrees of freedom.

Table 6
Heavy-Vehicle Driver Injury Severity Model Results for Major Collectors.

Variable	Coefficient	*t*-statistic	Marginal Effects		
			No Injury	Minor Injury	Major Injury
No Injury					
Constant	6.57	8.82			
Horizontal Geometrics (1 if Curve, 0 Otherwise)	−0.92	−3.10	−0.0235	0.0188	0.0047
Heavy Vehicle Type (1 if Tractor 2-Trailer, 0 Otherwise)	2.53	2.99	0.0062	−0.0052	−0.0009
Contributing Circumstances (1 if No Contributing Circumstances, 0 Otherwise)	0.90	3.00	0.0190	−0.0157	−0.0034
Point of Impact (1 if Rear Bumper, 0 Otherwise)	2.21	0.86	−0.0106	0.0086	0.0019
Standard Deviation of Parameter, Normally Distributed	*4.78*	*1.66*			
Minor Injury					
Constant	4.00	5.31			
Time of Year (1 if Winter, 0 Otherwise)	−0.78	−2.04	0.2681	−0.2419	−0.0261
City Limits (1 if Crash Occurred Within City Limits, 0 Otherwise)	−2.06	−2.53	0.0042	−0.0045	0.0003
Protective Device (1 if No Protective Device, 0 Otherwise)	1.25	3.48	−0.0135	0.0167	−0.0032
Vertical Geometrics (1 if Grade, 0 Otherwise)	0.57	1.81	−0.0105	0.0114	−0.0009
Lane of Impact (1 if Curb Line/Off Surface, 0 Otherwise)	0.72	1.38	−0.0412	0.0441	−0.0029
Standard Deviation of Parameter, Normally Distributed	*2.09*	*2.26*			
Major Injury					
Time of Day (1 if Between 10:00 PM and 5:00AM, 0 Otherwise)	1.84	2.84	−0.0049	−0.0020	0.0070
Location (1 if Crash Occurred Within 1 Mile of An Intersection, 0 Otherwise)	1.00	2.03	−0.0069	−0.0027	0.0096
Harmful Event (1 if Overturn, 0 Otherwise)	2.18	4.23	−0.0158	−0.0061	0.0219
Age (1 if Driver Greater Than 50 Years, 0 Otherwise)	1.55	2.95	−0.0108	−0.0038	0.0145
Protective Device (1 if No Protective Device, 0 Otherwise)	2.40	4.69	−0.0137	−0.0062	0.0200
Speed Limit (1 if Greater Than 55 mi/hr, 0 Otherwise)	0.93	1.70	−0.0034	−0.0012	0.0046
Weather (1 if Cloudy, 0 Otherwise)	−1.57	−1.79	0.0016	0.0006	−0.0022
Model Statistics					
Number of Observations	1,058				
Log-Likelihood at Zero	−483.27				
Log-Likelihood at Convergence	−371.63				
McFadden Pseudo R-Squared	0.23				

*Major Injury (fatality and incapacitating injury), Minor Injury (non-incapacitating injury and possible injury).

an injury severity for each road classification. For instance, cloudy weather decreases the likelihood of no injury on principal arterials, reduces the outcome probability of a major injury on major collectors, and decreases the outcome probability of a minor injury on interstates. In addition, the estimated parameter for cloudy weather conditions in the minor injury severity function on interstates was found to be random and normally distributed with a mean of -4.88 and standard deviation of 5.08. This suggests that for 16.7% of heavy-vehicles (a truck with a gross vehicle weight rating greater than 10,000 pounds) the estimated parameter mean is greater than zero, while 83.3% of heavy-vehicles have an estimated parameter mean less than zero. That is to say, sustaining a minor injury on interstates is more likely if the weather is cloudy for 16.7% of heavy-vehicles, yet less likely for 83.3% of heavy-vehicles. A possible explanation for the non–homogenous nature across observations in regard to cloudy weather may be attributed to driver behavior in such conditions (e.g., driver familiarity with weather conditions based on their region of origin). This result suggests that regardless of origin, heavy-vehicle drivers can benefit from training that involves exposure to all weather conditions.

Cloudy conditions have previously been found to influence injury severity. Specifically, Kim et al. (2013) found cloudy conditions to increase the likelihood of fatal crashes in California, however, Mohamed et al. (2013) found that cloudy conditions reduce the likelihood of fatal crashes in New York and Montreal; both works, however, did not find cloudy weather conditions to be heterogeneous. A possible explanation for injury severity reduction in New York, Montreal, and now Idaho, could be attributed to driver experience in cloudy conditions. As for the second variable found to be significant for all classifications, horizontal curves reduce no injury outcome probability for major collectors and interstates, but increase the likelihood of a major injury on principal arterials.

There were, however, more variables found to be significant between at least two of the road classifications. Major collectors and interstates have two shared significant variables, principal arterials and major collectors have three shared significant variables, and principal arterials and interstates have three shared significant variables. Of these variables, several were found to have estimated random parameters. The estimated parameter for crashes happening on the roadway (e.g., not on the shoulder or median) was found to be random and normally distributed for minor injury and major injury crashes on principal arterials. Particularly, for minor injury crashes, a mean of -4.35 and standard deviation of 2.57 suggests that for 4.5% of heavy-vehicles the estimated parameter mean is greater than zero and less than zero for 95.5%. Further, major injury crashes have a mean of -5.94 and standard deviation of 2.96, therefore increasing the likelihood of a major injury crash for 2.2% of heavy-vehicles and decreasing the outcome probability for 97.8%. A decrease in major injuries for crashes occurring on the roadway was also found by Xie et al. (2012), therefore suggesting that crashes happening on the roadway may lead to less severe injuries. Xie et al. (2012) also found that heterogeneity was present for crashes that happened on the roadway

Table 7
Heavy-Vehicle Driver Injury Severity Model Results for Interstates.

Variable	Coefficient	*t*-statistic	Marginal Effects		
			No Injury	Minor Injury	Major Injury
No Injury					
Constant	3.01	3.55			
Horizontal Geometrics (1 if Curve, 0 Otherwise)	−0.96	−2.80	−0.0156	0.0125	0.0030
Heavy Vehicle Type (1 if Tractor 1-Trailer, 0 Otherwise)	0.44	1.59	0.0160	−0.0135	−0.0025
Crash Location (1 if On Roadway, 0 Otherwise)	2.19	5.60	0.0724	−0.0625	−0.0099
Contributing Circumstances (1 if Speeding Contributed to Crash, 0 Otherwise)	−1.14	−2.63	−0.0121	0.0101	0.0019
Weather (1 if Snow, 0 Otherwise)	3.75	2.04	−0.0030	0.0030	0.0000
Standard Deviation of Parameter, Normally Distributed	*4.05*	*2.56*			
Protective Device (1 if Shoulder and Lap Belt, 0 Otherwise)	2.01	3.05	0.0286	−0.0238	−0.0048
Standard Deviation of Parameter, Normally Distributed	*1.93*	*2.61*			
Minor Injury					
Constant	3.06	3.64			
Location (1 if Crash Occurred Within 1 Mile of On/Off Ramp, 0 Otherwise)	0.65	1.91	−0.1643	0.1495	0.0148
Protective Device (1 if Seatbelt and Non-Activated Air Bag, 0 Otherwise)	−1.82	−3.61	0.0090	−0.0090	0.0001
Harmful Event (1 if Sideswipe in Same Direction, 0 Otherwise)	−0.98	−2.26	0.0062	−0.0064	0.0003
Weather (1 if Cloudy, 0 Otherwise)	−4.88	−1.96	−0.0076	0.0076	0.0001
Standard Deviation of Parameter, Normally Distributed	*5.08*	*2.39*			
Age (1 if Driver Less Than 30 Years, 0 Otherwise)	−2.96	−1.72	−0.0032	0.0030	0.0002
Standard Deviation of Parameter, Normally Distributed	*3.71*	*2.26*			
Major Injury					
Surface Conditions (1 if Dry, 0 Otherwise)	2.18	2.52	−0.0136	−0.0048	0.0185
Contributing Circumstances (1 if No Contributing Circumstances, 0 Otherwise)	−1.87	−2.17	0.0026	0.0007	−0.0033
Protective Device (1 if Seatbelt and Non-Activated Air Bag, 0 Otherwise)	−4.81	−1.49	0.0007	0.0002	−0.0009
Vertical Geometrics (1 if Level, 0 Otherwise)	−1.39	−2.09	0.0051	0.0018	−0.0069
Lane of Impact (1 if Center Lane or Median, 0 Otherwise)	−1.75	−0.68	−0.0065	−0.0017	0.0081
Standard Deviation of Parameter, Normally Distributed	*4.46*	*2.03*			
Age (1 if Driver Greater Than 50 Years, 0 Otherwise)	−0.28	−0.18	−0.0114	−0.0030	0.0144
Standard Deviation of Parameter, Normally Distributed	*2.53*	*1.76*			
Model Statistics					
Number of Observations	1,609				
Log-Likelihood at Zero	−708.37				
Log-Likelihood at Convergence	−605.69				
McFadden Pseudo R-Squared	0.15				

*Major Injury (fatality and incapacitating injury), Minor Injury (non-incapacitating injury and possible injury).

Table 8
Chi-Square Statistics and Degrees of Freedom for Road Classification Transferability Test.

X_1	X_2		
	Principal Arterial	Major Collector	Interstate
Principal Arterial	0	359.67 (12)	70.31 (12)
Major Collector	647.02 (10)	0	172.50 (10)
Interstate	250.39 (12)	358.96 (10)	0

through a latent class logit framework. Specifically, parameter estimates were significant in both classes, yet had differing signs (e.g., positive/negative) (Shaheed and Gkritza, 2014).

The estimated parameter for crashes that happened on a grade was found to be random and normally distributed on principal arterials for no injury crashes. With a mean of 1.05 and standard deviation of 4.61, 41% of heavy-vehicle drivers are less likely to sustain no injury and 59% of heavy-vehicle drivers are more likely to sustain no injury. The percent grade is not given in the data, or if the crash occurred while traveling up/down grade, therefore the randomness in this parameter may be attempting to account for such characteristics.

The estimated parameter for crashes with the rear bumper being the point of impact was found to be random and normally distributed on major collectors for no injury crashes. Rear bumper impact, with a mean of 2.21 and standard deviation of 4.78, suggests that 32.2% of heavy-vehicles have a decrease in no injury outcome probability and 67.8% of heavy-vehicles have an increase in no injury outcome probability. In regards to rear bumper impact, posted speed limits were provided in the crash data, but speed at the time of the crash was not. With this in mind, the estimated parameter for rear bumper impact may be random in an attempt to capture the speed at which the impact took place. For example, lower speed crashes are apt to result in less severe injuries while higher speed crashes often lead to more severe injuries.

The estimated parameter for drivers wearing a shoulder and lap belt was found to be random and normally distributed for no injury crashes on interstates. A mean of 2.01 and standard deviation of 1.93 suggests that for 14.9% of heavy-vehicles the likelihood of a no injury crash decreases, but increases the likelihood of a no injury crash for 85.1% of heavy-vehicles. Although seatbelts are designed to save lives, they have the potential to cause injuries in an attempt to mitigate a more serious injury due to unobserved factors (e.g., due to driver physiology). For instance, a head-on collision at high speed typically results in a driver being thrust forward causing the seatbelt to lock. Although the seatbelt may prevent the driver from being ejected and sustaining a more severe injury (possibly a fatal injury), there is the possibility that the seatbelt has injured the driver while mitigating the severity. Recent studies (see Kashani and Mohaymany, 2011; Obeng, 2011; Pahukula et al., 2015; Russo et al., 2014; Ye and Lord, 2014) have also found seatbelt usage to impact injury severity outcomes. In particular, Kashani and Mohaymany (2011) found that the probability of a more severe injury is higher when a seatbelt is not used; Obeng (2011) found that seatbelt usage decreases injury severity risk for both males and females; and, Russo et al. (2014) found that unbelted drivers have an increase in injury severity likelihood. However, each of these findings were homogenous across observations. On the other hand, Ye and Lord (2014) and Pahukula et al. (2015) found that seatbelt usage and its effect on injury severity varies across observations.

The estimated parameter for drivers under the age of 30 was found to be random and normally distributed on interstates. A mean of -1.72 and standard deviation of 2.29 suggests that for 22.6% of heavy-vehicles the likelihood of suffering a minor injury increases, but decreases the likelihood of a minor injury for 77.4% of heavy-vehicles. This finding is in-line with previous injury severity studies (Islam and Hernandez, 2013a; Pahukula et al., 2015; Yasmin et al., 2014). More specifically, Islam and Hernandez (2013a) found homogeneously that younger drivers are less likely to sustain a minor injury; Yasmin et al. (2014) found that younger drivers have a higher probability of sustaining no injury and lower probability of sustaining any injury (e.g., minor/severe), and, Pahukula et al. (2015) found that injury severity of younger drivers is not homogenous for specific time-of-day periods. These results suggest that as crash data is disaggregated to focus on specific crash types (e.g., time-of-day, roadway classification), the effect of young drivers on injury severity has the potential to vary across crash observations.

The estimated parameter for snowy weather, with a mean of 3.97 and standard deviation of 4.08, decreases the likelihood of no injury for 16.5% of heavy-vehicles, but increases the likelihood of no injury for 83.5% of heavy-vehicles. While Yasmin et al. (2014) find that inclement weather increase the likelihood of major injuries, the findings in the current study are in-line with several previous works that have found inclement weather (e.g., snow) to reduce the likelihood of major injuries or increase the likelihood of no injury (Behnood et al., 2014; Cerwick et al., 2014; Eluru et al., 2012; Eluru and Bhat, 2007; Islam et al., 2014; Islam and Hernandez, 2013b; Lemp et al., 2011; Manepalli et al., 2012; Milton et al., 2008; Yasmin and Eluru, 2013; Ye and Lord, 2014).

Marginal effect values for principal arterials indicate that straight horizontal geometrics have the greatest effect on injury severity. Marginal effects show that principal arterials with straight horizontal geometrics have a 0.368 higher probability of no injury, and a 0.343 and 0.025 lower probability of a minor injury and major injury, respectively. On major collectors, crashes happening in the winter have the greatest impact on injury severity. Marginal effects reveal that winter crashes have a 0.268 higher probability of no injury, yet a 0.242 and 0.026 lower probability of minor and major injuries. Interstates see the location of the crash having the greatest effect on injury severity. For crashes that happened within one mile of an on/off ramp, marginal effects indicate a 0.164 lower probability of no injury while showing a 0.150 and 0.015 higher probability for minor injury and major injury crashes.

With respect to low impact variables, Table 5 shows that crashes occurring between 10:00 p.m. and 5:00 a.m. on principal arterials decreases no injury probability by 0.006, on average, while increasing minor and major injury probability by 0.005 and 0.001. On major collectors, cloudy weather decreases the probability of a major injury by 0.002, on average, although increases the probability of a minor injury and no injury by 0.001 and 0.002, respectively. Table 7 shows that crashes with no contributing circumstances on interstates have a small-scale effect on injury severity outcomes[4]. Marginal effects indicate a 0.003 decrease in probability of a major injury, on average, yet a 0.001 and 0.003 increase in minor injury and no injury probability.

6.2. Factors significant to one roadway classification

As discussed previously, just two variables were found to be significant for each classification, namely, cloudy weather conditions and the presence of horizontal curves. With that in mind, nine factors were found to be significant on principal arterials that were not found to be significant on the other two classifications. For example, crashes occurring on weekends was significant exclusively for principal arterials and results in a 0.011 higher probability of a major injury crash according to marginal effects. This finding could be a result of heavy-vehicle, where a heavy-vehicle is a truck with gross vehicle weight rating greater than 10,000 pounds, drivers maneuvering with more risk due to the lack of typical commuter traffic seen on principal arterials during the week. Other notable factors significant purely on principal arterials include crashes that happened on the right shoulder (increases no injury likelihood), no traffic control devices (increases minor injury likelihood), and crashes that happened on the roadway (decreases major injury likelihood).

[4] Table 7 shows that "Seatbelt and Non-Activated Air Bag" have the smallest effect on injury severity, but due to this indicator being present in two severity functions (minor injury and major injury), the analyst is unable to determine the effect of this variable. The presence of this indicator in multiple severity functions generates uncertainty in inferences, therefore the authors do not infer marginal effect values for indicators that were found to be significant in more than one severity function.

With regard to major collectors, driving a tractor 2-trailer increases the outcome probability of no injury crashes and is exclusive to major collectors. Islam et al. (2014) also found multiple unit heavy-vehicles to effect injury severity, however it was found to increase minor injury probability. A possible explanation could be that crashes occurring on major collectors are happening at lower speeds, therefore despite the size of the vehicle less severe injuries could be expected. Other notable factors significant just to major collectors include crashes that happened during the winter (decreases minor injury likelihood), crashes in which no protective device was worn (increases likelihood of minor and major injuries), and crashes that took place within one mile of an intersection (increases major injury likelihood).

Moving to interstates, there is an increase in outcome probability of no injury crashes when a tractor 1-trailer is involved and is exclusive to interstates. The crashes represented in these observations may have occurred during congested conditions, therefore the crashes are happening at lower speeds and may be more apt to result in less severe injuries. Other notable factors significant exclusively to interstates include crashes that happened within one mile of an on/off ramp (increases minor injury likelihood), dry surface conditions (increases major injury likelihood), and level vertical geometrics (decreases the likelihood of a major injury). Interstates have higher posted speed limits, therefore, dry surface conditions may tempt drivers to travel at faster speeds that can result in more severe injuries. In regard to vertical geometrics, level segments of interstates (i.e., no grade) are often seen in urban areas where congestion occurs and, as a result, may decrease major injury likelihood contingent on the speed at which the crash occurred.

6.3. Factors shared by two road classifications

Although characteristics differ between classifications from a functional perspective (e.g., speed limits, traffic flow, etc.), factors significant between at least two of the classification were found. Crashes in which the rear bumper was the point of impact were found to be significant on principal arterials and major collectors. Specifically, rear bumper impact on principal arterials decreases the outcome probability of a no injury crash, yet rear bumper impact on major collectors increases the outcome probability of a no injury crash. This could be attributed to heavy-vehicles (a truck with a gross vehicle weight rating greater than 10,000 pounds) traveling at higher speeds on principal arterials as opposed to major collectors and, consequently, decreases the likelihood of no injury crashes on principal arterials while increasing the likelihood of a no injury crash on major collectors. Likewise, crashes that occurred during the hours of 10:00 p.m. to 5:00 a.m. were significant to principal arterials and major collectors. Crashes that happened during these hours on principal arterials decreases the likelihood of a no injury crash, however, crashes during the same time period on major collectors increases the outcome probability of a major injury crash. Traffic volumes during these hours is low and, accordingly, may tempt heavy-vehicle drivers to drive with less caution or less attentiveness resulting in a higher potential for more severe injuries.

Principal arterials and interstates shared significant contributing factors as well, namely, crashes in which a seatbelt was worn and no airbag was activated, and crashes that happened on the roadway. If a seatbelt was worn, but no airbag was activated, there is an increase in the likelihood of a no injury crash on principal arterials and a decrease in the likelihood of a minor injury crash on interstates. These results suggest that regardless of classification seatbelts contribute to less severe injury outcomes, as no protective device worn increases the likelihood of minor and major injury crashes on major collectors. In regard to crashes that happened on the roadway, a decrease in minor and major injury likelihood on principal arterials was found (the estimated parameters for both severities were also found to random as formerly discussed). As for interstates, crashes that took place on the roadway increases the outcome probability of a no injury crash. These findings may be a result of heavy-vehicle crashes happening during congested conditions on principal arterials and interstates, therefore less severe crashes could be expected (e.g., slight rear-end crashes at very low speeds).

Turning to significant contributing factors shared by major collectors and interstates, no contributing circumstances, vertical geometrics, and drivers over the age of 50 were significant for both classifications. Specifically, no contributing circumstances increases the likelihood of a no injury crash on major collectors while decreasing the likelihood of a major injury crash on interstates. This suggests that if a crash has no contributing circumstances (e.g., speeding, distraction, etc.) less severe crashes could be expected. With respect to vertical geometrics, crashes that happened on a grade were found to increase the outcome probability of a minor injury crash on major collectors. On interstates, however, level vertical geometrics were found to decrease the likelihood of a major injury. A possible explanation could be that the characteristics of the grade in which crashes happened (e.g., percent grade, limited visibility, etc.) on major collectors result in more severe injuries, while crashes on level geometrics on interstates do not prohibit drivers' visibility, ability to stop, or ability to avoid a crash. Regarding drivers over the age of 50, there is an increase in the outcome probability of a major injury crash on major collectors and a decrease in the likelihood of a major injury crash on interstates; however, the estimated parameter on interstates was found to be random. Specifically, with a mean of -0.26 and standard deviation of 2.53, 45.9% of heavy-vehicle drivers over the age of 50 have an increased likelihood of sustaining a major injury and 54.1% have a decreased likelihood of sustaining a major injury.

7. Insights and future work

The present study provides a heavy-vehicle driver injury severity analysis utilizing a mixed logit modeling framework that extends the heavy-vehicle injury severity literature, as well as fill the gap in literature in terms of heavy-vehicle driver injury severity by roadway classification (a heavy-vehicle is a truck with a gross vehicle weight rating greater than 10,000 pounds). The mixed logit method attempts to capture the heterogeneity in the Idaho crash data by assuming a given parameter varies across observations based on a normal distribution, however, several distributions were tested for statistical significance for the current study.

Using Idaho as a case study to investigate heavy-vehicle driver injury severity by roadway classification, it was determined that roadway classifications need to be modeled separately. In other words, the null hypothesis that roadway classifications need to be modeled holistically was rejected. In addition to the parameter transferability test, the acute number of statistically significant variables found to be exclusive to each classification further indicate that heavy-vehicle driver injury severity factors differ by roadway classification. However, two factors were found to impact injury severity regardless of classification, cloudy weather and horizontal curves. Further, there were factors that were found to influence severity on two of the three classifications (e.g., seatbelts, crashes that happened between 10:00 p.m. and 5:00 a.m.), but their sign and marginal effect was notably different. To highlight the difference in roadway classifications, 9 of the 17 significant variables for principal arterials were exclusive to principal arterials, 9 of the 16 significant variables for major collectors were exclusive to major collectors, and 9 of the 17 significant variables for interstates were exclusive to interstates.

With the highest percentage of heavy-vehicle crashes in Idaho occurring on road classifications presented in this study, State officials can use these findings as guidance to take action in an attempt to reduce heavy-vehicle crashes by focusing on specific factors that are unique to a specific road classification. For example, Idaho agencies can examine the grades on principal arterials and major collectors to determine if specific grade characteristics are impacting severity outcomes, such as visibility, posted speed limits, and grades that contain horizontal curves. Similarly, Idaho can consider strict seatbelt regulations for heavy-vehicle drivers and build training programs around severity factors presented in this study, such as training programs that focus on overnight driving or training programs that are prepared for older drivers.

In summary, this study presents heavy-vehicle driver injury severity contributing factors by roadway classification while also establishing that roadway classifications need to be considered separately for safety analyses. Empirical results suggest that future studies consist of modeling other roadway classifications based on the need of the study area to assist transportation agencies, planners, and engineers in developing the safest transportation infrastructure possible with the utmost precision to preserve and utilize available resources. That is, rather than generalizing the contributing factors that lead to injury severity, factors can be identified by geographic region and road classification within that area.

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