Journal of Transportation Safety & Security

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

A comprehensive analysis of factors that influence interstate highway crash severity in Alabama

Emmanuel Kofi Adanu, William Agyemang, Riffat Islam & Steven Jones

JOURNAL OF TRANSPORTATION SAFETY & SECURITY
https://doi.org/10.1080/19439962.2021.1949414

A comprehensive analysis of factors that influence interstate highway crash severity in Alabama

Emmanuel Kofi Adanu[a], William Agyemang[b], Riffat Islam[b], and Steven Jones[a,b]

[a]Alabama Transportation Institute, The University of Alabama System, Tuscaloosa, Alabama, USA; [b]Civil, Constrction, and Environmental Engineering, The University of Alabama System, Tuscaloosa, Alabama, USA

ABSTRACT

This paper identifies factors that influence the severity of interstate crash outcomes and how they vary depending on the location and manner of collision. Four separate injury severity models were developed to explore the differences and similarities in crash factors between single-and multi-vehicle crashes that occurred in rural and urban areas of the state. Random parameters multinomial logit with heterogeneity in means and variances modeling approach was used to account for unobserved heterogeneity in the crash data. The model estimation results show that some driver behavioral factors such as speeding, aggressive driving, failure to use seatbelt, and driving without a valid license were found to significantly contribute to some form of injury outcome. The influence of roadway features such as type of opposing lane separation, collision type, temporal and lighting conditions on crash outcomes were also explored. Some differences and similarities in the associations between these factors and crash injury severity based on the manner and location of crash were unraveled. These findings are expected to guide the implementation of crash countermeasures on interstates. The findings of this study further support the evidence for the analysis of subsets of crash data to unravel underlying complex relationships within factors that influence crash injury severity.

KEYWORDS

Interstate; crash severity; crash location; single-vehicle; multi-vehicle

1. Introduction

Interstate highways form an important part of the road network. They are generally designed as controlled-access highways with higher speed limits for rapid mobility of people and freight. The high-speed limits on interstate highways make them prone to fatal/major injury crashes. However, driving behaviors and factors that are associated with crash outcomes on these highways are not well understood. Early on, McCarthy (1998) states that other factors such as highway and vehicle design, speed enforcement,

CONTACT Emmanuel Kofi Adanu ekadanu@crimson.ua.edu Alabama Transportation Institute, The University of Alabama System, Tuscaloosa, AL 35487, USA.

roadway environment, and driver characteristics influence a driver's speed choice, beyond the posted speed limit. Shinar (1998) further observed that drivers observe posted speed limits only when they are constrained by environmental factors (such as lighting condition or roadway geometry), vehicle limitations, or when there is intense enforcement. Understanding these factors is a highly complex topic since different types of drivers have different reactions to different factors such as road environment, but on the other hand, it is an important precursor for improving overall highway safety.

Efforts to improve highway safety have led to some studies into the risk factors that may be addressed. Previous research clearly shows that increase in speed leads to an increase in crash severity (e.g., Baum, Wells, & Lund, 1990; Garber & Grahman, 1990; Joksch, 1993; Renski, Khattak, & Council, 1999; Shinar, 1998; Solomon, 1964). Some researchers focused on crashes involving certain vehicle categories while others based their studies on different driver populations, location characteristics, roadway and environmental factors, and mechanism of the crashes. For instance, Chen and Chen (2011) investigated difference in driver injury severities between single-vehicle and multi-vehicle crashes involving large trucks. Wang and Shi (2013) observed that the presence of ramp, freeway segment length, and weather conditions were important factors affecting truck safety performance on freeways, while Venkataraman, Ulfarsson, and Shankar (2013) found that lighting on both sides of interstate highways lead to improved safety compared to median lighting or right-side lighting which are linked to increased crash frequencies. Garber, Chowdhury, and Kalaputapu (1992) on the other hand observed that a higher proportion of truck crashes on interstate highways occurred on exit ramps and a significant percentage of the rear-end collisions involve large trucks running into other vehicles. It was further noted that sideswipe-same direction collisions were predominant at entry ramps while rear end and sideswipe-same direction collisions were predominant at exit ramps. Renski et al. (1999) assessed the effect of speed limit increases on single-vehicle interstate crash severities in North Carolina, where they observed that increasing speed limits from 55 to 60 mph and 55 to 65 mph increased the likelihood of sustaining minor and non-incapacitating injuries, but increasing speed limits from 65 to 70 mph did not have a significant effect on crash severity. Jung, Qin, and Noyce (2010) investigated the factors that influence the severity of single-vehicle crashes on Wisconsin interstate highways under rainy conditions. Their study found rainfall intensity, wind speed, roadway terrain, driver's gender and safety belt use to be statistically significant predictors of crash severities. Chen et al. (2016) also assessed the determinants of crash outcomes on rural interstate highways where they found road curve, maximum vehicle damage in a crash, number of vehicles in a crash, wet road surface, vehicle type, driver age, driver gender, driver seatbelt use and driver alcohol or drug involvement to be significantly associated with the crash injury severities. Ahmed, Franke, Ksaibati, and Shinstine (2018) observed that when a heavy track is involved in crash on state and interstate highways, the probability of a severe injury outcome increases by 2.3 and 4.5 times, respectively. They also found that severity of the crash to significantly increase under adverse weather conditions such as poor visibility, and when the roadway is icy and snowy. Haleem and Gan (2013) explored the effects of driver's age and side impact on crash severity along urban freeways. They observed that traffic volume, percent of trucks, distance the nearest ramp, and vehicle type influence the severity of urban freeway crashes. Ma, Chen, and Chen (2017) observed that the number of lanes, pavement condition, traffic volume and month of the year affect the severity of interstate crashes. Their study was based on crashes that happened on a mountainous portion of interstate I-70 in Colorado. Other interstate geometry standards have also been found to influence crash occurrence and crash outcomes. For instance, Chen, Saeed, Alinizzi, Lavrenz, and Labi (2019) found that casualty crashes on interstates are more sensitive to traffic volume and average vertical grade but less sensitive to the inside shoulder width and median width. Chen, Saeed, and Labi (2017) also observed that higher surface roughness of rural highways is generally associated with a lower expected crash frequency.

This paper contributes to the body of literature on interstate highway safety by undertaking an extensive analysis of the empirical factors that affect injury severity of interstate crashes in Alabama. To put the study in perspective, Alabama has 4,558 miles of interstate highways and other freeways/expressways make up 140 miles by functional system lane length and account for 21.7% and 0.7% of vehicle miles traveled (VMT) in the state. Also, 74.3% of the public road length in the state is in rural areas (USDOT, 2014). A total of 54,160 observed interstate crashes recorded between 2015 and 2018 were used in this study. The data was categorized into four based on the location and manner of collision as urban multi-vehicle, rural multi-vehicle, urban single-vehicle, and rural single-vehicle, and explored accordingly. Subsets of the crash data were considered to unravel underlying complex relationships within injury severity analysis. For instance, in single-vehicle crashes, the influence of other vehicles are eliminated and the factors that are found to influence the crash outcomes apply to the driver, whereas in multi-vehicle crashes, the reporting officer assigns the primary fault to one or more of the drivers. As such, the contributing factors of multi-vehicle crashes are difficult to unravel. To improve the accuracy of the findings on the relationship between various factors and crash outcomes and to improve the quality of countermeasure decisions from this study, random parameters multinomial logit with heterogeneity in means and variances modeling approach is used to account for unobserved heterogeneity in the data.

2. Methodology

Over the years, researchers have used a variety of methodological approaches to study the associations between various factors and crash outcomes (see Savolainen, Mannering, Lord, & Quddus, 2011 for a review of crash injury severity models and methods of analysis). To account for unobserved heterogeneity across crash observations heterogeneity models such as mixed logit (e.g. Anastasopoulos & Mannering, 2011; Behnood & Mannering, 2017; Eluru, Bhat, & Hensher, 2008; Kim, Ulfarsson, Kim, & Shankar, 2013; Milton, Shankar, & Mannering, 2008; Morgan & Mannering, 2011; Seraneeprakarn et al., 2017) and latent class (finite mixture) models (e.g. Adanu, Hainen, & Jones, 2018; Greene & Hensher, 2013; Shaheed & Gkritza, 2014; Xiong & Mannering, 2013; Yasmin, Eluru, Bhat, & Tay, 2014) have been predominantly used. Mixed logit technique uses continuous mixing distributions to capture heterogeneity, and allows the analyst to specify the functional form of the mixing distribution (for example, normal, log-normal, uniform, triangular, etc.), while latent class approach identifies unobserved classes without distributional assumptions, where unobserved heterogeneity is captured by membership of distinct classes (Greene & Hensher, 2003; Mannering & Bhat, 2014).

To capture the effects of unobserved heterogeneity (Mannering, Shankar, & Bhat, 2016) in understanding the determinants of interstate crash severity, this study used random parameters logit with heterogeneity in means and variances modeling techniques. Three discrete crash outcome categories are considered in this study: severe injury (defined as fatal or incapacitating injury outcome), minor injury (defined as non-incapacitating or possible injury), and no injury (or property damage only). To obtain an estimable model, we define an injury severity function S_{in} that determines the probability that crash n will result in injury severity i (McFadden, 1981), as:

$$S_{in} = \beta_i X_{in} + \varepsilon_{in} \quad (1)$$

Where β_i is a vector of estimable parameter for injury outcome i (severe injury, minor injury, and no injury), X_{in} is a vector of explanatory variables that affect the likelihood of injury outcome i in crash n and ε_{in} is the stochastic error term. If ε_{in} is assumed to follow an independent and identically distributed extreme value Type I distribution (McFadden, 1981), and parameter variations across observations are allowed by introducing a mixing distribution (McFadden & Train, 2000), the resulting mixed logit model is:

$$P_n(i) = \int \frac{\exp(\beta_i X_{in})}{\Sigma \exp(\beta_i X_{in})} f(\beta|\varphi) d\beta \tag{2}$$

Where $f(\beta|\varphi)$ is the density of β and φ corresponds to a vector of parameters of the density function (mean and variance), $P_n(i)$ is the probability of injury category i in crash n conditional on $f(\beta|\varphi)$. β now has the ability to account for observation-specific variations in the effect of X on injury outcome probabilities, with $f(\beta|\varphi)$ used to determine β. Mixed-logit probabilities are then a weighted average for different values of β across observations where some elements of β can be fixed across observations and some may vary across observations (known as random parameters). Heterogeneity in means and variances of random parameters is accounted for by allowing β_i to vary across crashes as (Seraneeprakarn et al., 2017):

$$\beta_i = \beta + \Theta_i Z_i + \sigma_i \exp(\omega_i W_i) \upsilon_i \tag{3}$$

where β is the mean parameter estimate across all crashes,Z_i is a vector of attributes that capture heterogeneity in the mean,Θ_i is a corresponding vector of estimable parameters,W_i is a vector of attributes that capture heterogeneity in standard deviation σ_i with corresponding parameter vector ω_i and a disturbance term υi, and Z_i and W_i may contain crash attributes or other sources of heterogeneity which may not be captured by variables recorded in the crash database. If no variables are found to be significant in W_i, the model is reduced to a heterogeneity in means only model. Similarly, if none of the variables in Z_i and W_i are found to be statistically significant, the reduced form model is the mixed logit model without heterogeneity in means and variances. This model is estimated by simulated maximum likelihood estimation with the logit probabilities shown in Eq. (3) approximated by drawing values of β from $f(\beta|\varphi)$ for given values of φ, using Halton draws (Halton, 1960; Bhat, 2003). In this study, 500 Halton draws is used to draw values of β_i from $f(\beta_i|\varphi)$ to compute the logit probabilities (Bhat, 2003; Halton, 1960). For the functional form of the parameter density functions, the normal distribution was used (e.g., Milton et al., 2008). Marginal effects were also computed to investigate the effect of the explanatory variables on the injury-severity outcome probabilities (Washington, Karlaftis, Mannering, & Anastasopoulos, 2020).

3. Data description

The study was based on 2015–2018 Alabama crash data obtained from the Critical Analysis Reporting Environment (CARE) system developed by the Center for Advanced Public Safety at the University of Alabama. The

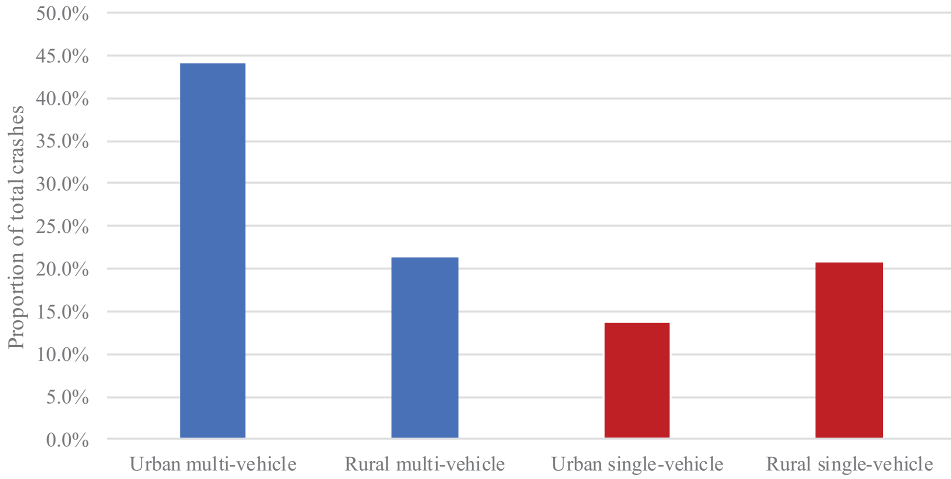

Figure 1. Distribution of interstate crashes by manner and location of crash.

database was queried to select interstate crashes. The data were error-checked and observations with missing or ambiguous values were omitted from the original dataset before performing the model estimation. This yielded a total of 54,160 observed crashes. The study used three injury-severity categories: severe injury (fatal or incapacitating injury), minor injury (non-incapacitating injury or possible injury), and no injury, as has been done in some previous crash injury severity studies (e.g., Islam et al., 2014; Adanu et al., 2018). Based on this classification, 2,221 of the crashes were severe injury. Minor and no injury crashes were 9,188 and 42,751, respectively. These statistics clearly underscore the need for studying interstate crashes toward improving the overall safety of the transportation system. Figure 1 shows a comparison of the interstate crashes based on the location and manner of collision and Table 1 presents the descriptive statistics of the dependent variables used in model building.

From Figure 1, the highest proportion of the total interstate crashes (44.1%) were urban multi-vehicle collisions, followed by rural multi-vehicle collisions (21.4%). Rural single-vehicle crashes made up 20.6% of the total crashes and urban single-vehicle crashes constituted the least, making up 13.9% of the crash observations used for the study. About 1.6% of the urban multi-vehicle crashes resulted in severe injury as shown in Table 2, whereas 17% led to minor injuries and the highest percentage of these crashes, 81.4% resulted in no injury outcome. In rural multi-vehicle crashes, 5.6% of them resulted in severe injuries, a perceptibly higher percentage when compared to the urban crashes. Additionally, 15.2% of the rural crashes were minor injury, while 79.2% resulted in no injury. The percentages of severe, minor injury and no injury occurrences for urban

Table 1. Distribution of interstate crashes by injury severity.

	Number of observation (%)			
Severity	Urban multi-vehicle	Rural multi-vehicle	Urban single-vehicle	Rural single-vehicle
Severe injury	388 (1.6%)	653 (5.6%)	378 (5.0%)	802 (7.2%)
Minor injury	4,051 (17.0%)	1,760 (15.2%)	1,697 (22.6%)	1,680 (15.0%)
No injury	19,437 (81.4%)	9,183 (79.2%)	5,434 (72.4%)	8,697 (77.8%)
Total	23,876 (100.0%)	11,596 (100.0%)	7,509 (100.0%)	11,179 (100.0%)

single-vehicle crashes were 5%, 22.6% and 72.4%, respectively, while those for rural single vehicle crashes were 7.2%, 15%, 77.8% respectively.

Table 2 presents the descriptive statistics of the explanatory variables that were used in model estimation. This preliminary analysis of the crash data revealed that speeding was responsible for a higher proportion of single-vehicle collisions in general, compared to multi-vehicle collisions. Specifically, speeding accounted for 23.9% and 23.4% of urban and rural single-vehicle crashes, respectively, while speeding accounted for only 4.3% and 6.8% of urban and rural multi-vehicle crashes, respectively. DUI on the other hand was responsible for a higher proportion of single-vehicle crashes, while aggressive driving was more pronounced in urban areas. More of the rural interstate crashes occurred at roadways sections that had cable median and unpaved median as opposing lane separation, whereas urban crashes occurred more where the opposing lane separation is concrete median. At-fault drivers who did not have a valid license at the time of the crash were higher in multi-vehicle collisions while those that failed to use seatbelt were more involved in single-vehicle crashes. Single-vehicle crashes that involved collision with an animal were higher in rural areas. Further, crashes involving drivers whose homes were more than 40.2 km (25 mi) away from the crash location were higher in rural areas.

4. Results

Four separate injury severity models were estimated for rural and urban single vehicle and multi-vehicle interstate crashes in Alabama. Likelihood-ratio tests were conducted to justify the development of these separate models (Washington et al., 2020). For assessing parameter transferability, the test statistic used is:

$$X^2 = -2[LL\Big(\beta_T) - \sum_{k=1}^{K} LL(\beta_k)], \quad (4)$$

where $LL(\beta_T)$ is the log-likelihood at convergence of the model estimated with all the data, $LL(\beta_k)$ is the log-likelihood at convergence of the model using subset k data (rural single-vehicle, rural multi-vehicle, urban single-vehicle and urban multi-vehicle) and K is the total number of data subsets

Table 2. Descriptive statistics of explanatory variables used in model estimation.

		Number of observations (%)							
Variables	Description	Urban multi-vehicle		Rural multi-vehicle		Urban single-vehicle		Rural single-vehicle	
Primary contributing factors									
Speeding	Primary contributing factor: 1 if Speeding, 0 otherwise	1027	4.3	789	6.8	1795	23.9	2616	23.4
DUI	Primary contributing factor: 1 if DUI, 0 otherwise	239	1.0	359	3.1	233	3.1	481	4.3
Aggressive driving	Primary contributing factor: 1 if aggressive driving, 0 otherwise	263	1.1	139	1.2	143	1.9	89	0.8
Follow too close	Primary contributing factor: 1 if following too close, 0 otherwise	8404	35.2	3444	29.7				
Lane changing	Primary contributing factor: 1 if lane changing, 0 otherwise	2913	12.2	2134	18.4				
Roadway features and condition									
Cable median	Opposing lane separation: 1 if cable median, 0 otherwise	1600	6.7	2064	17.8	954	12.7	2325	20.8
Unpaved median	Opposing lane separation: 1 if unpaved median, 0 otherwise	3581	15.0	4256	36.7	1427	19.0	4885	43.7
Concrete median	Opposing lane separation: 1 if concrete median, 0 otherwise	10983	46.0	3943	34.0	2861	38.1	2940	26.3
Straight and level	Roadway geometry: 1 if Straight and flat, 0 otherwise	16522	69.2	7155	61.7	4701	62.6	6953	62.2
Curve	Roadway geometry: 1 if curve, 0 otherwise	2937	12.3	974	8.4	1765	23.5	1476	13.2
Ramp	Crash location: 1 if entrance or exit ramp, 0 otherwise	2841	11.9	731	6.3	743	9.9	347	3.1
Wet roadway	Roadway condition: 1 if wet, 0 otherwise	4417	18.5	2168	18.7	3236	43.1	3644	32.6
Temporal factors and lighting condition									
Friday	Time of crash: 1 if Friday, 0 otherwise	4895	20.5	2180	18.8	931	12.4	3108	27.8
Weekend	Time of crash: 1 if weekend, 0 otherwise	3940	16.5	2969	25.6	2305	30.7	3432	30.7
Afternoon	Time of crash: 1 if between noon and 6PM, 0 otherwise	11866	49.7	5473	47.2	2350	31.3	3711	33.2
Dawn	Time of crash: 1 if between midnight and 6AM, 0 otherwise	907	3.8	974	8.4	1374	18.3	2023	18.1
Dark/unlit	Lighting condition: 1 if dark and unlit, 0 otherwise	4250	17.8	2737	23.6	946	12.6	4036	36.1
Summer	Time of crash: 1 if summer season, 0 otherwise	6017	25.2	3096	26.7	1915	25.5	3119	27.9
Winter	Time of crash: 1 if winter season, 0 otherwise	5420	22.7	2540	21.9	2050	27.3	2806	25.1
Driver and behavioral characteristics									
Female driver	At-fault driver gender: 1 if female, 0 otherwise	9741	40.8	3966	34.2	2898	38.6	4203	37.6
Male driver	At-fault driver gender: 1 if male, 0 otherwise	14135	59.2	7630	65.8	4611	61.4	6976	62.4
Invalid license	At-fault driver license status: 1 if invalid, 0 otherwise	2149	9.0	847	7.3	98	1.3	112	1.0
Younger driver	At-fault driver age: 1 if less than 25, 0 otherwise	6685	28.0	3177	27.4	2485	33.1	2929	26.2
Adult driver	At-fault driver age: 1 if between 25 and 45, 0 otherwise	10195	42.7	4627	39.9	3379	45.0	4740	42.4
No seatbelt	At-fault driver seatbelt use: 1 if no seatbelt, 0 otherwise	239	1.0	244	2.1	263	3.5	470	4.2
Vehicle type									
Motorcycle	At-fault vehicle type: 1 if motorcycle, 0 otherwise	96	0.4	35	0.3	120	1.6	123	1.1
Crash type									
Sideswipe	Crash type: 1 if sideswipe, 0 otherwise	4513	18.9	3850	33.2				
Rear-end collision	Crash type: 1 if rear-end collision, 0 otherwise	17334	72.6	7340	63.3				
Collision with animal	Crash type: 1 if collision with animal, 0 otherwise					128	1.7	503	4.5
Collision with ditch	Crash type: 1 if collision with ditch, 0 otherwise					526	7.0	1129	10.1
Location									
Far from home	Crash location: 1 if more than 40.2 km from driver residence, 0 otherwise	8213	34.4	7004	60.4	2756	36.7	7356	65.8

used. The X^2 statistic is chi-squared distributed with degrees of freedom equal to the sum of the number of estimated parameters in all subset models minus the number of estimated parameters in the full-sample model. The resulting X^2 statistic indicates whether or not the model for the subset data is significantly different than the model for the full-sample data.

Log-likelihood test was further performed to determine whether or not the subset models have parameters that are statistically different. The test statistic used is given by:

$$X^2 = -2[LL(\beta_T) - LL(\beta_k)], \tag{5}$$

where $LL(\beta_T)$ is the log-likelihood at convergence of the model estimated with all the data, $LL(\beta_k)$ is the log-likelihood at convergence of the model using subset k data. Based on the likelihood ratio tests performed, it was determined that four separate severity models were justified at 95% confidence level.

During model estimation, variables were included in the specification if they had t-statistics corresponding to the 90% confidence interval on a two-tailed t-test. The random parameters were also included if their standard deviations had t-statistics corresponding to the 90% confidence interval. Tables 3 and 4 present the modeling estimation results for the rural and urban multi-vehicle crashes and Tables 5 and 6 present the results of the single-vehicle crash models. The McFadden pseudo-ρ^2 values of all the models indicate good fits of the data. A wide variety of crash factors were found to be associated with the crash injury severity outcomes. In the urban area single-vehicle crash model, 15 crash factors each were found to be associated with the injury severity outcomes in both rural area and urban area single-vehicle crash models. For the urban area multi-vehicle model, 21 variables were found to be statistically significant whereas 18 variables were significant in the rural area multi-vehicle crash model.

Two random parameters were found to be statistically significant in the urban single-vehicle crash model (Friday indicator and winter indicator variables) and only one (wet roadway indicator) was found to be random the rural single-vehicle model. For the multi-vehicle crash models, four variables (Friday indicator, indicator for crashes that occurred between noon and 6PM, at-fault female driver indicator, and rear-end collision indicator) produced random parameters in the rural area model and two variables (rear-end collision and sideswipe indicator variables) were found to be random in the urban area model. Variables that produce random parameters indicate their varying influences on the injury severities. The normal distribution provided the best statistical fit for these random parameters. The effects of the rest of the crash factors were fixed across the crash samples.

Table 3. Mixed logit with heterogeneity in mean and variance estimation model for urban area multi-vehicle interstate crashes.

Variable	In severity function of	Parameter estimate	t-statistic	Marginal effects		
				Severe njury	Minor injury	No injury
Constant	Fatal/major injury	−2.85	−25.76			
Constant	No injury	1.35	15.95			
Primary contributing factors						
Speeding	Fatal/major injury	1.16	7.08	0.0022	−0.0004	−0.0018
DUI	Fatal/major injury	1.02	3.59	0.0006	−0.0001	−0.0005
Aggressive driving	Fatal/major injury	1.44	5.38	0.0010	−0.0002	−0.0008
Follow too close	Minor/possible injury	−0.26	−3.73	0.0002	−0.0078	0.0077
Lane changing	No injury	0.33	4.54	−0.0003	−0.0037	0.0040
Roadway features and condition						
Cable median	Fatal/major injury	0.63	3.33	0.0009	−0.0001	−0.0008
Unpaved median	Fatal/major injury	0.83	6.47	0.0032	−0.0004	−0.0027
Concrete median	No injury	−0.21	−4.37	0.0012	0.0096	−0.0108
Straight and level	Minor/possible injury	0.15	2.35	−0.0002	0.0105	−0.0103
Curve	No injury	0.19	2.24	−0.0003	−0.0020	0.0022
Ramp	Fatal/major injury	−0.63	−2.99	−0.0007	0.0001	0.0006
Temporal factors and lighting condition						
Weekend	Fatal/major injury	0.41	3.35	0.0016	−0.0002	−0.0013
Afternoon	No injury	0.13	2.62	−0.0008	−0.0056	0.0064
Dark/unlit	No injury	−0.36	−5.23	0.0012	0.0073	−0.0085
Driver and behavioral characteristics						
Female driver	Minor/possible injury	0.10	2.00	−0.0001	0.0040	−0.0039
Invalid license	Fatal/major injury	0.82	6.16	0.0026	−0.0004	−0.0022
Younger driver	Fatal/major injury	−0.70	−5.11	−0.0019	0.0003	0.0017
No seatbelt	Minor/possible injury	0.95	4.90	−0.0001	0.0014	−0.0013
Vehicle type						
Motorcycle	No injury	−2.78	−10.72	0.0007	0.0011	−0.0017
Crash type						
Sideswipe	No injury	0.94	13.95	−0.0012	−0.0161	0.0173
Random parameter						
Rear-end collision	Minor/possible injury	−1.18	−3.88	−0.0003	0.0201	−0.0198
Standard deviation of "Rear-end collision"		2.35	4.80			
Heterogeneity in means of random parameter						
Rear-end collision: Daylight		−0.29	−2.43			
Heterogeneity in variance in random parameter						
Rear-end collision: SUV		−0.09	−1.78			
Model fit statistics						
Number of observations		23,876				
Log likelihood constants		−26230.47				
Log likelihood at convergence		−12378.32				
McFadden pseudo-ρ^2		0.53				

The Friday variable defined for minor injury in the urban single-vehicle model was found to produce a random parameter with a mean of −0.76 and standard deviation of 1.51. This indicates that for 30.7% of urban single-vehicle crashes that occurred on Fridays, the probability of minor injury is low, whereas for the remaining 69.3% of the crashes the likelihood of minor injury is high. This shows that the likelihood of minor injury for single vehicle crashes in urban settings is generally low. Two variables (icy road and crash location more than 40.2 km (25 mi) from the causal driver's home) produced significant heterogeneity in the mean of the "Friday" random parameter. The results indicate that crashes that occurred on icy

Table 4. Mixed logit estimation model for rural area multi-vehicle interstate crashes.

Variable	In severity function of	Parameter estimate	t-statistic	Marginal effects: Severe injury	Minor injury	No injury
Constant	Severe injury	−0.85	−6.62			
Constant	No injury	2.18	19.42			
Primary contributing factors						
Speeding	Severe injury	0.75	5.66	0.0045	−0.0007	−0.0038
DUI	Severe injury	0.96	5.76	0.0036	−0.0006	−0.0030
Aggressive driving	Severe injury	1.55	6.65	0.0028	−0.0005	−0.0023
Lane changing	No injury	0.74	7.88	−0.0034	−0.0086	0.0121
Roadway features and condition						
Unpaved median	Severe injury	0.46	5.35	0.0107	−0.0016	−0.0091
Ramp	Severe injury	−0.91	−3.47	−0.0012	0.0002	0.0010
Straight and level	Minor injury	0.25	3.11	−0.0012	0.0136	−0.0124
Temporal factors and lighting condition						
Friday	Minor injury	−0.95	−1.90	−0.0002	0.0041	−0.0039
Standard deviation of "Friday"		1.95	2.68			
Summer	Minor injury	0.20	2.31	−0.0004	0.0047	−0.0043
Afternoon	No injury	0.45	2.47	0.0034	−0.0030	−0.0005
Standard deviation of "Afternoon"		1.04	2.96			
Dark/unlit	No injury	−0.62	−7.96	0.0093	0.0138	−0.0231
Driver and behavioral characteristics						
Younger driver	Severe injury	−0.23	−2.31	−0.0028	0.0004	0.0024
Adult driver	Minor injury	0.13	1.63	−0.0004	0.0045	−0.0041
Female driver	Minor injury	−0.35	−0.94	0.0117	−0.0461	0.0344
Standard deviation of "Female driver"		1.61	2.58			
Invalid license	Minor injury	0.25	1.86	−0.0002	0.0019	−0.0017
Crash type						
Rear-end collision	Minor injury	−0.60	−1.45	−0.0025	0.0409	−0.0384
Standard deviation of "Rear-end collision"		2.09	3.49			
Vehicle type						
Motorcycle	No injury	−3.62	−6.72	0.0008	0.0006	−0.0014
Location						
Far from home	Severe injury	0.16	1.80	0.0052	−0.0008	−0.0044
Model fit statistics						
Number of observations			11,596			
Log likelihood at zero	−12739.51					
Log likelihood at convergence	−7073.46					
McFadden pseudo-ρ^2			0.44			

roadway sections and those that occurred far from the driver's home on Fridays have increased likelihood to result in minor injury compared to crashes that occurred on dry roadway surface and crashes that occurred close to the home of the causal driver. The winter indicator variable defined for minor injury in the urban area single-vehicle crash model had a mean of −1.80 and standard deviation of 3.63. This implies that for 31% of the urban single-vehicle crashes that occurred during winter seasons, the probability of recording a minor injury is low while the chance of minor injury is high for the remaining 69% of the crashes. This shows that there is a high chance of minor injury in urban area single-vehicle crashes. The indicator variables for icy roadway surface and crash location more than 40.2 km (25 mi) from home of the causal driver also produced heterogeneity in mean of the winter random variable. These heterogeneity variables reduce the mean of the winter random variable, indicating that crashes that

Table 5. Mixed logit with heterogeneity in means estimation model for urban area single-vehicle interstate crashes.

Variable	In severity function of	Parameter estimate	t-statistic	Marginal effects: Severe injury	Minor injury	No injury
Constant	Fatal/major injury	−1.79	−22.51			
Constant	No injury	1.00	13.34			
Primary contributing factors						
Speeding	Fatal/major injury	−0.78	−4.86	−0.0048	0.0009	0.0039
Aggressive driving	Fatal/major injury	0.99	3.82	0.0021	−0.0006	−0.0015
DUI	Fatal/major injury	0.27	1.75	0.0006	−0.0002	−0.0004
Roadway features and condition						
Unpaved median	Fatal/major injury	0.48	3.90	0.0059	−0.0014	−0.0045
Cable median	No injury	0.18	1.97	−0.0007	−0.0029	0.0036
Wet roadway	Minor/possible injury	−0.42	−6.07	0.0013	−0.0223	0.0210
Temporal factors and lighting condition						
Friday	Minor/possible injury	−0.76	−1.66	0.0001	0.0012	−0.0013
Standard deviation of "Friday"		1.51	1.88			
Heterogeneity in means of random parameter						
Friday: Icy road		1.84	1.93			
Friday: Far from home		0.06	2.24			
Random parameter						
Winter	Minor/possible injury	−1.80	−2.42	−0.0003	0.0106	−0.0103
Standard deviation of "Winter"		3.63	3.24			
Heterogeneity in means of random parameter						
Winter: Icy road		−1.39	−2.43			
Winter: Far from home		−0.54	−1.68			
Dawn	No injury	−0.13	−1.64	0.0009	0.0031	−0.0040
Dark/unlit	No injury	0.24	2.43	−0.0011	−0.0034	0.0045
Driver and behavioral characteristics						
Invalid license	Minor/possible injury	0.45	1.72	−0.0001	0.0010	−0.0009
No seatbelt	No injury	−2.32	−14.39	0.0052	0.0085	−0.0137
Male driver	No injury	0.25	4.07	−0.0052	−0.0188	0.0240
Crash type						
Collision with animal	Minor/possible injury	−3.96	−3.39	0.0001	−0.0009	0.0008
Location						
Close to home	No injury	−0.28	−4.19	0.0034	0.0110	−0.0144
Model fit statistics						
Number of observations		7509				
Log likelihood constants		−8249.48				
Log likelihood at convergence		−5164.54				
McFadden pseudo-ρ^2		0.37				

occurred on icy roadways and those that occurred far from the home of the causal driver were less likely to result in minor injury. Similarly, interpretation of the mean and standard deviation values for the wet roadway indicator variable defined for minor injury in the rural single vehicle-crash model, reveal a decrease in the probability of minor injury in 25.9% of the crashes while the variable increases the likelihood of minor injury in the remaining 74.1% of the crashes. The collision with a tree indicator variable and the female driver variable produced significant heterogeneity in mean and variance of the wet roadway random variable. Wet road single-vehicle crashes that resulted in collision with a tree in rural areas were more likely to result in minor injury and female drivers increase the variance of the wet road indicator variable. For the multi-vehicle crash models, the Friday indicator variable was found to decrease the likelihood of minor injury for

Table 6. Mixed logit with heterogeneity in mean and variance estimation model for rural area single-vehicle interstate crashes.

Variable	In severity function of	Parameter estimate	t-statistic	Marginal effects: Severe injury	Marginal effects: Minor injury	Marginal effects: No injury
Constant	Fatal/major injury	−1.03	−14.69			
Constant	No injury	1.4	22.25			
Primary contributing factors						
Speeding	Fatal/major injury	−0.32	−3.11	−0.0035	0.0006	0.0030
Aggressive driving	Fatal/major injury	1.36	5.31	0.0019	−0.0005	−0.0014
DUI	Minor/possible injury	0.36	3.19	−0.0004	0.0025	−0.0020
Roadway features and condition						
Unpaved median	Fatal/major injury	0.67	8.39	0.0251	−0.0051	−0.0200
Cable median	No injury	0.30	4.49	−0.0021	−0.0059	0.0080
Straight and level	No injury	0.17	3.25	−0.0054	−0.0103	0.0156
Wet roadway	Minor/possible injury	−0.80	−2.32	−0.0135	−0.0639	0.0774
Standard deviation of "Wet roadway"		1.24	2.63			
Heterogeneity in mean of random parameter						
Wet roadway: Collision with tree		0.30	1.75			
Heterogeneity in variance in random parameter						
Wet roadway: Female driver		0.29	1.82			
Temporal factors and lighting condition						
Weekend	No injury	−0.11	−2.11	0.0018	0.0037	−0.0055
Dawn	No injury	−0.11	−1.73	0.0011	0.0021	−0.0032
Winter	No injury	0.13	2.17	−0.0016	−0.0030	0.0045
Driver and behavioral characteristics						
No seatbelt	No injury	−2.40	−20.81	0.0066	0.0119	−0.0185
Male driver	No injury	0.25	4.57	−0.0079	−0.0153	0.0232
Invalid license	Minor/possible injury	0.76	3.49	−0.0002	0.0014	−0.0012
Crash type						
Collision with animal	Minor/possible injury	−1.50	−5.95	0.0002	−0.0023	0.0020
Collision with ditch	Fatal/major injury	−1.07	−6.11	−0.0032	0.0007	0.0025
Model fit statistics						
Number of observations		11179				
Log likelihood constants		−12281.39				
Log likelihood at convergence		−7004.72				
McFadden pseudo-ρ^2		0.43				

31.3% of the crashes that occurred in rural areas, whereas for the remaining 68.7% of the crash observations, the Friday variable increased the chances of minor injury. This indicates that for multi-vehicle crashes that occurred in rural areas of the state, the chances of minor injury was high. For multi-vehicle crashes that occurred between noon and 6PM in rural areas, the likelihood of no injury was higher in 66.7% of the crashes while the chances for some form of injury was high in the remaining 33.3% of the crashes. Also, 41.4% multi-vehicle crashes that involved an at-fault female driver in rural areas were less likely to result in minor injury, meaning that for the remainder of the crashes involving at-fault female drivers the likelihood of minor injury was high. Finally, the rear-end collision indicator defined for minor injury outcome in both urban and rural multi-vehicle crash models reveal that minor injury was less probable in 38.7% of the rural area crashes and 28.3% of the urban area crashes. These findings show that minor injury outcome was more likely in 61.3% and 70.2% of rural and urban multi-vehicle crashes, respectively. Daylight variable produced a significant heterogeneity in mean of the rear-end collision indicator for the urban area multi-vehicle model while the SUV indicator variable was found to produce a significant heterogeneity in variance. For the remaining fixed variables, those with similar attributes are grouped together, compared among models, and discussed accordingly.

4.1. Primary contributory factors

Some of the variables were significant in both urban and rural multi-vehicle crash models. For instance, the speeding indicator variable was found to be significant in both models with a fixed effect for severe injury outcome. Table 3 shows that for urban multi-vehicle crash model, the probability of severe injury increases by 0.0022 and the probabilities of minor injury and no injury decrease by 0.0004 and 0.0018, respectively when the crash involved speeding. This finding is similar for the rural multi-vehicle crash model, where the speeding indicator variable was found to increase the probability of severe injury by 0.0045 and decrease the probabilities of minor injury and no injury by 0.0007 and 0.0038. The marginal effects show that the likelihood of interstate highway speed-related severe injury outcome is relatively higher in rural areas than urban settings. The model estimation results show that the indicator variable for speeding decreased the probability of severe injury by 0.0048 and 0.0035 in the urban and rural single-vehicle models, respectively. This means that major injury outcome from speeding for single-vehicle crashes is lower in rural areas. The DUI indicator variable was found to increase the likelihood of severe injury by 0.0006 and 0.0036 for urban and rural multi-vehicle crashes, respectively. Here again, the marginal effects show a higher increase in probability of severe injury outcome for DUI crashes that occurred in rural areas. The DUI indicator variable was also found to be significant in the single-vehicle crash models where it was observed to increase the likelihood of minor injury outcome by 0.0025 in rural areas and increase the probability of severe injury by 0.0006 in urban areas. The probability of a severe injury crash involving aggressive driving was higher for multi-vehicle collisions in urban areas than rural areas. The results also show that the variable for aggressive driving increased the probability of single-vehicle severe injury outcome by 0.0021 and 0.0019 in urban and rural areas, respectively, making severe injury comparatively more likely in urban areas. Lane changing showed a similar pattern for both urban and rural multi-vehicle crashes with fixed effect for no injury. The lane changing variable reveals that interstate crashes that involve lane changing were generally less likely to result in any form of injury. Further, the indicator variable for following too close was significant for the urban multi-vehicle crash model with fixed effect for minor injury. The marginal effects show that the probability of severe injury increased by 0.0002 for urban area crashes in which the at-fault driver was tailgating.

4.2. Roadway features and conditions

With respect to interstate opposing lane separation, the unpaved median variable was found to increase the probability of severe injury by 0.0032 and 0.0107 for urban and rural multi-vehicle collisions, respectively. This indicates that crashes that happen at interstate sections where the opposing lane separation is unpaved were more likely to result in severe injury in rural areas. Also, severe and minor injury outcomes were more likely to be recorded on interstate sections that have concrete median as the opposing lane separation in urban areas. Minor injury outcome was found to be more likely for crashes that occurred on straight and flat sections of interstates in both urban and rural areas. Similarly, crashes that occurred at ramp entrance or exit were observed to be more associated with minor injury in both urban and rural areas of the state, with the probability of minor injury outcome being higher in rural areas. The curved roadway section variable was found to be significant in only the urban multi-vehicle crash model, where it was observed to be less associated with injury outcomes.

The model estimation results show that the unpaved median indicator variable increased the likelihood of severe injury by 0.0251 for single-vehicle crashes that occurred in rural areas compared to an increase in probability of 0.0059 for single-vehicle crashes in urban settlements. The cable median indicator variable was found to increase the likelihood of no injury outcome in both urban and rural areas by 0.0036 and 0.0080 respectively. This finding indicates that interstate highway locations that have cable barrier as opposing lane separation had lower chances of recording injury-related single-vehicle crashes. In urban areas, single vehicle crashes that happened on wet roadways were more likely to lead to severe injury outcomes. The wet indicator variable was however significant in only the urban area model. With respect to the roadway curvature, the straight and flat roadway variable was found to increase the probability of no injury by 0.0156 in rural areas while the likelihood of injury outcomes was lower.

4.3. Crash types

The manner of multi-vehicle collisions influences the outcome of the crash. The findings from this study show that rear-end crashes that occurred in urban areas were more likely to result in an injury outcome. In fact, the marginal effects reveal that there was 0.0201 increase in the probability that the crash resulted in minor injury. Rear-end crashes that happened in rural areas were also more likely to record minor injury outcome. The sideswipe crash indicator variable was significant in the urban multi-vehicle crash model only. The results show that crashes involving sideswipe on urban sections of the interstates were less likely to record any form of injury. The results also show that collision with animal indicator for the urban area single-vehicle crash model decreased the probability of minor injury by 0.0009 compared to 0.0023 in rural areas but increased the probability of severe injury outcome marginally by 0.0001 and 0.0002 in urban and rural areas, respectively. It was further observed that the collision with ditch indicator variable reduces the likelihood of severe injury by 0.0032 but increased the probability of minor injury by 0.0007 for single-vehicle crashes in rural settlements.

4.4. Driver and behavioral characteristics

The female driver variable was significant in both urban and rural multi-vehicle crash models. The results show that in urban areas, crashes involving at-fault female drivers were more likely to result in minor injury, with an increase in probability of 0.004. However, crashes involving at-fault female drivers in rural multi-vehicle collisions on interstates had 0.0117 higher probability to result in severe injury. Younger drivers were found to more likely be involved in minor injury crashes in both urban and rural area multi-vehicle crashes. Adult drivers that were at fault in multi-vehicle crashes were also more likely to sustain minor injury. The adult driver indicator variable was however found to be significant in the rural area model only. The invalid license status variable showed different injury outcome associations for urban and rural multi-vehicle crashes. For the urban crash model, the indicator variable for invalid license increased the probability of severe injury outcome by 0.0026, whereas in the rural area model, this variable decreased the probability of severe injury but increased the likelihood of minor injury by 0.0019. The no seatbelt use variable was significant in only the urban multi-vehicle crash model. The results show that the probability of minor injury outcome for crashes in which the at-fault driver failed to wear a seatbelt was 0.0014 higher, though the chances of severe injury outcome is significantly lower. The variable for crash location more than 40.2 km (25 mi) away from the residence of the at-fault driver was only significant for the rural multi-vehicle crash model. This variable increased the probability of severe injury outcome by 0.0052, indicating that crashes that involved drivers that were far away from home were more likely to result in severe injury.

For the single-vehicle models, the model estimation results show that the indicator variable for invalid license increased the probability of minor injury by 0.0010 and 0.0014 in the urban and rural area models, respectively. This finding indicates that the probability of minor injury is marginally higher in rural areas for at-fault drivers who did not have a valid license at the time of the crash. The study also found that the variable for no seatbelt decreased the probability of no injury by 0.0137 and 0.0185 in urban and rural areas, respectively. This means that the likelihood of sustaining injury is higher when the at-fault driver did not use a seatbelt. In fact, the probability of severe injury increased by 0.0052 in urban areas and 0.0064 in rural areas. This further indicates that single-vehicle crashes in rural areas were marginally more likely to result in severe injury outcome. Single-vehicle crashes involving at-fault male drivers were found to generally have lower chances of leading to injury. The variable for crash location less than 40.2 km away from the residence of the at-fault driver was significant for the urban single-vehicle crash model. This variable increased the probability of no severe outcome by 0.0034, indicating that single-vehicle crashes that happened on urban interstates that involved drivers that were closer to home were more likely to result in injury.

4.5. Temporal factors and lighting conditions

The weekend indicator variable was significant in the urban multi-vehicle crash model whereas Friday indicator variable was found to be significant in the rural model. Crashes that occurred during weekends were observed to have increased probability of recording severe injury in urban areas. On the other hand, crashes that occurred on Fridays in rural areas were more likely to record minor but not severe injuries. Interstate multi-vehicle crashes that occurred between noon and 6PM were less likely to result in any form of injury in urban areas. However, in rural areas, the probability of severe injury for crashes that occurred between noon and 6PM increased by 0.0034. The summer variable was significant for only the rural multi-vehicle crash model. The model estimation results show that crashes that occurred during summer months had 0.0047 higher probability of minor injury in rural areas. The dark and unlit roadway section variable showed a similar pattern for both urban and rural crash models. This variable increased the probability of severe injury and minor injury by 0.0012 and 0.0075, respectively under urban settings. For the rural multi-vehicle crash model, the dark and unlit variable increased the probability of severe and minor injuries by 0.0093 and 0.0138, respectively. These findings show that multi-vehicle crashes that happen under dark and unlit roadway conditions on interstates were more likely to record some form of injury in both urban and rural areas. The marginal effects indicate that the chances of injury are higher in rural areas than urban settings.

For the single-vehicle models, the winter season indicator variable was found to be significant in both urban and rural areas. This variable increased the probability of minor injury by 0.0106 in the urban area model but decreased the likelihood of any injury outcome in the rural area model. The results also reveal that the probabilities of severe injury and minor injury outcomes for single vehicle crashes that occurred during weekends in rural areas are respectively higher by 0.0018 and 0.0037. On the other hand, the Friday indicator variable was significant in the urban area model, where it was found to increase the chances of severe injury and minor injury outcomes by 0.0001 and 0.0012, respectively. The dark and unlit roadway indicator variable was found to increase the likelihood of no injury outcome in urban areas by 0.0045, indicating that single-vehicle crashes that occurred in urban areas under dark and unlit roadway conditions were less likely to result in injury. However, single-vehicle crashes that happened between midnight and 6AM were more likely to result in some form of injury in both urban and rural areas.

4.6. Vehicle characteristics

The study considered motorcycles as the only vehicle category for modeling purposes due to their vulnerability in multi-vehicle crashes. Although less than 0.5% of the multi-vehicle interstate crashes involved motorcycles, there was a similar injury outcome pattern for both urban and rural areas. The motorcycle indicator variable increased the probability of severe injury and minor injury by 0.0007 and 0.0011, respectively in urban areas. On the other hand, the motorcycle variable increased the probability of severe and minor injuries by 0.0008 and 0.0006, respectively in rural areas. The marginal effects show that the chances of severe injury outcome involving motorcycles is slightly higher on interstate sections that go through rural areas of the state.

5. Discussions

Evidence from previous studies suggest that speeding increases the severity of crashes. This is particularly so on interstate highways where the posted speed limits are generally high (Renski et al., 1999; Shinar, 1998). Findings from this study generally confirm this evidence as the model estimation results show that the likelihood of speed-related severe injury outcome is high in multi-vehicle crashes with the likelihood being relatively higher in rural areas than urban settings. However, for probability of severe injury is low for single-vehicle crashes. The results show that minor injury outcome is highly probable in speed-related single vehicle crashes in both urban and rural areas in the state. Several studies have documented the role of DUI in crash occurrence and crash injury severity (e.g., Abdel-Aty, 2003; Dabbour, 2017; Tavris, Kuhn, & Layde, 2001). Further, studies have found a high proportion of severe injury crashes involving single-vehicle crashes to have a good chance to be DUI-related (e.g., Adanu, Smith, Powell, & Jones, 2017; Ostrom & Eriksson, 1993; Schneider, Savolainen, & Zimmerman, 2009). Consistent with previous studies, this study revealed that interstate crashes that involved DUI significantly resulted in either severe injury or minor injury. Aggressive driving was found to be significantly associated with severe injury outcome regardless of the manner and location of the crash. This finding is also consistent with previous studies that have also found a strong correlation between aggressive driving and severe injury crash outcome (Chliaoutakis et al., 2002; Dahlen, Edwards, Tubré, Zyphur, & Warren, 2012; Islam & Mannering, 2020; Paleti, Eluru, & Bhat, 2010). While failure to use seatbelt may not directly lead to crash occurrence, it certainly affects the severity of the crash outcome (Abdel-Aty, 2003; Chen & Chen, 2011; Kim et al., 2013) and also reveal risk-taking behavior of drivers. In this study, the probability of injury was higher for crashes in which the driver failed to wear a seatbelt. Failure to use seatbelt was observed to be high in single-vehicle crashes. The marginal effects results also show that the probability of a severe injury outcome increased when the at-fault driver had no driver's license. This finding is consistent with observations from past researches (e.g. Adanu et al., 2018; Blows, Ameratunga, Ivers, Lo, & Norton, 2005).

Table 1 showed that the highest proportion of interstate crashes occurred in rural areas, with single-vehicle crashes accounting for most of these crashes. This trend in the crash data is similar to findings from Xie, Zhao, and Huynh (2012) where it was observed that fatal injury single-vehicle crashes occurred more often in rural areas. Dabbour (2017) found that severe injuries are associated with rural roads under dark and unlit roadway condition. Findings from this study reveal a similar trend. The results show that dark and unlit sections of the highways are prone to severe injury crashes. This is particularly the case for interstate sections that pass through rural areas of the state. Weekends and Fridays were found to be times that recorded severe injury crashes on interstates across the state. This study also observed that a higher proportion of the single vehicle crashes occurred between midnight and 6AM and the model estimation results show that these crashes were more likely to result in some form of injury. Further, considering that nearly half (47.2% for rural areas and 49.7% for urban areas) of the multi-vehicle crashes occurred within this time window, these findings provide evidence for increased law enforcement during these time frames and particularly along the stretch of interstate highways that pass through rural areas in the state. Engineering countermeasures such as guardrails to prevent collision with roadside features and grade separation for safe animal crossings may become necessary as crashes that involved collision with animals and collisions with ditch were observed to be associated with severe injury outcome.

Ultimately, the findings from this study reveal some risky road user behaviors that increase the occurrence and severity of interstate crashes in the state. This calls for a comprehensive road user education and road safety campaign across the state. An effective strategy could involve disseminating road safety information through print and electronic media to ensure that all age groups of road users are targeted. Additionally, since speed calming measures may not be appropriate on interstate highways, frequent message signs, such as variable message signs, may be designed and placed along highways to caution drivers about engaging in risky driving behaviors. Alternatively, speed cameras can be placed at locations that have been identified to record the high number of severe injury crashes, such as highway sections that have unpaved median as opposing lane separation, to deter drivers from engaging in risky behaviors and to punish those that do.

6. Conclusions

This paper presents a comprehensive injury severity analysis of interstate crashes in Alabama. The study was based on 2015-2018 Alabama crash data obtained from the Critical Analysis Reporting Environment (CARE) system developed by the Center for Advanced Public Safety at the University of Alabama. A total of 54,160 observed interstate crashes were used in this study. The data was categorized into four based on the location and manner of collision as urban multi-vehicle, rural multi-vehicle, urban single-vehicle, and rural single-vehicle, and explored accordingly. Preliminary data analysis revealed that the highest proportion of the total interstate crashes (44.1%) were urban multi-vehicle collisions, followed by rural multi-vehicle collisions (21.4%). Rural single-vehicle crashes made up 20.6% of the total crashes and urban single-vehicle crashes constituted the least, making up 13.9% of the crash observations. Four random parameters multinomial logit models were developed to investigate how various factors are associated with crash outcomes in each crash data subset.

The model estimation results show that some driver behavioral factors such as speeding, aggressive driving, DUI, failure to use seatbelt, and driving without a valid license were found to significantly contribute to some form of injury outcome. The influence of roadway features such as type of opposing lane separation, collision type, temporal and lighting conditions on crash outcomes were also explored. Some differences and similarities in the associations between these factors and crash injury severity based on the manner and location of crash were unraveled. For instance, aggressive driving was found to be associated with severe injury outcome under all the scenarios considered, while speeding was found to increase the likelihood of severe injury in multi-vehicle collisions but not in single-vehicle collisions. Similarly, dark unlit roadway sections were associated with severe injury in multi-vehicle collisions but not in urban single-vehicle collisions.

The findings from the study provide some basis for countermeasure implementation. For instance, the findings that point to a high correlation between risky driver behavior and severe injury outcome call for a comprehensive road user education and road safety campaign across the state. Media strategies may be employed to disseminate safety information and policies to road users. Additionally, law enforcement may be intensified along roadway sections and time periods that have been found to be prone to a high number of crashes. Also, speed cameras may be installed at roadway sections that may be difficult for state troopers to frequently patrol.

Acknowledgements

The authors would like to thank the Center for Advanced Public Safety (CAPS) at the University of Alabama for providing the crash data used for this study. The authors would also thank the Alabama Transportation Institute (ATI) for supporting this study.

Declaration of interests

The authors declare no conflict of interests in the conduct of this study

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

Adanu, E. K., Hainen, A., & Jones, S. (2018). Latent class analysis of factors that influence weekday and weekend single-vehicle crash severities. *Accident; Analysis and Prevention*, *113*, 187–192. doi:10.1016/j.aap.2018.01.035

Adanu, E. K., Smith, R., Powell, L., & Jones, S. (2017). Multilevel analysis of the role of human factors in regional disparities in crash outcomes. *Accident; Analysis and Prevention*, *109*, 10–17. doi:10.1016/j.aap.2017.09.022

Ahmed, M. M., Franke, R., Ksaibati, K., & Shinstine, D. S. (2018). Effects of truck traffic on crash injury severity on rural highways in Wyoming using Bayesian binary logit models. *Accident; Analysis and Prevention*, *117*(May), 106–113. doi:10.1016/j.aap.2018.04.011

Anastasopoulos, P. C., & Mannering, F. L. (2011). An empirical assessment of fixed and random parameter logit models using crash-and non-crash-specific injury data. *Accident Analysis & Prevention*, *43*(3), 1140–1147. doi:10.1016/j.aap.2010.12.024

Baum, H. M., Wells, J. K., & Lund, A. K. (1990). Motor vehicle crash fatalities in the second year of 65 mph speed limits. *Journal of Safety Research*, *21*(1), 1–8. doi:10.1016/0022-4375(90)90042-A

Behnood, A., & Mannering, F. (2017). Determinants of bicyclist injury severities in bicycle-vehicle crashes: A random parameters approach with heterogeneity in means and variances. *Analytic Methods in Accident Research*, *16*, 35–47. doi:10.1016/j.amar.2017.08.001

Bhat, C. R. (2003). Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. *Transportation Research Part B: Methodological*, *37*(9), 837–855. doi:10.1016/S0191-2615(02)00090-5

Blows, S., Ameratunga, S., Ivers, R. Q., Lo, S. K., & Norton, R. (2005). Risky driving habits and motor vehicle driver injury. *Accident Analysis & Prevention*, *37*(4), 619–624. doi:10.1016/j.aap.2005.03.003

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

Chen, S., Saeed, T. U., Alinizzi, M., Lavrenz, S., & Labi, S. (2019). Safety sensitivity to roadway characteristics: A comparison across highway classes. *Accident; Analysis and Prevention*, *123*, 39–50. doi:10.1016/j.aap.2018.10.020

Chen, S., Saeed, T. U., & Labi, S. (2017). Impact of road-surface condition on rural highway safety: A multivariate random parameters negative binomial approach. *Analytic Methods in Accident Research*, *16*, 75–89. doi:10.1016/j.amar.2017.09.001

Chen, C., Zhang, G., Liu, X. C., Ci, Y., Huang, H., Ma, J., Chen, Y., & Guan, H. (2016). Driver injury severity outcome analysis in rural interstate highway crashes: A two-level Bayesian logistic regression interpretation. *Accident; Analysis and Prevention*, *97*, 69–78. doi:10.1016/j.aap.2016.07.031

Chliaoutakis, J. E., Demakakos, P., Tzamalouka, G., Bakou, V., Koumaki, M., & Darviri, C. (2002). Aggressive behavior while driving as predictor of self-reported car crashes. *Journal of Safety Research*, *33*(4), 431–443. doi:10.1016/S0022-4375(02)00053-1

Dabbour, E. (2017). Investigating temporal trends in the explanatory variables related to the severity of drivers' injuries in single-vehicle collisions. *Journal of Traffic and Transportation Engineering (English Edition))*, *4*(1), 71–79. doi:10.1016/j.jtte.2016.03.010

Dahlen, E. R., Edwards, B. D., Tubré, T., Zyphur, M. J., & Warren, C. R. (2012). Taking a look behind the wheel: An investigation into the personality predictors of aggressive driving. *Accident; Analysis and Prevention*, *45*, 1–9. doi:10.1016/j.aap.2011.11.012

Eluru, N., Bhat, C. R., & Hensher, D. A. (2008). A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. *Accident; Analysis and Prevention*, *40*(3), 1033–1054. doi:10.1016/j.aap.2007.11.010

Garber, N. J., Chowdhury, M. A., & Kalaputapu, R. (1992). Accident characteristics of large trucks on highway ramps. Washington DC: AAA Foundation for Traffic Safety.

Garber, S., & Grahman, J. D. (1990). The effects of the new 65 mile-per-hour speed limit on rural highway fatalities: A state-by-state analysis. *Accident; Analysis and Prevention*, *22*(2), 137–149. doi:10.1016/0001-4575(90)90065-s

Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological*, *37*(8), 681–698. doi:10.1016/S0191-2615(02)00046-2

Greene, W. H., & Hensher, D. A. (2013). Revealing additional dimensions of preference heterogeneity in a latent class mixed multinomial logit model. *Applied Economics*, *45*(14), 1897–1902. doi:10.1080/00036846.2011.650325

Haleem, K., & Gan, A. (2013). Effect of driver's age and side of impact on crash severity along urban freeways: A mixed logit approach. *Journal of Safety Research*, *46*, 67–76. doi:10.1016/j.jsr.2013.04.002

Halton, J. H. (1960). On the efficiency of certain quasi-random sequences of points in evaluating multi-dimensional integrals. *Numerische Mathematik*, *2*(1), 84–90. doi:10.1007/BF01386213

Islam, S., Jones, S. L., & Dye, D. (2014). Comprehensive analysis of single-and multi-vehicle large truck at-fault crashes on rural and urban roadways in Alabama. *Accident Analysis & Prevention*, *67*, 148–158. doi:10.1016/j.aap.2014.02.014

Islam, M., & Mannering, F. (2020). A temporal analysis of driver-injury severities in crashes involving aggressive and non-aggressive driving. *Analytic Methods in Accident Research*, *27*, 100128. doi:10.1016/j.amar.2020.100128

Joksch, H. C. (1993). Velocity change and fatality risk in a crash–a rule of thumb. *Accident Analysis & Prevention*, *25*(1), 103–104. doi:10.1016/0001-4575(93)90102-3

Jung, S., Qin, X., & Noyce, D. A. (2010). Rainfall effect on single-vehicle crash severities using polychotomous response models. *Accident; Analysis and Prevention*, *42*(1), 213–224. doi:10.1016/j.aap.2009.07.020

Kim, J. K., Ulfarsson, G. F., Kim, S., & Shankar, V. N. (2013). Driver-injury severity in single-vehicle crashes in California: A mixed logit analysis of heterogeneity due to age and gender. *Accident; Analysis and Prevention*, *50*, 1073–1081. doi:10.1016/j.aap.2012.08.011

Ma, X., Chen, S., & Chen, F. (2017). Analytic methods in accident research multivariate space-time modeling of crash frequencies by injury severity levels. *Analytic Methods in Accident Research*, *15*, 29–40. doi:10.1016/j.amar.2017.06.001

Mannering, F. L., & Bhat, C. R. (2014). Analytic methods in accident research: Methodological frontier and future directions. *Analytic Methods in Accident Research*, *1*, 1–22. doi:10.1016/j.amar.2013.09.001

Mannering, F. L., Shankar, V., & Bhat, C. R. (2016). Unobserved heterogeneity and the statistical analysis of highway accident data. *Analytic Methods in Accident Research*, *11*, 1–16. doi:10.1016/j.amar.2016.04.001

McCarthy, P. (1998). Effect of speed limits on speed distributions and highway safety: A survey of the literature. In *Special Report 254: Managing Speed: Review of Current Practice for Setting and Enforcing Speed Limits*. Washington DC: TRB, National Research Council.

McFadden, D. (1981). Econometric models of probabilistic choice. *Structural Analysis of Discrete Data with Econometric Applications*, *14*, 198–272.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, *15*(5), 447–470. doi:10.1002/1099-1255(200009/10)15:5<447::AID-JAE570>3.0.CO;2-1

Milton, J. C., Shankar, V. N., & Mannering, F. L. (2008). Highway accident severities and the mixed logit model: An exploratory empirical analysis. *Accident; Analysis and Prevention*, *40*(1), 260–266. doi:10.1016/j.aap.2007.06.006

Morgan, A., & Mannering, F. L. (2011). The effects of road-surface conditions, age, and gender on driver-injury severities. *Accident; Analysis and Prevention*, *43*(5), 1852–1863. doi:10.1016/j.aap.2011.04.024

Öström, M., & Eriksson, A. (1993). Single-vehicle crashes and alcohol: A retrospective study of passenger car fatalities in northern Sweden. *Accident; Analysis and Prevention*, *25*(2), 171–176. doi:10.1016/0001-4575(93)90057-4

Paleti, R., Eluru, N., & Bhat, C. R. (2010). Examining the influence of aggressive driving behavior on driver injury severity in traffic crashes. *Accident; Analysis and Prevention*, *42*(6), 1839–1854. doi:10.1016/j.aap.2010.05.005

Renski, H., Khattak, A. J., & Council, F. M. (1999). Effect of speed limit increases on crash injury severity: Analysis of single-vehicle crashes on North Carolina interstate highways. *Transportation Research Record: Journal of the Transportation Research Board*, *1665*(1), 100–108. doi:10.3141/1665-14

Savolainen, P. T., Mannering, F. L., Lord, D., & Quddus, M. A. (2011). The statistical analysis of highway crash-injury severities: A review and assessment of methodological alternatives. *Accident; Analysis and Prevention*, *43*(5), 1666–1676. doi:10.1016/j.aap.2011.03.025

Schneider, W. H., Savolainen, P. T., & Zimmerman, K. (2009). Driver injury severity resulting from single-vehicle crashes along horizontal curves on rural two-lane highways. *Transportation Research Record: Journal of the Transportation Research Board*, *2102*(1), 85–92. doi:10.3141/2102-11

Seraneeprakarn, P., Huang, S., Shankar, V., Mannering, F., Venkataraman, N., & Milton, J. (2017). Occupant injury severities in hybrid-vehicle involved crashes: A random parameters approach with heterogeneity in means and variances. *Analytic Methods in Accident Research*, *15*, 41–55. doi:10.1016/j.amar.2017.05.003

Shaheed, M. S., & Gkritza, K. (2014). A latent class analysis of single-vehicle motorcycle crash severity outcomes. *Analytic Methods in Accident Research*, *2*, 30–38. doi:10.1016/j.amar.2014.03.002

Shinar, D. (1998). Speed and crashes: A controversial topic and an elusive relationship. Appendix B in: Managing speed: Review of current practice for setting and enforcing speed limits. *Special Report 254. Transportation Research Board TRB, Committee for Guidance on Setting and Enforcing Speed Limits*. Washington DC: National Academy Press.

Solomon, D. (1964). Accidents on main rural highways related to speed. *Driver, and Vehicle*, *23*.

Tavris, D. R., Kuhn, E. M., & Layde, P. M. (2001). Age and gender patterns in motor vehicle crash injuries: Importance of type of crash and occupant role. *Accident; Analysis and Prevention*, *33*(2), 167–172. doi:10.1016/s0001-4575(00)00027-0

U.S. Department of Transportation. (2014). *Highway statistics series, Alabama state statistical abstract*. Washington DC: Policy and Governmental Affairs, Office of highway policy information.

Venkataraman, N., Ulfarsson, G. F., & Shankar, V. N. (2013). Random parameter models of interstate crash frequencies by severity, number of vehicles involved, collision and location type. *Accident; Analysis and Prevention*, *59*, 309–318. doi:10.1016/j.aap.2013.06.021

Wang, H. L., & Shi, Z. K. (2013). Hierarchical regression model for truck collision severity analysis. In *Advanced materials research* (Vol. 671, pp. 2889–2892). Trans Tech Publications Ltd. doi:10.4028/www.scientific.net/AMR.671-674.2889

Washington, S., Karlaftis, M. G., Mannering, F., & Anastasopoulos, P. (2020). *Statistical and econometric methods for transportation data analysis*. Boca Raton: CRC press.

Xie, Y., Zhao, K., & Huynh, N. (2012). Analysis of driver injury severity in rural single-vehicle crashes. *Accident; Analysis and Prevention*, *47*, 36–44. doi:10.1016/j.aap.2011.12.012

Xiong, Y., & Mannering, F. L. (2013). The heterogeneous effects of guardian supervision on adolescent driver-injury severities: A finite-mixture random-parameters approach. *Transportation Research Part B: Methodological*, *49*, 39–54. doi:10.1016/j.trb.2013.01.002

Yasmin, S., Eluru, N., Bhat, C. R., & Tay, R. (2014). A latent segmentation based generalized ordered logit model to examine factors influencing driver injury severity. *Analytic Methods in Accident Research*, *1*, 23–38. doi:10.1016/j.amar.2013.10.002