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Role of Passengers in Single-Vehicle Drunk-Driving Crashes: An Injury-Severity Analysis

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Abstract: Background: Drunk-driving is a major crash risk factor, and crashes resulting from this risky behavior tend to be serious and have significant economic and societal impacts. The presence of passengers and their demographics and activities can influence risky driving behaviors such as drunk-driving. However, passengers could either be an "enabling" factor to take more risks or could be an "inhibiting" factor by ensuring safe driving by a drunk-driver. Objective: This study examines whether the presence of passengers affects the contributing factors of single-vehicle (SV) drunk-driving crashes, by presenting a severity analysis of single- and multi-occupant SV drunk-driving crashes, to identify risk factors that contribute to crash severity outcomes, for the effective implementation of relevant countermeasures. Method: A total of 7407 observations for 2012–2016 from the crash database of the State of Alabama was used for this study. The variables were divided into six classes: temporal, locational, driver, vehicle, roadway, and crash characteristics and injury severities into three: severe, minor, and no injury. Two latent class multinomial logit models—one each for single- and multi-occupant crashes—were developed, to analyze the effects of significant factors on injury severity outcomes using marginal effects. Results: The estimated results show that collision with a ditch, run-off road, intersection, winter season, wet roadway, and interstate decreased the probability of severe injuries in both single- and multi-occupant crashes, whereas rural area, road with downward grade, dark and unlit roadway, unemployed driver, and driver with invalid license increased the likelihood of severe injuries for both single- and multi-occupant crashes. Female drivers were more likely to be severely injured in single-occupant crashes, but less likely in multi-occupant crashes. A significant association was found between severe injuries and weekends, residential areas, and crash location close (<25 mi ≈40.23 km) to the residence of the at-fault driver in multi-occupant crashes. Sport utility vehicles were found to be safer when driving with passengers. Conclusions: The model findings show that, although many correlates are consistent between the single- and multi-occupant SV crashes that are associated with locational, roadway, vehicle, temporal, and driver characteristics, their effect can vary across the single- and multi-occupant driving population. The findings from this study can help in targeting interventions, developing countermeasures, and educating passengers to reduce drunk-driving crashes and consequent injuries. Such integrated efforts combined with engineering and emergency response may contribute in developing a true safe systems approach.

Keywords: drunk-driving; single-vehicle; passengers; single-occupant; multi-occupant; crash severity; latent class; DUI

1. Introduction

Globally, some 370,000 (of 900,000) annual alcohol-related deaths are attributable to road crashes; of these, 187,000 affect passengers, not drivers [1]. In the United States, drunk-driving or driving under the influence (DUI), is designated by the National Highway Traffic Safety Administration (NHTSA) as one of six key risky driving behaviors [2]. DUI is a major crash risk factor, and crashes resulting from this risky behavior tend to be serious and have significant economic and societal impacts [3,4]. Notably, some 29% of 2018 road fatalities in the U.S. were reported as attributable to driving under the influence (DUI) [5]. Although there was a reported 3.6% decrease in national DUI-related crashes from 2017 to 2018, the extent and significance of the problem has by no means diminished [6]. The economic cost of these fatalities has been estimated to be more than $50 billion annually [7].

Alcohol impairs the cognitive ability to react to driving situations and control of the vehicle during evasive measures, such as steering, braking, or accelerating under risky conditions [8,9]. Myriad previous studies have documented the role that DUI plays in crash frequency and severity [8,10–18]. A high proportion of DUI crashes are single-vehicle (SV) collisions, and they tend to be severe [8,10,15–17,19]. In 2016, about 30 percent of U.S. drivers involved in SV fatal crashes were impaired, compared to 12 percent in multi-vehicle fatal crashes [20]. Considering that passengers may also have some influence on SV drunk-driving crashes, this study examines the effects of passenger presence on injury severities, by identifying the similarities and differences among contributing factors of single- and multi-occupant crashes. A multi-occupant crash is when at least one passenger is present in the vehicle along with the driver at the time of the crash, whereas a single-occupant crash is when the driver is driving alone at the time of the crash.

2. Background

Other studies have addressed the role of passengers in crash outcomes [21–26], noting that the presence of passengers, their demographics, and activities while in the vehicle can influence risky driving behaviors. In particular, DUI crashes have been found to be socially influenced by passengers [22,23]. Specifically, family and friends who also engage in this risky practice have been found to be most influential on the behaviors of drunk-drivers [24]. The presence of these passengers (who might also be drunk in some cases) can induce fellow passengers and the drunk-drivers to underestimate the level of risk involved. A study to understand the effects of alcohol on injury-severity of the occupants found that 20 percent of the fatally-injured passengers were under the influence of alcohol, and drunk-drivers were at fault in 21 percent of the crashes [27]. However, the presence of sober passengers in the vehicle can, in many cases, be advantageous. A study found that the risk of loss of control by a drunk-driver was sometimes reduced in the presence of passengers in the vehicle [10]. Furthermore, although DUI increases the propensity of severe injuries of occupants, a crash involving a fully-occupied vehicle was found to be less likely to result in severe-injuries [21]. This could presumably be due to the driver being careful or perhaps passengers positively influencing the driver behavior.

To better understand the factors that influence drunk-driving crashes and their severities, it is important to eliminate the contributing role of other vehicles. As such, SV drunk-driving crashes present analysts with an opportunity to explain how external roadway, environmental factors, vehicle characteristics, and driver attributes affect crash outcomes by eliminating the influence of other road users in the crash. This is particularly so for multi-occupant SV DUI crashes, as passengers could either be an "enabling" factor to take more risks or be a source of distraction for a drunk-driver [25,28], or could be an "inhibiting" factor by ensuring safe driving by a drunk-driver [10]. As such, the aim of this study is to examine the effects of passenger presence on the injury severity outcomes of drunk-driving crashes, by identifying factors that contribute to crash outcomes. This study specifically presents a severity analysis of single- and multi-occupant SV DUI crashes in Alabama. Such an in-depth analysis of risk factors that contribute to crash severity outcomes is critical for effective implementation of countermeasures. For instance, drivers are mostly the targets of drunk-driving countermeasures, however, extending the countermeasures to include anyone who is a potential passenger could prove effective in improving overall traffic safety, like NHTSA's safety campaign "Friends Don't Let Friends Drive Drunk" in 1983, "If You Feel Different, You Drive Different" in 2018, and "Drive Sober or Get Pulled Over" in 2019 [29–31]. The identification of such diverse factors and its impact on the overall road safety in Alabama is expected to help in developing integrated and multifaceted solutions to create a Safe Systems approach for the state [32].

3. Materials and Methods

3.1. Data and Empirical Setting

The study is based on 2012–2016 crash data obtained from the Critical Analysis Reporting Environment (CARE) system developed by the University of Alabama's Center for Advanced Public Safety (CAPS). CARE is the primary database where crash records input directly by all traffic safety law enforcement officers in the State of Alabama are maintained. Each year, the data go through a rigorous QA/QC process, consistent with typical traffic safety databases maintained by state agencies throughout the U.S. The database was queried to select SV crashes, in which the primary contributing factor was driving under the influence of alcohol. Observations with missing or ambiguous values were omitted from the original dataset before performing the model estimation. This yielded a total of 7407 observed crashes. The crash data set obtained from the CARE system categorizes severities into five severities (fatal, incapacitating, non-incapacitating, possible injury, and property damage only), corresponding to the KABCO system set out in the Highway Safety Manual [33]. For the purposes of this study, severities were grouped into severe injury (fatal or incapacitating injury), minor injury (non-incapacitating injury or possible injury), and no injury (property damage only) crashes, which is a common practice, as evidenced in other studies [13,34,35]. Here, injury severity is defined as the highest injury recorded by an occupant of an SV crash, meaning it could be a passenger or driver in the case of a multi-occupant crash. It should be noted that the reported injury severities are solely based on the judgement and discretion of the reporting officer and are subjected to some inaccuracies [36–38]. Such inaccuracies, if present in the data, may result in potential biases [39,40] and are a known concern in road safety research. To investigate whether there are differences in factors contributing to the crash severities, the data were grouped between single-occupant (no passenger accompanying the driver) and multi-occupant (at least one passenger riding with the driver).

Based on the categorization, the distribution of crashes by severity outcome reveals that nearly 30% of the SV crashes during the study period resulted in an injury outcome and 70% were no injury crashes. Though 23% of SV crashes involved multi-occupant vehicles they contributed to about 46% of severe injury crashes. On the other hand, 77% of SV crashes were single-occupant, but they constituted 58% of no injury crashes. This highlights the importance of identifying the factors that are associated with each severity outcome between single- and multi-occupant and subsequently proposing countermeasures to improve safety. Table 1 shows the frequencies and percentages of the variables in the sampled data used in model estimation. For example, of the 7407 observations, 405 crashes resulted in severe injuries in the single-occupant category and represented 7.1% of the total single-occupant crashes. Similarly, in the multi-occupant category, 870 were no injury crashes, which were 51.9% of the total multi-occupant crashes. All model variables were binary except for "Age", which was the only continuous variable in the data, and is described in Table 1 by its mean and standard deviation.

A preliminary analysis of the data showed that 62% of single-occupant and 66% of multi-occupant SV crashes occurred during weekends. Approximately 25% of each of the single- and multi-occupant SV crashes occurred in every season (autumn, winter, spring, and summer). Similarly, the majority of these crashes occurred between 6 p.m. and 6 a.m. Rural areas accounted for 65% of the crashes, and 80% of the crash observations happened within 25 miles (≈40.23 km) from the drivers' residence. Female drivers accounted for 22% and 25% in single- and multi-occupant crashes, respectively. About a quarter of the drivers in both crash categories did not have a valid driving license at the time of the crash. Moreover, about 22% and 26% drivers were unbelted in single- and multi-occupant SV crashes, respectively. Additionally, more than half of the crashes in both crash categories took place in dark and unlit roadway conditions.

Table 1. Summary statistics of variables included in the latent class logit model.

		Variables	Single-Occupant	Multi-Occupant
			Frequency (%)	Frequency (%)
Dependent		Severe injury (fatal or incapacitating injury)	405 (7.1)	345 (20.6)
		Minor injury (non-incapacitating or possible injury)	1017 (17.7)	460 (27.5)
		No injury (property damage only)	4310 (75.2)	870 (51.9)
Explanatory Characteristics	*Crash*	Run-off road	1368 (23.9)	373 (22.3)
		Collision with ditch	1187 (20.7)	341 (20.4)
		Collision with tree	661 (11.5)	206 (12.3)
		Unrestrained driver	1256 (21.9)	442 (26.4)
	Roadway/Environmental	Interstate	422 (7.4)	161 (9.6)
		Federal highway	601 (10.5)	158 (9.4)
		State highway	940 (16.4)	252 (15.0)
		County road	2703 (47.2)	761 (45.4)
		Municipal road	1043 (18.2)	334 (19.9)
		Wet roadway condition	921 (16.1)	293 (17.5)
		Roadway curved right	1248 (21.8)	383 (22.9)
		Roadway curved left	708 (12.4)	245 (14.6)
		Downward grade	1258 (22.0)	391 (23.3)
		Two lane highway	4511 (78.7)	1280 (76.4)
		Four lane highway	874 (15.3)	280 (16.7)
		Daylight	1436 (25.1)	400 (23.9)
		Dark and unlit roadway	2911 (50.8)	856 (51.1)
		Clear weather condition	3961 (69.1)	1122 (67.0)
		Poor visibility	1750 (30.5)	545 (32.5)
	Location	Rural area	3768 (65.7)	1074 (64.1)
		Urban area	1407 (24.6)	601 (35.9)
		Crash location is open country	3740 (65.3)	1096 (65.4)
		Crash location is residential area	1391 (24.3)	403 (24.1)
		Crash location <25 mi from driver residence	4672 (81.5)	1348 (80.4)
		Crash location >25 mi from driver residence	964 (16.8)	301 (18.0)
		Crash location is an Intersection	1423 (24.8)	429 (25.6)
	Temporal	Winter (Dec-Feb)	1431 (25.0)	406 (24.2)
		Spring (Mar-May)	1413 (24.7)	413 (24.7)
		Summer (Jun-Aug)	1442 (25.1)	414 (24.7)
		Autumn (Sept-Oct)	1446 (25.2)	442 (26.4)
		Weekend	3581 (62.5)	1108 (66.2)
		Between midnight and 6 a.m.	2123 (37.0)	627 (37.4)
		Between 6 p.m. and midnight	2227 (38.9)	684 (40.8)
	Vehicle	Sedan	2805 (48.9)	863 (51.5)
		Pickup truck	1614 (28.2)	420 (25.1)
		SUV	1020 (17.8)	323 (19.3)
	Driver	Female	1237 (21.58)	421 (25.1)
		Invalid license	1468 (25.6)	459 (27.4)
		Employed driver	2891 (50.4)	779 (46.5)
		Unemployed driver	1749 (30.5)	626 (37.4)
		Self-employed driver	345 (6.0)	80 (4.8)
		Age [*Mean (Std. Dev)*]	[35.5 (0.6)]	[30.2 (1.8)]

3.2. Latent Class Logit Model

Since crash injury severity is typically reported as discrete outcomes, various discrete-outcome models, such as ordered (probit and logit models) and unordered models, are extensively used for analyzing injury severities of different types of crashes. For example, both ordinal and sequential logistic regression models were used for predicting the severities of rainy weather crashes [41], and nested and multinomial logit models were used to estimate motorcyclists' injury severities in single- and multi-vehicle crashes [42]. A multinomial logit model was also used for studying factors contributing towards the injury severities of SV crashes [43]. However, many of the traditional discrete outcome models fail to account for unobserved heterogeneity across injury-severity observations [44]. Ignoring the effect of unobserved variables in injury-severity studies can lead to biased estimates and incorrect inferences [13,45]. To address the problem of unobserved heterogeneity in injury severity analysis, heterogeneity models such as mixed logit and latent class models are often used. While mixed logit models account for unobserved heterogeneity across crash observations by making continuous distribution assumptions for random parameters, the latent class analysis uses a discrete distribution in which unobserved heterogeneity is captured by membership within distinct classes determined by revealed associations [13,44]. As such, this study applies a latent class multinomial logit modeling approach, to address the issue of unobserved heterogeneity, as well as to generate additional insight through the inspection of the revealed latent classes.

The latent class logit model allows the crash severity to have different classes, each with its own parameters. If M different classes are considered, the probability that a crash event belongs to a class m is given by [13]:

$$P_n(m) = \frac{\exp(\theta_m Z_n)}{\sum_{\forall M} \exp(\theta_m Z_n)} \tag{1}$$

where Z_n represents a vector that shows the probabilities of m for crash n, and θ_m represents the class-specific estimable parameters. The unconditional probability that a crash n will result in injury severity i is given by:

$$P_n(i) = \sum_{\forall M} P_n(m) \times P_n(i \mid m) \tag{2}$$

where $Prob_n(i \mid m)$ is the probability that a crash n with injury severity level i belongs to class m. Based on the two equations above, the latent class logit model for class m will be:

$$P_n(i \mid m) = \frac{\exp(\beta_m X_{in})}{\sum_{\forall N} \exp(\beta_m X_{in})} \tag{3}$$

where β_m is a class-specific parameter vector that takes a finite set of values, and X_{in} is a set of explanatory variables. In this paper, three discrete severity levels are considered in order to model crash-injury severity: severe injury (fatal or incapacitating), minor injury (non-incapacitating or possible injury), and no injury (property damage only). These groupings were done in order to ensure that an adequate number of observations are available for the modeling purpose.

The latent class logit model can be estimated with maximum likelihood procedures [46]. The latent class method, however, does not account for the variable randomness within a class, since it assumes homogeneous characteristics of the within-class observations [45]. A random parameter latent class model is an extension of the latent class logit model that captures interactions with observed contextual effects within the latent classes [47,48]. In this study, marginal effects [49] were computed to investigate the effect of individual parameters on the crash-severity outcome probabilities.

4. Results

Likelihood ratio tests [49] were performed to determine whether separate models by the occupant type is justified. The test statistic is given by:

$$\chi^2 = -2\left[LL(\beta_\tau) - \sum_{k=1}^{K} LL(\beta_k)\right] \tag{4}$$

where $LL(\beta_\tau)$ 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 (single- and multi-occupant), and K is the total number of data subsets used. The χ^2 statistic is chi-squared distributed, with the 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 χ^2 statistic indicates whether the model for the subset data is significantly different than the model for the full-sample data.

A log-likelihood test was further performed to determine whether the subset models have parameters that are statistically different. The test statistic used is given by:

$$\chi^2 = -2[LL(\beta_\tau) - LL(\beta_k)] \quad (5)$$

where $LL(\beta_\tau)$ is the log-likelihood at convergence of the model estimated with all the data (single- and multi-occupant), $LL(\beta_k)$ is the log-likelihood at convergence of the model using subset k data (single- and multi-occupant). Results of the likelihood ratio tests performed show that two separate severity models (for single- and multi-occupant) should be developed.

Tables 2 and 3 present the detailed latent class multinomial logit model estimation results for single- and multi-occupant SV crashes involving alcohol, respectively. Two distinct classes with homogeneous attributes were found to be significant for each crash category. Estimation results with more than two latent classes did not statistically improve the models in terms of data fit. The latent class probabilities for single-occupant crashes were 0.775 (latent class 1) and 0.225 (latent class 2), whereas for multi-occupant crashes, were 0.405 (latent class 1) and 0.595 (latent class 2). The class specific probabilities are a set of fixed constants (see Equation (1)), as examining segmentation based on crash specific characteristics did not result in a superior model fit. Tables 2 and 3 also show the models fit statistics.

Table 2. Latent class logit model estimation results for single-occupant driving under the influence (DUI) crashes.

Variable	**Characteristics**	**Latent**	**Class 1**	**Latent**	**Class 2**
		Parameter	***t*-Statistic**	**Parameter**	***t*-Statistic**
Defined for Severe injury					
Collision with ditch	Crash	−0.747	−3.66	−0.586	−1.36
Road with downward grade	Road/Environ	0.429	2.53	0.105	0.31
Autumn months	Road/Environ	−0.369	−1.72	1.191	3.11
Two lane road	Road/Environ	−0.371	−1.66	0.963	2.53
Residential location	Location	−0.897	−2.85	0.522	1.21
Rural area	Location	0.159	0.73	0.599	1.79
>25 mi from driver residence	Location	−1.505	1.00	2.119	3.91
Weekend	Temporal	0.027	2.17	−0.134	−0.46
Unemployed	Driver	0.441	2.47	−0.906	−2.19
Invalid license	Driver	0.103	0.62	0.497	2.58
SUV	Vehicle	0.125	2.66	−0.162	−0.41
Defined for Minor injury					
Constant	-	−5.649	−3.21	4.436	5.33
Dark and unlit roadway	Road/Environ	1.260	2.43	−0.276	−1.13
Summer month	Temporal	1.258	1.76	−0.583	−1.91
Female driver	Driver	1.530	2.03	−0.097	−0.33
Younger driver	Driver	−0.250	−0.36	0.049	2.21
Pickup truck	Vehicle	2.267	2.00	−0.274	−1.02
Defined for No injury					
Run-off road	Crash	0.966	3.57	−0.540	−0.99
Interstate	Road/Environ	0.993	2.31	2.216	4.41
Wet roadway	Road/Environ	0.022	0.11	1.079	2.50
Intersection	Location	0.915	3.77	0.914	2.15
<25 mi from driver residence	Location	1.730	7.29	1.965	2.76
Winter month	Temporal	0.574	2.95	0.387	0.91
Between 6 p.m. and midnight	Temporal	0.283	1.70	−0.467	−1.06

Table 2. *Cont.*

Variable	Characteristics	Latent	Class 1	Latent	Class 2
		Parameter	t-Statistic	Parameter	t-Statistic
Latent class probability		0.775	43.23	0.225	12.52
Number of observations	5732				
Restricted log likelihood	−6297.25				
LL at convergence	−3976.29				
McFadden Pseudo R-sq	0.37				

Table 3. Latent class logit model estimation results for multi-occupant DUI crashes.

Variable	Characteristics	Latent	Class 1	Latent	Class 2
		Parameter	t-Statistic	Parameter	t-Statistic
Defined for Severe injury					
Constant	-	−8.506	−0.62	−0.927	−4.33
Collision with ditch	Crash	0.463	0.09	−0.571	−2.67
Road with downward grade	Road/Environ	−0.301	−0.06	0.465	2.54
Poor visibility	Road/Environ	1.183	2.52	−0.034	−0.18
Residential location	Location	3.241	2.23	−0.217	−1.04
Weekend	Temporal	5.032	0.37	0.357	2.22
Defined for Minor injury					
Unrestrained	Crash	10.597	3.29	−5.447	−0.53
Dark and unlit roadway	Road/Environ	−1.112	−1.54	−0.337	−1.79
Interstate	Road/Environ	−3.868	−2.40	0.152	0.42
Four lane highway	Road/Environ	3.598	2.66	−0.539	−1.66
Unemployed	Driver	2.941	2.90	−0.519	−2.57
SUV	Vehicle	−1.558	−1.69	0.400	1.75
Defined for No injury					
Run-off road	Crash	−1.828	−1.70	0.572	2.23
Wet roadway	Road/Environ	−1.406	−1.45	0.789	2.90
Intersection	Location	−0.765	−0.92	0.744	3.19
<25 mi from driver residence	Location	0.622	0.75	−0.380	−1.86
Rural area	Location	3.703	1.77	−0.319	−1.36
Winter month	Temporal	1.261	1.62	0.486	2.21
Female driver	Driver	0.582	1.72	0.133	0.59
Driver age	Driver	0.120	2.75	−0.033	−3.61
Invalid license	Driver	2.206	2.38	−0.419	−1.81
Self-employed driver	Driver	−9.587	−3.00	2.728	4.26
Sedan	Vehicle	1.033	2.34	0.245	1.23
Latent class probability		0.405	14.77	0.595	21.66
Number of observations	1675				
Restricted log likelihood	−1840.18				
LL at convergence	−1585.48				
McFadden Pseudo R-sq	0.14				

A total of 23 explanatory variables were found to be statistically significant at a 5% significance level for single-occupant crashes, and 22 were similarly found to be significant for multi-occupant crashes. These variables can be grouped into categories, describing crash-specific, location, temporal, roadway/environmental, vehicle, and driver characteristics. The model estimation results for each class show that each variable has a set of two parameters, associated with it corresponding to the two latent classes. It can also be observed that some parameters have the same sign across the two classes (for example, rural, collision with ditch, wet roadway in single-occupant and weekend, winter, female in multi-occupant crashes), while others have opposite signs (for example, weekend, unemployed, pickup truck in single-occupant and poor visibility, unrestrained, SUV age in multi-occupant crashes), or are not significant in both classes (for example, wet roadway, female, weekend for single-occupant and collision with ditch, interstate, road with downward grade for multi-occupant crashes), i.e., significant in only one class. This suggests that there is heterogeneity between the classes of each crash category and underlines the need for further segmentation of the crashes. For this reason, the interpretation of the model results cannot be based on the magnitude and sign of the parameters, but rather on the marginal effects [13] shown in Figures 1–6 for single- and multi-occupant crashes, respectively. For ease of interpretation, the variables with similar attributes are grouped together, and the marginal effects are discussed for each group in the following subsections.

4.1. Crash Characteristics

Collision with a ditch and run-off road variables were found significant in both single- and multi-occupant SV drunk-driving crashes. Based on the marginal effects, when the most harmful event in a single-occupant SV DUI crash is a collision with a ditch, the probability of severe injury decreases by 0.0071, major injury increases by 0.0014 and that of no injury increases by 0.0056. Similarly, when a multi-occupant SV DUI crash involves a collision with a ditch, the probability of severe injury decreases by 0.0118, major injury increases by 0.0049, and that of no injury increases by 0.0069. In the single-occupant crashes where the first harmful event was run-off road, the likelihood of severe injury decreases by 0.0042, the likelihood of minor injury increases by 0.0016, and that of no injury increases by 0.0026. However, for multi-occupant crashes in which the first harmful event was run-off road, the likelihood of severe injury decreases by 0.0056 and that of major and no injury increases by 0.0021 and 0.0045 respectively. A comparison of marginal effects of the collision with ditch and run-off road variables between single- and multi-occupant crashes indicate that the decrease in probability of a severe injury is greater for multi-occupant SV crashes, as compared to single-occupant SV crashes.

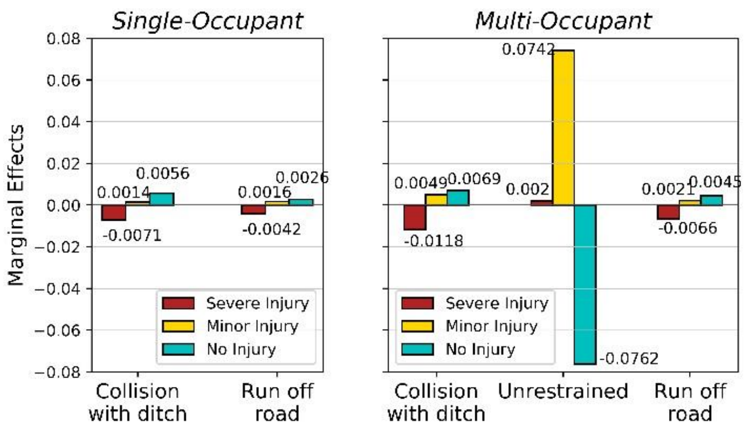

Figure 1. Estimated marginal effects of Crash Characteristics.

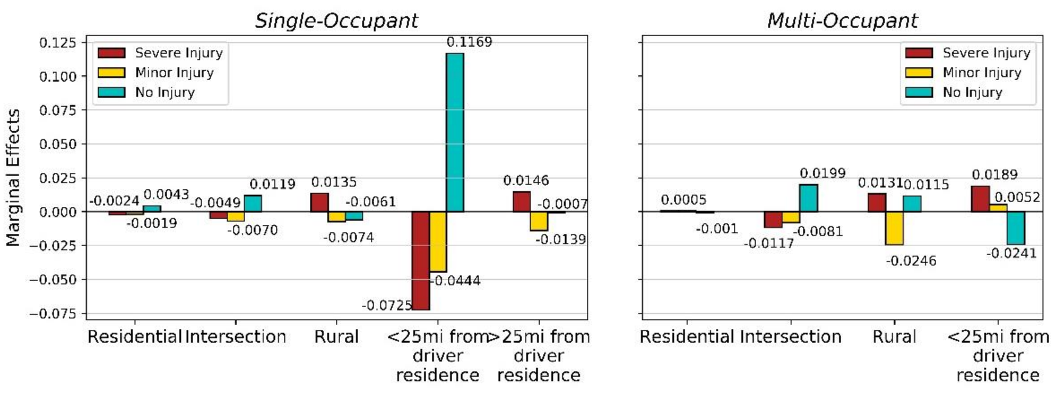

Figure 2. Estimated marginal effects of Location Characteristics.

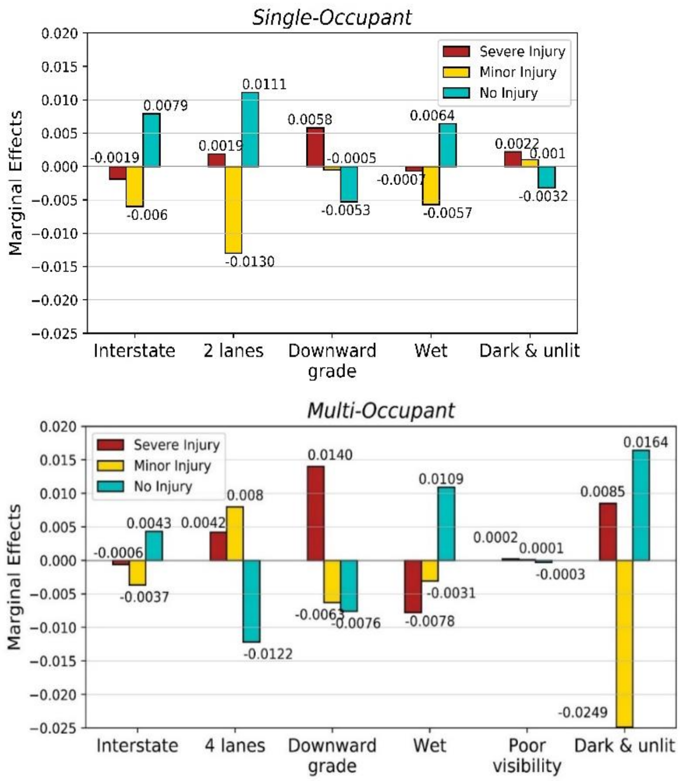

Figure 3. Estimated marginal effects of Roadway/Environmental Characteristics.

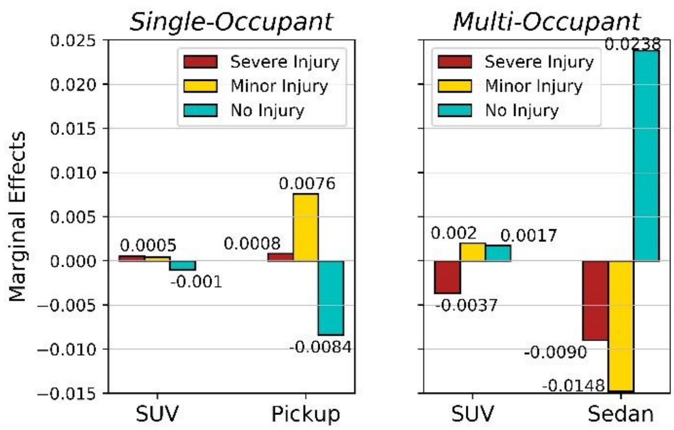

Figure 4. Estimated marginal effects of Vehicle Characteristics.

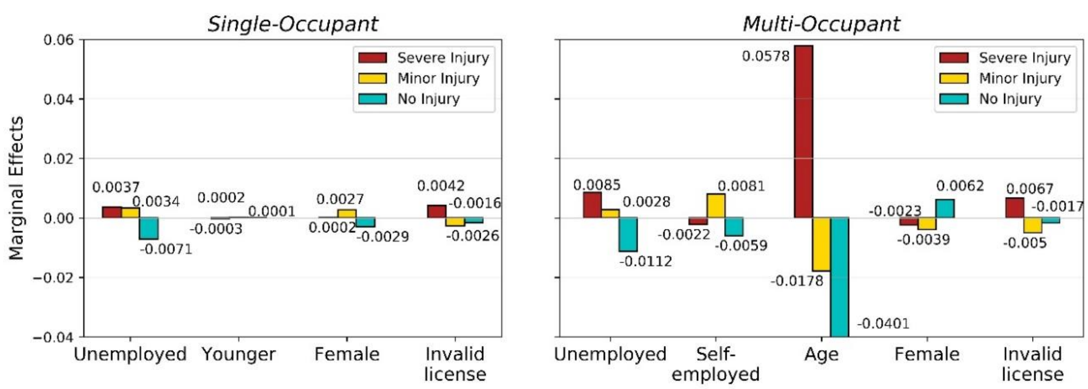

Figure 5. Estimated marginal effects of Driver Characteristics.

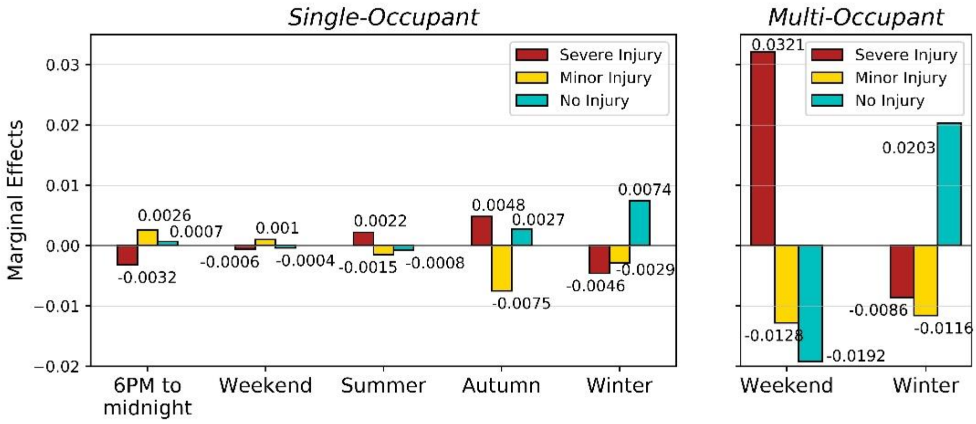

Figure 6. Estimated marginal effects of Temporal Characteristics.

Further, failure to use a seatbelt is known to increase the severity of crash injuries [15,50]. Evidently, in this study, failure to use a seatbelt in multi-occupant crashes was found to increase the likelihood of severe and minor injuries by 0.002 and 0.0742 respectively, and decrease the probability of no injury by 0.0762. This underlines the negative effect of the presence of passengers on the risky behavior of drunk-drivers, as found in past studies [23,26,51].

4.2. Location Characteristics

In terms of locational characteristics, intersections, rural areas, residential areas, and crashes, locations close to residences (<25 mi) were found to be associated with crash outcomes for both single- and multi-occupant SV drunk-driving crashes. In addition, the variable for the crash location being more than 25 miles (≈40.23 km) from the drivers' residence (>25 mi) was found to be significantly linked to the severity in single-occupant crashes only.

Rural locations are often associated with relatively high levels of road fatalities [43,52,53]. In the current study, alcohol-impaired crashes that occurred in rural areas were likely to increase the probability of severe injury. For example, rural areas were found to increase the likelihood of severe injury by 0.0135 for single-occupant crashes and 0.0131 for multi-occupant crashes. The intersection indicator variable decreases the severe injury probability by 0.0049 and 0.0006, minor injury by 0.0007 and 0.0037, and increases the probability of no injury by 0.0119 and 0.0043, for single- and multi-occupant crashes, respectively. The residential location indicator variable shows opposing effects for single- and multi-occupant SV crashes. The residential location variable for single-occupant SV crashes decreases the likelihood of severe and minor injury by 0.0024 and 0.0019 respectively, and increases the probability of no injury by 0.0043. Whereas, for multi-occupant SV crashes, the residential location variable increases the probability of severe and minor injury by 0.0005 and decreases the likelihood of no injury by 0.001.

Further, the indicator variable for crash location close (<25 mi) to the driver residence for multi-occupant crashes was found to increase the probabilities of severe and minor injury by 0.0189 and 0.0052 respectively. Contrarily, the indicator variable for the crash location close to the driver residence (<25 mi) for single-occupant crashes was found to decrease the probabilities of severe and minor injuries by 0.0725 and 0.0444, respectively. The probability of severe injury was found to increase by 0.0135 for single-occupant SV crashes, where the crash location was away (>25 mi) from the driver's residence.

4.3. Roadway/Environmental Characteristics

The model estimation results show that crashes that happened on roads with downward grade and in dark and unlit conditions were likely to record some severe injuries in both single- and multi-occupant SV drunk-driving crashes. For the road with a downward grade indicator variable, the probability of severe injury was found to increase by 0.0058 for a single-occupant crash, compared to 0.014 for a multi-occupant crash. Similarly, the likelihood of a severe crash increases by 0.0022 and 0.0085 for a single- and multi-occupant crash, if the crash happened under dark and unlit roadway conditions. At night, unlit roadways are often dark, and that could affect motorists' visibility. The finding regarding the night variable from this study is therefore consistent with other studies that found dark roadways to be a significant contributing factor in major injury crashes [50,54,55]. Some studies have also explored the role of wet roadway conditions on crash injury severity [34]. For this study, in both single- and multi-occupant cases, wet roadway condition decreases the probability of severe injury by 0.0007 and 0.0078, and that of minor injury by 0.0057 and 0.0031, and increases the probability of no injury by 0.0062 and 0.0109, respectively. In addition, the interstate variable was found to decrease the probability of severe injury by 0.0019 and 0.0006, minor injury by 0.0057 and 0.004, and increase the probability of no injury by 0.0079 and 0.0043 for single- and multi-occupant crashes, respectively. Poor visibility variable increased the probability of severe injury by 0.0002 and the four-lane road indicator increased the likelihood of severe injury by 0.0042 for multi-occupant crashes. The variable for two-lane road increased the chances of severe injury by 0.0019 for single-occupant crashes.

4.4. Vehicle Characteristics

Vehicle type also affects the severity of crashes. For this study, it was observed that SUVs increase the probability of severe injury by 0.0005 for single-occupant crashes, whereas SUVs decrease the probability of severe injury for multi-occupant crashes. Sedans were found to increase the likelihood of no injury by 0.0238 in multi-occupant cases, whereas pickup trucks were found to increase the probability of severe and minor injury by 0.0008 and 0.0076, respectively, in single-occupant SV crashes.

4.5. Driver Characteristics

Driver characteristics are often cited as the most important factor associated with crash outcomes and serve as a critical pillar in road safety improvement using the safe systems approach [32,56]. In this study, unemployment and invalid license variables were found to be common to both single- and multi-occupant crashes and had similar effects on injury severities. The unemployed driver variable was found to increase the likelihood of severe injury by 0.0037 and 0.0085, minor injury by 0.0034 and 0.0028, and decrease the likelihood of no injury by 0.0072 and 0.0112 in single- and multi-occupant crashes respectively. Similarly, the indicator variable for a driver with an invalid license was found to increase the probability of severe injury by 0.0042 and 0.0067, but decrease the probability of minor injury by 0.0026 and 0.005 and no injury by 0.0016 and 0.0017 in single- and multi-occupant crashes, respectively. Driving without a valid license may be indicative of risky driving behavior, and it has previously been shown to increase the chances of major injuries [14,15,57,58].

The probability of severe and minor injury when the driver was female decreased by 0.0023 and 0.0039 respectively for multi-occupant crashes compared to an increase by 0.0002 and 0.0027, respectively, for single-occupant crashes. Furthermore, driver age was found to be significant in both single- and multi-occupant SV DUI crashes. The results show that, for single-occupant crashes, the younger (<25 years age) driver indicator variable decreases the probability of severe injury by 0.0003 and increases the probability of minor and no injury by 0.0002 and 0.0001, respectively. However, in the case of multi-occupant crashes, an increase in driver age was found to increase the probability of severe injury by 0.0578 and decrease the probability of minor and no injury by 0.0178 and 0.0401 respectively. The self-employed driver variable for multi-occupant crashes decreases the probability of severe injury by 0.0022, but increases the probability of minor injury by 0.0081.

4.6. Temporal Characteristics

The differences in the effects of temporal factors on SV multi-occupant crashes involving alcohol are worth noting. Weekend nights are typically found to show an increase in drunk-driving cases [59]. When a single-occupant crash occurs on a weekend, the probability of severe injury decreases by

0.0006, compared to an increase of 0.0321 in case of a multi-occupant crash. Similarly, SV crashes with no passengers had a lower probability of severe injury if it occurred between 6 p.m. and midnight. The winter indicator variable decreases the probability of severe injury by 0.0046 and 0.0086, that of minor injury by 0.0029 and 0.0116 and increases the chances for no injury by 0.0074 and 0.0203 for single- and multi-occupant crashes respectively. On the other hand, both summer and autumn indicator variables were found to increase the chance of severe injury by 0.0022 and 0.0048, respectively, for single-occupant crashes. It is interesting to observe that severe injury associated with SV drunk-driving crashes exhibit temporal dimensions. Such findings are particularly important in reducing the number and severity of alcohol-involved crashes, as enforcement programs can be appropriately targeted.

5. Discussion

Broadly, the results indicate three categories of variables that significantly contribute to the severity of SV alcohol-impaired crashes with respect to vehicle occupancy status. The first class of variables are those that are common and have similar effects on crash outcomes in both single- and multi-occupant crashes. The second and third classes are, respectively, those variables that are common, but have opposite effects and those that have been found to be unique to each (one of single- or multi-occupant) category of crashes. For example, variables defining collision with ditch, run-off road, intersection, winter season, wet roadway, and interstate were found to decrease the probability of severe injuries and increase the probability of no injury. These results are consistent with the findings of other studies [19,25,60–64]. In contrast, variables defining rural area, road with downward grade, dark and unlit roadway, unemployed driver, and driver with invalid license were found to increase the probability of severe injuries in both single- and multi-occupant categories. These observations are also consistent with the findings of other research studies [51,53,55,57,58,65,66].

The variables that show opposite effects in the single- and multi-occupant crashes may perhaps present an interesting insight in the quest to improve overall road safety relating to drink-driving. For example, a drunk female driver driving alone has an increased likelihood of getting severely injured, but the chances of any form of injury are significantly reduced when she has at least one passenger. Not only is this observation interesting in Alabama, but this finding is consistent with other past studies from other regions [43,67]. Furthermore, considering that many social activities that may involve alcohol use take place over the weekends, drivers are likely to carry more passengers on weekends. This increases the chances of SV crashes [28]. While the presence of passengers increases the chances of injury in a crash, this study found that the likelihood of a severe injury decreases in single-occupant crashes, but increases for multi-occupant crashes that happen during weekends. This implies the impact of the presence of passengers that passengers are less helpful in reducing driver's crash potential and are more likely to distract drivers [28]. Locational characteristics, such as residential location and close (<25 mi) to home, were found to increase the likelihood of severe injuries when passengers were present in the vehicle. This finding is important in crafting safety campaigns, as many drunk-drivers may overate their abilities to be able to drive home, considering their proximity from their intended destination. Drivers may be encouraged to use shared-mobility options (Uber, Lyft, etc.) rather than driving drunk, no matter how short the distance may be.

Previous research has shown that injuries tend to be less severe among impaired drivers with no passengers, compared to crashes involving multi-occupants, as the passengers may create more distractions for an already impaired driver [25]. Findings from this study show that this also depends on the vehicle characteristics. For example, SUVs and sedans were found to decrease the likelihood of severe injury in multi-occupant crashes, while crashes involving SUVs and pickup trucks were more likely to record severe injuries where there were no passengers. However, the effect of a vehicle type on the crash severity cannot be clearly defined without regard to the driver. Furthermore, drunk-driving has often been associated with failure to use seatbelt [68–70]. Other studies have shown that the risks associated with the failure to use safety equipment are similar to impaired driving [25]. Consistent with the findings from previous studies, the results of this study indicate that increased risk for some form of injury when the drunk-driving crash involved no seatbelt use [57,71]. In identifying risky driver populations, the findings from this study show that drunk-driving crashes involving younger drivers (age <25 years) with no passengers tend to have lower chances of leading to severe injuries as also found in other studies [71]. However, older drivers of multi-occupant vehicles have increased risks of severe injuries. Given the complexity of road transport, it is difficult to fully understand the specific cause(s) of DUI crashes. As such, crash severity analysis in this paper helps in characterizing single- and multi-occupant SV DUI crashes. The identification of such diverse factors and its impact on the overall road safety in Alabama can help in developing integrated and multifaceted solutions to create a safe systems culture, not only in the state, but also in the U.S. [32].

6. Limitations

This study has some strengths, but also some limitations. Like many data-based modeling studies, there may be some inherent data deficiencies that may bias the research findings. This study relied on only police-reported crashes in Alabama. This means that the true prevalence of DUI in the state may not have been captured, as unreported crashes did not make it into the crash database and hence were not used in the study. Furthermore, the demographic characteristics of the passengers were not used in the multi-occupant crash model. As such, it is not clear how different passengers influence driving behaviors of drunk-drivers and the crashes they get into. However, despite these limitations, the study made some interesting findings that can help in enforcement strategies, designing safety campaigns and outreach programs to address the risks of DUI in the state.

7. Conclusions

Passenger presence can have differing effects on the driving behavior of a drunk-driver and can impact the crash severity outcomes differently. Hence, some countermeasures to reduce DUI crashes should also be targeted towards the passengers of drunk-drivers, for which understanding the similarities and differences between the underlying contributing factors is important. This study used the 2012–2016 police-reported crash data for single- and multi-occupant SV drunk-driving crashes in Alabama. A latent class multinomial logit modeling approach was used to analyze the effects of temporal, locational, driver, vehicle, and roadway characteristics, along with crash contributing factors on three different injury severities: severe, minor, and no injury. Variables such as collision with ditch, run-off road, intersection, winter season, wet roadway, and interstate were found to have similar effects of decreased probabilities of severe injuries, in both single- and multi-occupant crashes, whereas rural area, road with downward grade, dark and unlit roadway, unemployed driver, and driver with invalid license were found to increase the likelihood of severe injuries in both categories.

Further, a female driver who when driving alone increased the severe injury likelihood, but not when driving with at least one passenger. Similarly, the presence of passengers also increased the chances of severe injury in SV crashes during weekends. Proximity (<25 mi ≈ 40.23 km) to the residence increased the severity of injuries when passengers were present in the vehicle. The same held true for a crash location that is a residential area. As against this, SUVs are safer when driving with passengers. The model findings show that, although many correlates are consistent between the single- and multi-occupant SV crashes associated with locational, roadway, vehicle, temporal, and driver characteristics, their effect can vary across the single- and multi-occupant driving population. Such variability may be of particular importance for developing intervention strategies and drunk-driving safety campaigns.

Safety and education campaigns that raise awareness of driving with risky passengers and/or passenger distractions are likely to have a beneficial impact on the reduction of injury severity levels. Similarly, the implementation of stricter enforcement laws, especially on weekends, can be one of the effective approaches for increasing restraint usage and mitigating driving with no or invalid license. Furthermore, promoting the use of ride-share services and initiatives such as late-night transits can help in significantly reducing drunk-driving related crashes and injuries [72,73]. Ultimately, the findings from this study can help in crafting and targeting countermeasures to reduce DUI crashes and consequent injuries. These measures may be focused on changing drunk-driving behaviors and passenger education to mitigate the risks that come with drunk-driving. The temporal and location factors observed to influence crash outcomes can inform when, where, and how law enforcement strategies may be carried out to achieve greater safety benefits. Furthermore, integrating such educational and enforcement efforts with engineering and emergency response can truly produce a holistic plan to improve road users' health and safety, leading to a true safe systems approach.

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References

1. World Health Organization. *Global Status Report on Alcohol and Health 2018*; World Health Organization: Geneva, Switzerland, 2018.
2. National Highway Traffic Safety Administration (NHTSA) Risky Driving/NHTSA. Available online: https://www.nhtsa.gov/risky-driving (accessed on 7 April 2020).
3. Hingson, R.; Winter, M. Epidemiology and Consequences of Drinking and Driving. *Alcohol Res. Health* **2003**, *27*, 63–78.
4. Scott, M.S.; Emerson, N.J.; Antonacci, L.B.; Plant, J.B. *Drunk Driving Problem-Oriented Guides for Police Problem-Specific Guides Guides Series No. 36*; Office of Community Oriented Policing Services, U.S. Department of Justice: Washington, DC, USA, 2006; ISBN 1-932582-57-6.
5. National Highway Traffic Safety Administration (NHTSA). *Traffic Safety Facts 2018 Data: Alcohol-Impaired Driving*; NHTSA Technical Report DOT HS 812 864; NHTSA: Washington, DC, USA, 2019.
6. National Highway Traffic Safety Administration (NHTSA). U.S. Transportation Secretary Elaine L. Chao Announces Further Decreases in Roadway Fatalities. Available online: https://www.nhtsa.gov/press-releases/roadway-fatalities-2018-fars (accessed on 7 April 2020).
7. Blincoe, L.; Miller, T.R.; Zaloshnja, E.; Lawerence, B.A. *The Economic and Societal Impact of Motor Vehicle Crashes, 2010 (Revised)*; NHTSA Technical Report DOT HS 812 013; NHTSA: Washington, DC, USA, 2015.
8. Dabbour, E. Investigating temporal trends in the explanatory variables related to the severity of drivers' injuries in single-vehicle collisions. *J. Traffic Transp. Eng.* **2017**, *4*, 71–79. [CrossRef]
9. De Blasiis, M.R.; Ferrante, C.; Veraldi, V. Driving risk assessment under the effect of alcohol through an eye tracking system in virtual reality. In *Advances in Safety Management and Human Factors*; Arezes, P., Ed.; Springer: Cham, Switzerland, 2020; Volume 969, pp. 329–341, ISBN 9783030204969.
10. Tavris, D.R.; Kuhn, E.M.; Layde, P.M. Age and gender patterns in motor vehicle crash injuries: Importance of type of crash and occupant role. *Accid. Anal. Prev.* **2001**, *33*, 167–172. [CrossRef]
11. Abdel-Aty, M. Analysis of driver injury severity levels at multiple locations using ordered probit models. *J. Saf. Res.* **2003**, *34*, 597–603. [CrossRef] [PubMed]
12. Keall, M.D.; Frith, W.J.; Patterson, T.L. The influence of alcohol, age and number of passengers on the night-time risk of driver fatal injury in New Zealand. *Accid. Anal. Prev.* **2004**, *36*, 49–61. [CrossRef]
13. Shaheed, M.S.; Gkritza, K. A latent class analysis of single-vehicle motorcycle crash severity outcomes. *Anal. Methods Accid. Res.* **2014**, *2*, 30–38. [CrossRef]
14. Adanu, E.K.; Smith, R.; Powell, L.; Jones, S. Multilevel analysis of the role of human factors in regional disparities in crash outcomes. *Accid. Anal. Prev.* **2017**, *109*, 10–17. [CrossRef]

15. Öström, M.; Eriksson, A. Single-vehicle crashes and alcohol: A retrospective study of passenger car fatalities in Northern Sweden. *Accid. Anal. Prev.* **1993**, *25*, 171–176. [CrossRef]
16. Schneider, W.H.; Savolainen, P.T.; Zimmerman, K. Driver Injury Severity Resulting from Single-Vehicle Crashes along Horizontal Curves on Rural Two-Lane Highways. *Transp. Res. Rec. J. Transp. Res. Board* **2009**, *2102*, 85–92. [CrossRef]
17. Xie, Y.; Zhao, K.; Huynh, N. Analysis of driver injury severity in rural single-vehicle crashes. *Accid. Anal. Prev.* **2012**, *47*, 36–44. [CrossRef]
18. Chen, H.; Liu, P.; Lu, J.J.; Behzadi, B. Evaluating the safety impacts of the number and arrangement of lanes on freeway exit ramps. *Accid. Anal. Prev.* **2009**, *41*, 543–551. [CrossRef] [PubMed]
19. Liu, C.; Subramanian, R. *Factors Related to Fatal Single-Vehicle Run-Off-Road Crashes*; NHTSA DOT HS 811 232; NHTSA: Washington, DC, USA, 2009.
20. National Highway Traffic Safety Administration. *2016 Data: Alcohol-Impaired Driving*; NHTSA Technical Report DOT HS 812 450; NHTSA: Washington, DC, USA, 2017.
21. Eluru, N.; Paleti, R.; Pendyala, R.M.; Bhat, C.R. Modeling Injury Severity of Multiple Occupants of Vehicles. *Transp. Res. Rec.* **2010**, *2165*, 1–11. [CrossRef]
22. Simons-Morton, B.G.; Ouimet, M.C.; Zhang, Z.; Klauer, S.E.; Lee, S.E.; Wang, J.; Chen, R.; Albert, P.; Dingus, T.A. The effect of passengers and risk-taking friends on risky driving and crashes/near crashes among novice teenagers. *J. Adolesc. Health* **2011**, *49*, 587–593. [CrossRef]
23. Cartwright, J.; Asbridge, M. Passengers' decisions to ride with a driver under the influence of either alcohol or cannabis. *J. Stud. Alcohol Drugs* **2011**, *72*, 86–95. [CrossRef]
24. Stephens, A.N.; Bishop, C.A.; Liu, S.; Fitzharris, M. Alcohol consumption patterns and attitudes toward drink-drive behaviours and road safety enforcement strategies. *Accid. Anal. Prev.* **2017**, *98*, 241–251. [CrossRef] [PubMed]
25. Maistros, A.; Schneider, W.H.; Savolainen, P.T. A comparison of contributing factors between alcohol related single vehicle motorcycle and car crashes. *J. Saf. Res.* **2014**, *49*, e1–e135. [CrossRef] [PubMed]
26. Neyens, D.M.; Boyle, L.N. The influence of driver distraction on the severity of injuries sustained by teenage drivers and their passengers. *Accid. Anal. Prev.* **2008**, *40*, 254–259. [CrossRef]
27. Ahlm, K.; Eriksson, A. Driver's Alcohol and Passenger's Death in Motor Vehicle Crashes. *Traffic Inj. Prev.* **2006**, *7*, 219–223. [CrossRef]
28. Lee, C.; Abdel-Aty, M. Presence of passengers: Does it increase or reduce driver's crash potential? *Accid. Anal. Prev.* **2008**, *40*, 1703–1712. [CrossRef]
29. The National Law Review Impact of Safety Campaigns on Reducing Drunk Driving/The National Law Review. Available online: https://www.natlawreview.com/article/impact-safety-campaigns-reducing-drunk-driving (accessed on 7 April 2020).
30. NHTSA. Drive Sober or Get Pulled over This Holiday Season. Available online: https://www.nhtsa.gov/drunk-driving/drive-sober-or-get-pulled-over-holidays (accessed on 6 May 2020).
31. NHTSA. U.S. Department of Transportation Launches New Ad Campaign to Stop Impaired Driving/NHTSA. Available online: https://www.nhtsa.gov/press-releases/us-department-transportation-launches-new-ad-campaign-stop-impaired-driving (accessed on 6 May 2020).
32. Dumbaugh, E.; Merlin, L.; Signor, K.; Kumfer, W.; Lajeunesse, S.; Carter, D. *Implementing Safe Systems in the United States: Guiding Principles and Lessons from International Practice. Collaborative Sciences Center for Road Safety Report No. CSCRS-R7*; Collaborative Sciences Center for Road Safety: Chapel Hill, NC, USA, 2019.
33. *Highway Safety Manual*; American Association of State Highway Transportation Officials (AASHTO): Washington, DC, USA, 2010.
34. Morgan, A.; Mannering, F.L. The effects of road-surface conditions, age, and gender on driver-injury severities. *Accid. Anal. Prev.* **2011**, *43*, 1852–1863. [CrossRef]
35. Shaheed, M.S.B.; Gkritza, K.; Zhang, W.; Hans, Z. A mixed logit analysis of two-vehicle crash severities involving a motorcycle. *Accid. Anal. Prev.* **2013**, *61*, 119–128. [CrossRef] [PubMed]
36. Farmer, C.M. Reliability of police-reported information for determining crash and injury severity. *Traffic Inj. Prev.* **2003**, *4*, 38–44. [CrossRef]
37. Brubacher, J.R.; Chan, H.; Erdelyi, S. Injury severity in police collision reports correlates poorly with requirement for hospital admission. *J. Transp. Health* **2019**, *14*, 100606. [CrossRef]

38. Lee, Y.M.; Platts-Mills, T.F.; MacWilliams, J.B.; Sochor, M.R.; Jones, J.S.; Domeier, R.M.; Schneider, L.W.; McLean, S.A. Descriptions of motor vehicle collisions by participants in emergency department-based studies: Are they accurate? *West. J. Emerg. Med.* **2012**, *13*, 329–334. [CrossRef] [PubMed]
39. Abay, K.A. Investigating the nature and impact of reporting bias in road crash data. *Transp. Res. Part A Policy Pract.* **2015**, *71*, 31–45. [CrossRef]
40. Imprialou, M.; Quddus, M. Crash data quality for road safety research: Current state and future directions. *Accid. Anal. Prev.* **2019**, *130*, 84–90. [CrossRef]
41. Jung, S.; Qin, X.; Noyce, D.A. Rainfall effect on single-vehicle crash severities using polychotomous response models. *Accid. Anal. Prev.* **2010**, *42*, 213–224. [CrossRef]
42. Savolainen, P.; Mannering, F. Probabilistic models of motorcyclists' injury severities in single- and multi-vehicle crashes. *Accid. Anal. Prev.* **2007**, *39*, 955–963. [CrossRef]
43. Islam, S.; Mannering, F. Driver aging and its effect on male and female single-vehicle accident injuries: Some additional evidence. *J. Saf. Res.* **2006**, *37*, 267–276. [CrossRef]
44. Mannering, F.L.; Bhat, C.R. Analytic methods in accident research: Methodological frontier and future directions. *Anal. Methods Accid. Res.* **2014**, *1*, 1–22. [CrossRef]
45. Mannering, F.L.; Shankar, V.; Bhat, C.R. Unobserved heterogeneity and the statistical analysis of highway accident data. *Anal. Methods Accid. Res.* **2016**, *11*, 1–16. [CrossRef]
46. Greene, W.H.; Hensher, D.A. A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transp. Res. Part B Methodol.* **2003**, *37*, 681–698. [CrossRef]
47. Greene, W.H.; Hensher, D.A. Revealing additional dimensions of preference heterogeneity in a latent class mixed multinomial logit model. *Appl. Econ.* **2013**, *45*, 1897–1902. [CrossRef]
48. Bujosa, A.; Riera, A.; Hicks, R.L. Combining Discrete and Continuous Representations of Preference Heterogeneity: A Latent Class Approach. *Environ. Resour. Econ.* **2010**, *47*, 477–493. [CrossRef]
49. Washington, S.; Karlaftis, M.G.; Mannering, F.L. *Statistical and Econometric Methods for Transportation Data Analysis*, 2nd ed.; Chapman and Hall/CRC: Boca Raton, FL, USA, 2010; ISBN 9781420082852.
50. Cook, L.J.; Knight, S.; Olson, L.M. A comparison of aggressive and DUI crashes. *J. Saf. Res* **2005**, *36*, 491–493. [CrossRef]
51. Fu, J.; Anderson, C.L.; Dziura, J.D.; Crowley, M.J.; Vaca, F.E. Young unlicensed drivers and passenger safety restraint use in U.S. Fatal crashes: Concern for risk spillover effect? *Ann. Adv. Automot. Med. Assoc. Adv. Automot. Med. Annu. Sci. Conf.* **2012**, *56*, 37–43.
52. Czech, S.; Shakeshaft, A.P.; Byrnes, J.M.; Doran, C.M. Comparing the cost of alcohol-related traffic crashes in rural and urban environments. *Accid. Anal. Prev.* **2010**, *42*, 1195–1198. [CrossRef]
53. Yadav, A.K.; Velaga, N.R. Alcohol-impaired driving in rural and urban road environments: Effect on speeding behaviour and crash probabilities. *Accid. Anal. Prev.* **2020**, *140*, 105512. [CrossRef]
54. Kim, J.K.; Ulfarsson, G.F.; Kim, S.; Shankar, V.N. Driver-injury severity in single-vehicle crashes in California: A mixed logit analysis of heterogeneity due to age and gender. *Accid. Anal. Prev.* **2013**, *50*, 1073–1081. [CrossRef]
55. Rodríguez-López, J.; Rebollo-Sanz, Y.; Mesa-Ruiz, D. Hidden figures behind two-vehicle crashes: An assessment of the risk and external costs of drunk driving in Spain. *Accid. Anal. Prev.* **2019**, *127*, 42–51. [CrossRef]
56. Salmon, P.M.; Read, G.J.M.; Stevens, N.; Walker, G.H.; Beanland, V.; McClure, R.; Hughes, B.; Johnston, I.R.; Stanton, N.A. Using the abstraction hierarchy to identify how the purpose and structure of road transport systems contributes to road trauma. *Transp. Res. Interdiscip. Perspect.* **2019**, *3*, 100067. [CrossRef]
57. Valen, A.; Bogstrand, S.T.; Vindenes, V.; Frost, J.; Larsson, M.; Holtan, A.; Gjerde, H. Driver-related risk factors of fatal road traffic crashes associated with alcohol or drug impairment. *Accid. Anal. Prev.* **2019**, *131*, 191–199. [CrossRef] [PubMed]
58. Sagberg, F. Characteristics of fatal road crashes involving unlicensed drivers or riders: Implications for countermeasures. *Accid. Anal. Prev.* **2018**, *117*, 270–275. [CrossRef] [PubMed]
59. Barone, R.; Pelletti, G.; Garagnani, M.; Giusti, A.; Marzi, M.; Rossi, F.; Roffi, R.; Fais, P.; Pelotti, S. Alcohol and illicit drugs in drivers involved in road traffic crashes in Italy. An 8-year retrospective study. *Forensic Sci. Int.* **2019**, *305*, 110004. [CrossRef] [PubMed]
60. Gong, L.; Fan, W.D. Modeling single-vehicle run-off-road crash severity in rural areas: Accounting for unobserved heterogeneity and age difference. *Accid. Anal. Prev.* **2017**, *101*, 124–134. [CrossRef]

61. Federal Highway Administration Highway Statistics. 2017. Available online: https://www.fhwa.dot.gov/policyinformation/statistics/2017/fi220.cfm (accessed on 17 March 2020).
62. Bernat, D.H.; Dunsmuir, W.T.M.; Wagenaar, A.C. Effects of lowering the legal BAC to 0.08 on single-vehicle-nighttime fatal traffic crashes in 19 jurisdictions. *Accid. Anal. Prev.* **2004**, *36*, 1089–1097. [CrossRef]
63. Jonsson, T.; Ivan, J.N.; Zhang, C. Crash Prediction Models for Intersections on Rural Multilane Highways. *Transp. Res. Rec. J. Transp. Res. Board* **2007**, *2019*, 91–98. [CrossRef]
64. Donnell, E.T.; Mason, J.M. Predicting the Severity of Median-Related Crashes in Pennsylvania by Using Logistic Regression. *Transp. Res. Rec. J. Transp. Res. Board* **2004**, *1897*, 55–63. [CrossRef]
65. Stamatiadis, N.; Puccini, G. Socioeconomic descriptors of fatal crash rates in the Southeast USA. *Inj. Control Saf. Promot.* **2000**, *7*, 165–173. [CrossRef]
66. Yu, R.; Abdel-Aty, M. Multi-level Bayesian analyses for single- and multi-vehicle freeway crashes. *Accid. Anal. Prev.* **2013**, *58*, 97–105. [CrossRef]
67. Doherty, S.T.; Andrey, J.C.; MacGregor, C. The situational risks of young drivers: The influence of passengers, time of day and day of week on accident rates. *Accid. Anal. Prev.* **1998**, *30*, 45–52. [CrossRef]
68. Allen, S.; Zhu, S.; Sauter, C.; Layde, P.; Hargarten, S. A comprehensive statewide analysis of seatbelt non-use with injury and hospital admissions: New data, old problem. *Acad. Emerg. Med.* **2006**, *13*, 427–434. [CrossRef] [PubMed]
69. Gross, E.A.; Axberg, A.; Mathieson, K. Predictors of seatbelt use in American Indian motor vehicle crash trauma victims on and off the reservation. *Accid. Anal. Prev.* **2007**, *39*, 1001–1005. [CrossRef] [PubMed]
70. Bogstrand, S.T.; Larsson, M.; Holtan, A.; Staff, T.; Vindenes, V.; Gjerde, H. Associations between driving under the influence of alcohol or drugs, speeding and seatbelt use among fatally injured car drivers in Norway. *Accid. Anal. Prev.* **2015**, *78*, 14–19. [CrossRef] [PubMed]
71. Behnood, A.; Roshandeh, A.M.; Mannering, F.L. Latent class analysis of the effects of age, gender, and alcohol consumption on driver-injury severities. *Anal. Methods Accid. Res.* **2014**, *3*, 56–91. [CrossRef]
72. Elam, C.; McKaig, R.N.; Jacobs, B.; Whitlow, M.; Gros Louis, K.R. Examining a Safe Ride Program: An Assessment of the Midnight Special Late Night Bus Service. *J. Stud. Aff. Res. Pract.* **2011**, *43*, 358–376.
73. Greenwood, B.N.; Wattal, S. Show Me the Way to Go Home: An Empirical Investigation of Ride Sharing and Alcohol Related Motor Vehicle Homicide. *Fox Sch. Bus.* **2015**. [CrossRef]