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Single-Vehicle Crashes on Rural Two-Lane Highways and Injury Severity: Does the Age Matter?

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Abstract

Single-vehicle crashes on rural two-lane highways impose a considerable risk to road users due to their higher severity outcome compared to other crashes on these facilities. Furthermore, considerable variation in the severity among various age groups (young, middle-aged, and older drivers) has been noticed, corroborating the need for analyzing age-classified data. Crash data from Alabama was compiled and classified based on the age group. For each age class, a generalized ordered logit model was developed to identify the effect of various variables on injury severity. This model can consider ordered nature of severity as well as provide flexibility in calculating the parameter estimates. Driver gender, seatbelt use, damage to the vehicle, driving on county roads, hitting a fixed object and animal, and speeding were found to be significant in all developed models. Intoxication is a significant factor that affects injury severity for young drivers. Time of day also significantly affects the injury severity for older drivers. Vehicle age and driving with invalid license were not found to affect injury severity for older drivers, while they affected the other age groups. It was shown that some factors have significant effect on the injury severity for all age groups while others have varying effect across different age groups. The results of this study highlight the importance of considering separate injury severity models for different age groups, specifically separating older drivers from others, as the difference among older drivers and others are substantial.

Keywords: Age Difference; Single-Vehicle Crash; Rural Two-Lane Highways; Generalized Ordered Logit Model

1. Introduction

Crashes happened on rural two-lane highways tend to be more severe, resulting in higher proportion of incapacitating injuries and fatalities compared to crashes on urban roadways, [1, 2]. A review on crashes in Alabama reveals that rural areas account for 24.4% of total crashes within 2010-2014 resulting in 11.9% severe crashes (non-incapacitating and fatal) while this number for urban areas drops to 4.2%, [3]. Additionally, the average fatalities rate per 100 million vehicle miles traveled (VMT) during the same period is 1.78 and 1.06 for rural and urban areas, respectively. Studies conducted in other states, such as Texas, Arizona, and Kentucky also show the same trend, [4-6]. For example, New Mexico annual crash report shows that from 2008 to 2012, rural fatalities were almost 2.3 times of the fatalities in urban areas while the number of crashes happened in urban areas was 5.1 times more than those happened in rural areas, [7]. A nationwide scale comparison between rural and urban fatalities also demonstrate that in 2013, 53% of fatalities in the United States (U.S.) happened on rural areas, [8]. Past works have measured factors affecting rural highway injury severities and notable variations by age are observed, [9-12]. In a recent study, Lopez et al. collected and analyzed single-vehicle crashes occurred on rural two-lane highways in the province of Granada, Spain, over a seven-year time period, [12]. Accordingly, it was found that younger drivers are associated with higher crash severities, requiring specific actions on driver's behaviors within this age group. Abay et al. investigated a 7-year dataset for two-vehicle, two-driver crashes in Denmark. The analysis using multivariate ordered-response model indicated a higher injury risk propensity, on average, for drivers older than 60 years compared to younger driver [13]. Morgan and Mannering also developed several models for crash injury severities based on the differences in age, gender, and road surface condition [14]. In doing so, they used a series of likelihood ratio tests to confirm having separate models based on these criteria. Liu et al. employed Maximum Abbreviated Injury Scale (MAIS) to delineate among crash severities across various age groups [15]. Their study revealed different patterns for the predefined age groups in terms of severities sustained. Nevertheless, there is still much to learn, especially when it comes to the difference in age. This variation corroborates the need for developing age-classified injury severity models to further explore the effect of age. Table 1 summarizes some of the studies analyzing injury severity factors of the age-classified crashes.

The review on the existing literature reveals that although there are several studies that have focused on severity analysis of crashes specific to a certain age group, almost all of them have analyzed all types of crashes without any distinction between single-vehicle and multi-vehicle crash types. Additionally, to our knowledge, there is no study to explore the variations in injury severity caused by age using the same dataset, which provides an accurate and more reliable comparison between these factors due to the consistency in the database used.

2. Methods

2.1. Data Collection and Segregation

Alabama crash database, accessed through Critical Analysis Reporting Environment (CARE) was used in this study. This database encompasses three major levels of crash characteristics including person, vehicle, and environment along with corresponding injury severity coded in the scale of KABCO, with K being "fatal injury," A being "incapacitating injury," B being "non-incapacitating injury," C being "possible injury," and O being "property damage only." Any fatality caused within 30 days of the crash occurrence is coded as fatal in CARE, [28].

Table 1- Existing Age-Classified Injury Severity Studies

Explanatory Variable	Older Drivers								Younger Drivers					
	65+ [16]	65+ [17]	65+ [18]	65+ [19]	50+ [20]	55+ [21]	65+ [22]	65+ [23]	25- [24]	25- [17]	25- [25]	25- [26]	20- [27]	25- [23]
Driver Characteristics														
Driver's Gender (based of Male)														
Female	↓[a]	↑	↑	↓	–	–	↑	↑	–	↑	↓	↓	↓	↑
Driver Condition (based of Normal)														
DUI	↑[b]	↓	↑	↑	–	–	–	–	↑	↑	↑	↑	↑	–
Asleep	–[c]	–	–	↑	–	–	–	–	–	–	↑	↑	–	–
License Status (based of Valid)														
Invalid	–	–	↑	–	–	–	–	–	–	–	–	↑	–	–
Safety Belt In-use (based of Yes)														
No	↑	↑	↑	↑	↑	–	↑	↑	–	↑	–	↑	↑	↑
Vehicle Characteristics														
Vehicle Type (based of Passenger Car)														
Pickup	–	–	↓	–	↑	↑	↑	–	–	–	–	–	–	–
SUV	–	–	↓	–	↑	–	↑	–	–	–	–	↑	–	–
Truck	–	–	↓	↑	↑	↓	–	–	–	–	–	–	↑	–
Van	–	–	↓	↑	↑	↑	↑	–	–	–	–	↑	↑	–
Crash Characteristics														
Season (based of Spring)														
Summer	–	–	↑	–	–	–	–	–	–	–	–	–	↑	–
Fall	–	–	↑	–	–	–	–	–	–	–	–	–	↑	–
Winter	–	–	↑	–	–	–	–	–	–	–	–	–	↑	–
Time of Day (based of Morning)														
Afternoon	–	–	↑	↑	–	–	–	–	↑	–	–	↑	↓	–
Evening	–	–	↑	↑	–	–	–	–	↓	–	–	↑	↑	–
Night	–	–	↑	↑	–	–	–	–	↓	–	↑	↑	↑	–
Day of Week (base of Weekday)														
Weekend	–	–	–	↑	–	–	–	–	↑	–	–	–	↑	–
Lighting Condition (based of Daylight)														
Dark - Roadway Lit	–	–	–	↑	↑	↑	–	–	↑	↑	–	↑	↓	–
Dark - Roadway Not Lit	↑	–	–	↑	↑	↑	↑	–	↑	↑	–	↑	↓	–
Dawn/Dusk	–	–	–	↑	↑	↑	–	–	–	↑	–	↓	↑	–
Weather Condition (based of Clear/Cloudy)														
Rain	–	–	–	↓	–	↑	↑	↓	↓	–	–	↑	↓	↓
Fong/Mist	–	–	–	–	–	↑	–	–	↓	–	–	↑	↓	–
Type of Setting (based of Urban)														
Rural	↑	↑	↑	–	↑	–	–	–	–	↑	–	–	–	–
Roadway Condition (based of Dry)														
Wet	–	–	↑	↓	–	–	↓	–	↓	–	–	–	↓	–
Crash Classification (based of Overturn)														
Fixed	↑	↑	–	–	↑	–	↑	–	–	–	–	–	–	–
Animal	↓	–	–	–	–	–	↓	–	–	–	–	–	–	–
Presence of Other Passengers (based of No)														
Yes	–	–	↑	–	–	–	↓	–	–	–	↑	↑	–	–
Speeding Involved (based of No)														
Yes	–	–	–	↑	↑	–	–	↑	–	↑	–	↑	↑	↑

Notes:
[a] Increasing effect on injury severity
[b] Decreasing effect on injury severity
[c] Not studied/Non-significant

Given the focus of this study, only single-vehicle crashes happened on rural two-lane highways from 2010 to 2014 were considered for analysis. This way, the effect of the presence of other drivers/vehicles and complexity arising by their varying characteristics will be offset, providing more reliable and accurate results, [29]. After all these considerations, a final dataset with 38,481 single-vehicle crashes on rural two-lane highways were remained for further analysis. In the next step, crashes were categorized based on the driver's age using the following classification: young drivers (less than 24 years old) with 13,965 records, middle-aged drivers (between 25 and 65 years old) with 22,625 records, and older drivers (older than 65) with 1,891 records. In this study, to ensure enough observation in each injury severity category, the five-level scale of KABCO was converted to a three-level scale of PDO comprising no injury crashes, non-severe (NON) comprising B- and C-injury crashes, and severe (SEV) comprising K and A-injury crashes, [30]. The summary of interesting characteristics can also be found in Table 2.

Table 2- Summary of Interesting Characteristics

Explanatory Variable	Young Drivers			Middle-aged Drivers			Older Drivers		
	PDO (n=8,411)	NON (n=3,478)	SEV (n=2,076)	PDO (n=14,277)	NON (n=4,696)	SEV (n=3,652)	PDO (n=1,078)	NON (n=426)	SEV (n=387)
Driver Characteristics									
Driver's Gender									
Male	62.1%	53.4%	60.3%	57.8%	52.7%	59.1%	60.9%	56.8%	58.1%
Female	37.9%	46.6%	39.7%	42.2%	47.3%	40.9%	39.1%	43.2%	41.9%
Driver Condition									
Normal	84.2%	79.7%	69.8%	77.0%	62.6%	51.6%	83.0%	70.9%	55.8%
DUI	9.1%	10.7%	18.7%	15.8%	23.7%	30.9%	6.0%	7.3%	11.4%
Asleep	4.4%	6.5%	5.1%	3.6%	6.8%	6.6%	6.4%	12.4%	12.4%
License Status									
Valid	93.3%	90.5%	86.4%	90.0%	82.8%	78.9%	97.2%	97.2%	96.6%
Invalid	6.7%	9.5%	13.6%	10.0%	17.2%	21.1%	2.8%	2.8%	3.4%
Safety Belt In-use									
Yes	92.3%	78.3%	60.5%	91.4%	75.8%	59.1%	94.6%	85.0%	72.4%
No	6.6%	20.5%	38.0%	6.5%	22.3%	39.0%	4.1%	14.3%	25.8%
Vehicle Characteristics									
Vehicle Type									
Passenger Car	59.4%	56.6%	54.9%	50.3%	48.4%	44.7%	49.3%	51.9%	48.8%
Pickup	24.1%	22.4%	23.1%	26.4%	25.4%	28.1%	28.3%	28.6%	28.4%
SUV	15.3%	19.6%	20.3%	19.0%	22.1%	22.7%	15.4%	13.8%	16.8%
Truck	0.1%	0.1%	0.0%	0.9%	0.4%	0.6%	1.0%	0.7%	0.8%
Van	1.1%	1.3%	1.6%	3.5%	3.7%	3.8%	6.0%	4.9%	5.2%
Vehicle Age									
Less than 5 years	15.7%	11.1%	10.1%	21.8%	13.6%	10.4%	25.0%	17.6%	17.3%
5 to 15 years	71.3%	70.8%	69.6%	64.7%	66.7%	66.2%	61.7%	63.6%	60.7%
More than 15 years	13.0%	18.1%	20.4%	13.5%	19.7%	23.4%	13.4%	18.8%	22.0%
Crash Characteristics									
Time of Day									
Morning	21.6%	23.1%	20.4%	22.9%	25.0%	21.9%	28.4%	32.2%	35.4%
Afternoon	28.2%	29.1%	27.0%	25.1%	29.1%	29.6%	35.3%	48.6%	42.9%
Evening	31.0%	29.5%	30.0%	32.6%	28.1%	29.9%	28.6%	15.3%	17.1%
Night	19.2%	18.3%	22.5%	19.5%	17.8%	18.6%	7.7%	4.0%	4.7%
Lighting Condition									
Daylight	48.9%	51.9%	47.6%	45.0%	53.2%	51.5%	59.7%	76.8%	74.9%
Dark - Roadway Lit	1.5%	1.3%	1.0%	1.4%	1.4%	0.9%	1.0%	0.7%	0.8%
Dark - Roadway Not Lit	45.3%	42.6%	47.4%	48.5%	41.4%	43.4%	34.5%	18.8%	20.9%
Dawn/Dusk	4.3%	4.2%	3.9%	5.0%	3.9%	4.2%	4.7%	3.8%	3.4%
Highway Classification									
Federal	4.7%	3.7%	4.7%	6.0%	5.4%	6.2%	6.1%	6.8%	8.5%
State	14.4%	15.9%	17.2%	19.1%	18.8%	20.7%	27.4%	24.2%	23.3%
County	80.8%	80.4%	78.1%	75.0%	75.8%	73.1%	66.5%	69.0%	68.2%
Crash Classification									
Overturn	23.1%	41.7%	43.7%	14.5%	32.1%	37.3%	9.2%	24.6%	28.9%
Fixed	66.0%	56.7%	55.6%	60.2%	63.7%	61.0%	61.2%	71.4%	69.8%
Animal	10.9%	1.7%	0.7%	25.3%	4.3%	1.7%	29.6%	4.0%	1.3%
Speeding Involved									
No	60.2%	46.6%	36.5%	74.9%	55.9%	44.9%	87.2%	77.7%	66.1%
Yes	37.9%	50.6%	60.4%	22.6%	40.5%	52.3%	10.9%	17.8%	29.5%

2.2. Generalized Ordered Logit Model

Given the nature of our dependent variable (injury severity – which is an ordered discrete variable), an ordered-response model could be considered. The standard form of the traditional ordered logit model is as follows, [31]:

$$P(Y_i > j) = \frac{exp(X_i\beta - \alpha_j)}{1+[exp(X_i\beta - \alpha_j)]} \qquad j = 1,2,\dots,M-1 \tag{1}$$

where $\boldsymbol{Y_i}$ represents the severity for crash i, j denotes each severity category, M is the number of severity categories in the ordered-response model, $\boldsymbol{X_i}$ is a vector of explanatory variables (driver, vehicle, and crash characteristics), $\boldsymbol{\beta}$ is a vector of the corresponding parameter estimations, and $\boldsymbol{\alpha_j}$ is the cutpoint for the threshold in the model. Traditional ordered logit models, while predominantly used in the current literature, are known for a limitation due to parallel regression assumption. This limitation comes from the fact that in Equation 1, only the $\boldsymbol{\alpha}$s differ across values of j that cause the M-1 regression lines be parallel. Per this assumption, the relationship between each pair of the response variables is constant within the dataset. If this assumption is violated, then the probability of injury severity for a given crash needs to be formulated using a generalized ordered logit model (GOLM) as follows, [32]:

$$P(Y_i > j) = \frac{exp(X_i\beta_j - \alpha_j)}{1+[exp(X_i\beta_j - \alpha_j)]} \qquad j = 1,2,\dots,M-1 \tag{2}$$

where, $\boldsymbol{\beta_j}$ is the vector of parameter estimations that vary across equations for different injury severities. Before developing the appropriate model, it is necessary to test whether this assumption is valid to choose between the models. In this study a Brant test is proposed to determine whether any of the variables violates this assumption, hence, justifying the use of GOLM instead of traditional ordered logit, [33].

The interpretation of the results from ordered-response models needs more attention for GOLM. In traditional ordered logit model with just one parameter estimate calculated for each variable, the positive parameter estimate demonstrates an increase in the probability of observing that variable in the higher category of the outcome. For the GOLM, where there are different parameter estimates for one specific variable, the positive parameter estimates indicate that higher values of that specific variables are associated with an increase in the probability that the specific variable will be observed in the higher category of the dependent variable than the current one (e.g., more likely to be NON or SEV than PDO). The same interpretation can be applied to negative parameter estimates, [34].

2.3. Model Specification Test

To test the justification of developing separate age-classified models, a likelihood-ratio test will be conducted. The likelihood-ratio test statistic, which follows a χ^2 distribution is calculated as follows:

$$LR = -2\left[LL(\beta_{all}) - LL(\beta_{young}) - LL(\beta_{middle-aged}) - LL(\beta_{older})\right] \tag{3}$$

where, $\boldsymbol{LL(\beta_{all})}$, $\boldsymbol{LL(\beta_{young})}$, $\boldsymbol{LL(\beta_{middle-aged})}$, and $\boldsymbol{LL(\beta_{older})}$ are the log-likelihood at convergence of the models estimated with all the data, young drivers, middle-aged drivers, and older drivers, respectively. The degrees of freedom for this test statistic is the difference between estimated parameters in the all data model and separate models together. If the calculated test statistic is higher than the χ^2 value with the same degrees of freedom at the specific confidence level, it can be concluded that the null hypothesis “all data model and separate models are not significantly different” is rejected and separate models for each age category is required.

3. Results and Discussion

As the first step and using the Brant test, it was found that the GOLM is more appropriate than standard ordered logit model with statistically significant Brant test statistic. To make a more parsimonious model, variables with p-value of less than 0.10 on at least one of the thresholds were remained in the final model. Table 3 summarizes the fitted models results across age classes. Columns labeled “Threshold 1” are the parameter estimations for the threshold for PDO versus NON and SEV crashes together. “Threshold 2” columns contain the parameter estimates for the threshold between PDO and NON versus SEV crashes. The likelihood ratio chi-square statistics of 3,275.64, 6,582.64, and 682.09 are calculated for young, middle-aged, and older drivers, respectively. These values are substantially larger than the respective critical chi-square value of 83.68 with 64 degrees of freedom at 95% confidence level, demonstrating that the presence of exogenous variables significantly improves the quality of the model’s estimation. Regarding the model specification test, the test statistic is calculated as follows, which proves the rejection of null hypothesis and necessity of developing separate models:

$$\begin{aligned} LR &= -2[-30{,}447.716 + 11{,}418.518 + 17{,}326.070 \\ &\quad + 1{,}513.661] = 378.934 > 183.186 \\ &= \chi^2_{128,99.9\%} \end{aligned}$$

3.1. Driver Characteristics

Turning to specific estimation results in Table 3, driver’s gender was found to be a significant factor for almost all severity thresholds across all age groups. Female drivers were found associated with the reduced probability of PDO crashes across all age groups compared to male drivers while this reduction is more obvious for young drivers. However, as the crashes become more severe, the role of female drivers becomes more obvious. Compared to severe crashes, the probability of female drivers getting involved in NON and PDO crashes are found to be greater. Previous studies have also shown that male drivers are associated with decreased injury levels [35].

In terms of driver condition, the results intensify the role of driver condition on the severity of crashes while corroborating the higher impact of being asleep compared to DUI. The reason might be related to the prevalence of alcohol establishments in urban areas compared to rural areas and the fact that rural roadways are more used and driven during nighttime conditions, increasing the risk of fatigued driving and in turn higher risk of more severe injuries, [36]. However, young drivers are found to suffer more from DUI driving than other age groups.

Table 3- Summary of Fitted Model (GOLM)

Explanatory Variable		Young Drivers		Middle-aged Drivers		Older Drivers	
		Threshold 1	Threshold 2	Threshold 1	Threshold 2	Threshold 1	Threshold 2
Driver Characteristics							
Driver's Gender							
	Male [a]	-	-	-	-	-	-
	Female	0.571***	0.238***	0.413***	0.207***	0.260**	0.190
Driver Condition							
	Normal [a]	-	-	-	-	-	-
	DUI	0.001	0.221***	-0.042	0.011	0.066	0.143
	Asleep	0.393***	0.025	0.523***	0.381***	0.335*	0.197
Local Drivers							
	Yes [a]	-	-	-	-	-	-
	No	-0.193***	-0.191**	-0.053	-0.070	0.030	-0.003
License Status							
	Valid [a]	-	-	-	-	-	-
	Invalid	0.205***	0.235***	0.121***	0.051	-0.346	-0.292
Safety Belt In-use							
	Yes [a]	-	-	-	-	-	-
	No	1.470***	1.359***	1.427***	1.277***	1.403***	1.118***
Vehicle Characteristics							
Vehicle Type							
	Passenger Car [a]	-	-	-	-	-	-
	Pickup	-0.096*	-0.148**	-0.026	0.028	-0.201	-0.147
	SUV	0.076	0.038	0.087**	0.106**	-0.22	-0.003
	Truck	0.061	-0.850	-0.337*	0.036	-0.447	-0.412
	Van	0.301*	0.433**	0.189**	0.232**	0.040	0.164
Vehicle Age							
	Less than 5 years [a]	-	-	-	-	-	-
	5 to 15 years	0.175***	0.131	0.176***	0.233***	0.023	-0.129
	More than 15 years	0.582***	0.449***	0.426***	0.441***	0.198	0.110
Damage to Vehicle							
	Minor	-	-	-	-	-	-
	Major - Not Disabling [a]	0.270**	0.559***	0.088	0.011	0.225	0.516
	Major - Disabling	1.388***	1.561***	1.387***	1.463***	1.789***	1.75***
Crash Characteristics							
Season							
	Spring [a]	-	-	-	-	-	-
	Summer	0.101*	0.002	0.033	0.014	0.109	0.142
	Fall	0.075	0.117	0.036	-0.002	-0.013	-0.009
	Winter	-0.008	0.013	-0.067	-0.127**	-0.065	-0.124
Time of Day							
	Morning [a]	-	-	-	-	-	-
	Afternoon	-0.057	-0.008	-0.011	0.058	-0.009	-0.185
	Evening	-0.092	0.027	-0.069	0.058	-0.725***	-0.456
	Night	-0.126	0.050	-0.101	-0.002	-0.603*	-0.397
Lighting Condition							
	Daylight [a]	-	-	-	-	-	-
	Dark - Roadway Lit	-0.043	-0.430	-0.201	-0.599***	0.125	-0.036
	Dark - Roadway Not Lit	0.071	0.007	-0.076	-0.086	0.200	0.175
	Dawn/Dusk	0.068	-0.022	-0.151*	-0.045	0.164	0.051
Weather Condition							
	Clear/Cloudy [a]	-	-	-	-	-	-
	Rain	-0.073	-0.102	-0.080	-0.231**	-0.083	-0.104
	Fong/Mist	-0.141	-0.283*	-0.068	-0.181	-0.406	-0.104
Roadway Condition							
	Dry [a]	-	-	-	-	-	-
	Wet	-0.095	-0.006	-0.153***	-0.024	-0.403*	-0.453
Highway Classification							
	Federal [a]	-	-	-	-	-	-
	State	0.193*	0.010	0.043	-0.007	-0.289	-0.383
	County	-0.202**	-0.423***	-0.268***	-0.417***	-0.399*	-0.526**

Crash Classification						
Overturn [a]	-	-	-	-	-	-
Fixed	-0.502***	-0.283***	-0.447***	-0.294***	-0.638***	-0.394***
Animal	-1.980***	-1.938***	-1.89***	-1.891***	-2.592***	-2.722***
Presence of Other Passengers						
No [a]	-	-	-	-	-	-
Yes	0.459***	0.297***	0.420***	0.283***	0.156	0.029
Speeding Involved						
No [a]	-	-	-	-	-	-
Yes	0.327***	0.403***	0.496***	0.542***	0.376**	0.590***
Constant	-2.010***	-3.503***	-1.726***	-3.127***	-0.656*	-1.953***
Number of Observations		13,965		22,625		1,891
LL at constant		-13,055.703		-20,616.450		-1,854.749
LL at convergence		-11,418.518		-17,326.070		-1,513.661
LR chi^2 (64)		3,275.640		6,582.640		682.090
Prob > chi^2		<0.001		<0.001		<0.001
McFadden's Pseudo R^2		0.1254		0.1596		0.1839

Notes:
*** Significant at the 99% confidence interval
** Significant at the 95% confidence interval
* Significant at the 90% confidence interval
[a] Reference category for the variable

In-transit (non-local) young drivers are negatively associated with aggravated injury severity. The effect of this variable is not found significant for the other age groups. The decreased probability of severe crashes for non-local drivers compared to local drivers can be reasonable as non-local drivers are more cautious than local drivers enhancing their safety in non-familiar areas, [37]. Instead, the familiarity of the driver with surroundings might lead to more risky driving actions and inattentive behaviors.

Previous studies have deemed that drivers with invalid licenses are more likely to get involved in risky driver behaviors than others, [38]. However, the change in this risky behavior and the probable outcome is not identified across various age groups. Per the results, license status is found to significantly increase the injury severity in young and middle-aged driver groups, and not older drivers. A recent research by Sivak and Schoettle shows a decreasing trend in the percentage of young licensed drivers and this age group are more likely to drive while unlicensed or with invalid license, [39].

Seat belt usage has one of the strongest effects on the injury severity as this factor is found to be significant among all age groups. The value of this parameter estimate shows a considerable increase in the probability of having more severe injuries for all models. This result is in line with other studies that have shown the significant role of seat belt usage on the severity of crashes, [11, 40, 41].

3.2. Vehicle Characteristics

While most drivers were driving passenger cars, the type of vehicle shows various effects across studied age groups. Despite vehicle type being non-significant for older drivers, vans are responsible for increased severity of crashes for both young and middle-aged drivers. SUVs are also found associated with increased probability of more severe crashes; however, the magnitude of this change in the probability is found stronger for vans compared to SUVs. The reason can be attributed to the fact that vans usually carry more passengers and they are less likely to wear seatbelt which indeed increases the likelihood of being more severely injured, [42]. Pickups are also responsible for higher probability of less severe crashes and indicate safer drive for both the driver and accompanying passengers.

Vehicle age significantly affects the severity of crashes for non-older drivers. Specifically, it is found that driving an old vehicle (older than 5 years) could increase the likelihood of having more severe crashes, while this increase is stronger for vehicles 15 years old and above. Interestingly, our database reveals the tendency of older drivers towards newer vehicles and the tendency of young drivers towards older vehicles. Past research has found the same trend in terms of increasing likelihood of injury severity based on the vehicle age and the vulnerability of novice drivers driving older vehicles during car accidents, [42-44].

3.3. Crash Characteristics

Non-significant differences between seasons are found for injury severities for most thresholds. However, the summer season is determined to significantly decrease the probability of PDO crashes and, consequently, increase the probability of more severe crashes for young drivers. This result is in line with the study by Li, [45]. Winter season is also associated with the decreased likelihood of severe crashes for middle-age drivers.

Temporal distribution of the studied crashes over time of day was not found to be significant for all the age groups except older drivers that sustain a higher likelihood of PDO crashes during evening and nighttime conditions. The reason is perhaps related to the visual ability of older drivers that is heavily affected by lighting conditions. This situation not only causes older drivers to drive slower but also, in the event of the crash, causes less serious injuries to the driver and passenger. The effect of lighting was not found to be significant for most lighting conditions in three developed models except for middle-aged drivers driving during dawn/dusk and on the lit roadways during nighttime conditions. However, lighting is found to be a major contribution to severe crashes in the past, [46]. Crashes caused by this group were less likely to be severe when the roadway is lit and more likely to be PDO during dawn/dusk.

Regarding weather and roadway condition, middle-aged drivers faced lower risk of sustaining a severe injury during rainy days. Foggy/misty weather condition also significantly decreased the likelihood of severe injuries for young drivers. These results can be explained as during the inclement weather condition or when sufficient sight distance is not provided, drivers tend to show risk-compensating behaviors and pay more attention to their surroundings, including roadway and other vehicles, and drive at lower speeds compared to clear/cloudy days, [47, 48]. In addition to weather condition, real-time pavement surface condition is also of high importance. Accordingly, the variable indicating wet pavement surface was found to significantly decrease the severity of crashes for middle-aged and older drivers. The same reason that applies to justify increased likelihood of PDO crashes during inclement weather condition also applies to this parameter.

Except for young and middle-aged drivers on state roads that show varying outcomes in terms of severity of crashes, older drivers on state highways and all age groups on county highways show a downward trend towards less severe crashes. The reason for lower severity of crashes is that generally the speed limit on county and state highways is less than federal highways so that the outcome would be less severe. Specifically, the average speed for federal, state, and county highways based on our database is 55 mph, 51 mph, and 42 mph, respectively.

Compared to overturn crashes, hitting a fixed object or an animal is associated with lower probability of severity outcome for all age categories while the magnitude of likelihood reduction is stronger when hitting animals. These results are consistent with prior research showing that overturn crashes are more likely to be injury-prone compared to crashes with fixed objects and animals, [47, 49].

The presence of accompanying passenger with drivers is correlated with increased injury severity for young and middle-aged driver groups, while this factor is not statistically significant for older drivers. A review on the existing literature shows different results for this variable. For example, while Yasmin et al. show a generally lower likelihood of severe injuries with the presence of more passengers supposedly because of more responsible driving behavior, Weiss et al. found varying results in terms of injury severity based on the age and gender of accompanying passenger, [26, 50].

The results of the model indicate that the probability of non-severe and severe injuries increases considerably with travelling at speeds higher than designated speed limit. This effect varies for different injury levels with the highest effect observed on severe crashes. The relationship between speeding and injury severity can be explained as higher speeds should lead to higher probability of overturn and higher impact speeds with fixed objects and animals, increasing the likelihood of more severe injuries.

4. Conclusions

The results of our analysis of single-vehicle crashes on rural two-lane highways identified several factors affecting the severity of crashes that were found to be common and with the same direction among all developed models. These variables include driver gender (associated with lower injury severity), being sleepy (associated with higher injury severity), not using safety belt (associated with higher injury severity), extent of damage imposed to vehicle (associated with higher injury severity), driving on county roads (associated with lower injury severity), hitting animal or fixed object (associated with lower injury severity), and speeding (associated with higher injury severity). On the other hand, a difference among contributing factors to injury severity for various age groups is also noticeable. While this difference between young and middle-aged drivers is explicit, the difference between older drivers and the other two age groups is substantial, mainly related to driver condition, license status, presence of other passengers, and time of day.

Per the results, appropriate countermeasures can be employed based on the age of drivers to decrease the severity of crashes. For example, to address DUI driving in young drivers, enacting more restrictive laws and enforcements, having educational programs and campaigns, and continual surveillance of alcohol use, specifically in this age group in Alabama, might help increase the public awareness of the drunk driving and decrease the severity of crashes. The same solutions can be applied to the speeding violations, safety belt usage, and driving with invalid license.

We concluded that developing three separate age-classified models for this kind of crashes can effectively delineate between contributing factors specific to each group. As a recommendation for future studies, the inclusion of other factors (e.g., amount of clear zone provided, type of object within the clear zone, roadside slope) might strengthen the model, depending on the level of details of information provided in the crash reports or other data sources. A comparison between single-vehicle crashes with other crash types might also highlight some other facts. This study has some limitations as well:

1. It only used crash data from a single state (Alabama); though, bolstering crash database by incorporating data from other states can strengthen the conclusions.
2. Adding other site-specific data, such as geometric design elements data, can also be helpful as crash records lack such information.
3. The crash reporting dollar threshold affects the number of crashes being reported, specifically for single-vehicle crashes which necessitates further studies to overcome this issue by providing appropriate solutions such as having adjustment factors to account for underreported number of crashes.

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