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Factors Affecting Crash Severity among Elderly Drivers: A Multilevel Ordinal Logistic Regression Approach

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Abstract: This study modeled the crash severity of elderly drivers using data from the state of Virginia, United States, for the period of 2014 through to 2021. The impact of several exogenous variables on the level of crash severity was investigated. A multilevel ordinal logistic regression model (M-OLR) was utilized to account for the spatial heterogeneity across different physical jurisdictions. The findings discussed herein indicate that the M-OLR can handle the spatial heterogeneity and lead to a better fit in comparison to a standard ordinal logistic regression model (OLR), as the likelihood-ratio statistics comparing the OLR and M-OLR models were found to be statistically significant, with p-value of <0.001. The results showed that crashes occurring on two-way roads are likely to be more severe than those on one-way roads. Moreover, the risks for older, distracted, and/or drowsy drivers to be involved in more severe crashes escalate than undistracted and nondrowsy drivers. The data also confirmed that the consequences of crashes involving unbelted drivers are prone to be more severe than those for belted drivers and their passengers. Furthermore, the crash severity on higher-speed roads or when linked to high-speed violations is more extreme than on low-speed roads or when operating in compliance with stated speed limits. Crashes that involve animals are likely to lead to property damage only, rather than result in severe injuries. These findings provide insights into the contributing factors for crash severity among older drivers in Virginia and support better designs of Virginia road networks.

Keywords: crash severity; crash modeling; multilevel modeling; ordinal logistic regression; spatial heterogeneity; road safety; elderly drivers; transportation safety

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1. Introduction

The human costs of road crashes worldwide are significant, leading to 1.35 million fatalities yearly, with an additional 50 million people incurring some form of disability [1]. According to the World Health Organization (WHO), road accidents are projected to be the seventh primary cause of death by 2030. Moreover, driving-related accidents leading to sudden death or permanent disability impose tremendous economic, social, and human capital losses. It is estimated, for example, that road crashes are responsible for approximately a 3% loss in gross domestic product (GDP) for most nations [1].

Current demographic trends associated with an aging population [2,3] are increasing the likelihood of automobile accidents involving drivers aged 65 and older. The number of licensed elderly drivers in the United States, for example, climbed by 65% during the period of 1997 to 2018 [4]. Moreover, the injury and death risk among older drivers involved in automobile accidents continues to rise; indeed, the fatality rates for older drivers and their passengers are ranked higher in crash severity than any other road accident fatalities [5–10]. The Insurance Institute for Highway Safety [11] has found that drivers over the age of 80 have about a 0.658% chance of being killed in a car accident, which is almost four times greater than that for those between the ages of 30 and 39 (0.137%). Previous studies have confirmed the significant difference in nonfatal and fatal crash risks among subgroups of older drivers, with the highest crash risk being among elderly drivers [12].

The high risk of injury and fatality among older drivers is attributed to the diverse facets associated with aging—notably, deficits in physical, cognitive, and visual competence. These particular impairments represent significant challenges for this cohort of drivers. Older drivers can experience numerous challenges that put them at a higher risk of crashes [13–15]. For instance, it can be stressful for these drivers to assess traffic patterns, change lanes, or make turns [2]. Research also shows that older drivers can find it challenging to drive on congested roads, in unfamiliar areas, during wet conditions, and in regions with unfamiliar obstacles that need maneuvering [6]. Another study confirmed that it can often be problematic for older drivers to track the movement of pedestrians, read signs, and perceive conflicting vehicles at night [16]. Older drivers often find it tiring to drive on long journeys and are less adept at coping with an automotive breakdown [6].

Previous studies have indicated that there is a relationship between drivers' socioeconomic demographics (SEDs) and their likelihood of being involved in speeding behavior and traffic crashes [17]. Different age-groups are associated with distinct psychological and physiological features that affect how they react to unexpected situations (e.g., a traffic accident) [18]. It is these physiological elements that make older drivers vulnerable to run-off-the-road types of crashes [19]. Specific factors include risk-taking behavior, diminished vision, reaction times, and other age-related deficits [18]. Higher crash rates for the elderly have also been documented as a result of decreases in the cognitive and physical abilities of the aging population, who typically require longer perception–reaction times when driving [20]. For instance, elderly drivers are more frequently associated with surveillance errors, which can be attributed to looking but not really seeing [11]. Such errors occur due to declines in the speed and efficacy of information processing and the ability to achieve visual attention division. Even healthy older adults experience functional declines in cognitive, physical, and sensory areas, which affect their driving and make them vulnerable to crashes [6]. Road crashes vary in terms of the level of injury and the incidence of fatalities [21]. Previous studies have indicated that older traffic victims present with skeletal injuries (e.g., rib fractures) that are linked to internal injuries at higher rates than younger victims, who are treated for crash-related internal injuries unrelated to rib fractures [18]. The overall physical fragility of the elderly due to aging makes them highly susceptible to injuries or being killed during a crash [22].

While many studies have focused on vehicle traffic crash severity, less attention has been paid to more vulnerable road users—senior drivers in particular. Thus, analyzing the crash-severity statistics connected to this population may help in identifying the factors influencing crash-severity occurrence. The reliability of modeling techniques and a thorough analysis of road crashes are crucial in reducing severe injuries and fatalities resulting from vehicular accidents. The majority of previous studies utilized traditional statistical approaches for modeling crash-severity levels, which are mainly based on using the logit and ordered probit models while ignoring the cluster-specific effect. However, these techniques lack the potential to adequately model the injury severity of the occupant and the damage of the vehicle when other correlations exist between the items that are involved in several crashes of vehicles [23]. For example, it is indicated that the fatality risk is always dependent on other vehicle characteristics [24]. Crashes that occur in a specific segment are given risk factors that can be studied over time [23]. The repetitive measurements in such situations are nested in crashes that are nested in segments to create varying severity levels [25]. Moreover, the spatial heterogeneity in crash severity creates a variance that is within the strata, which is below that of between the strata [26]. Such is evidenced by the aspects of geographical division, rural–urban difference, land-use maps, climatic zones, and functional area [27]. In short, spatial heterogeneity is known to influence the severity of crash-related injuries. Hence, it is vital to ensure that all of the clustering levels are accounted for when undertaking a multilevel crash-data analysis. Ignoring the cluster-specific effect would likely lead to statistical errors, including the estimation of biased parameters, the underestimation of standard errors, and the overestimation of statistical significance.

This study aimed to model the crash severity among older/elderly drivers, defined herein as drivers 65 years of age and older. Crash data were obtained from the Commonwealth of Virginia (USA) and encompassed the period of 2014 to 2021. For this study, crash severity was assessed using multilevel ordinal logistic regression (M-OLR) modeling to account for the cluster-specific affect. This study also investigated crash-severity contributing factors. The contributions of this paper are as follows: first, we explored and identified the factors responsible for crash severity for vulnerable road users, specifically elderly drivers in Virginia. Second, we examined and quantified the effects of various exogenous variables (i.e., driver characteristics and site-specific conditions) on crash severity for elderly drivers. Identifying the main factors that influence crash severity will help to mitigate the risk and improve the safety of road users. Third, we integrated a multilevel ordinal logistic regression analysis technique to consider the heterogeneity derived from different physical jurisdictions.

2. Data Description

The crash dataset assessed for this study was obtained from the Virginia Department of Transportation (VDOT). The database included crash reports for 8 years: from 2014 to 2021, with a total of 986,101 crashes reported within the Commonwealth of Virginia during this period. We examined the crash severity of motor vehicle crashes involving senior drivers who were 65 years of age and older. The selection of this age threshold is based on the National Highway Traffic Safety Administration [28]. Within this subdataset, senior drivers were involved in 157,800 crashes, all of which were included in the analysis. The crash-severity level is presented using the KABCO scale. Following prior research [29,30], we classified crash severity into three categories: (a) PDO for property damage only, designated as O; (b) minor injuries designated as B + C; and (c) possible fatalities denoted as K + A.

The dataset for this study was collected from 313 physical jurisdictions, which are the VDOT's nomenclature for apportioning Virginia's counties, towns, and cities. Eighteen variables were considered in the analysis, and their descriptive statistics are presented in Table 1. These variables include the crash type, traffic signals, weather conditions, roadway alignment, roadway type, work zone, alcohol use, belt usage, bike involvement, distraction, drowsiness, drug usage, pedestrian involvement, speed violation, area type, animal involvement, posted speed, and time of the week (i.e., whether the accident occurred on a weekend). Figures 1 and 2 provide a visual reference for total crashes and those involving possible fatalities within Virginia's physical jurisdictions over the eight-year period of data collection.

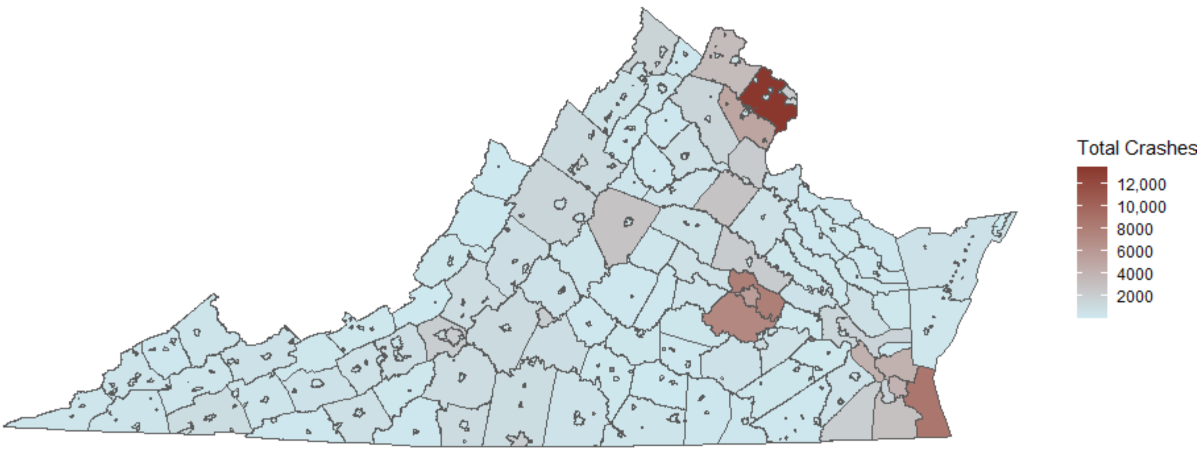

Figure 1. Total crashes across the physical jurisdictions of Virginia.

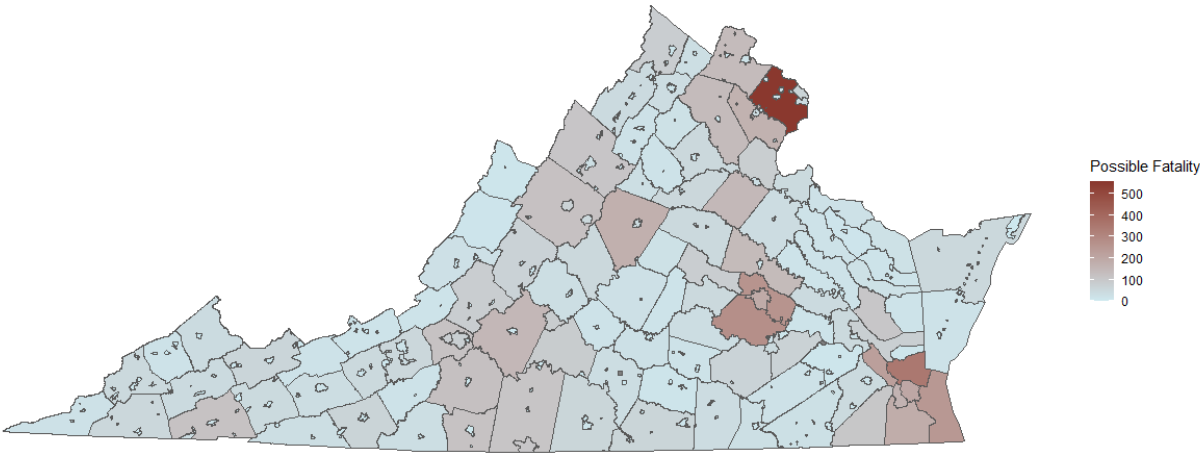

Figure 2. Crashes involving possible fatalities within Virginia's physical jurisdictions.

Table 1. Variables' descriptive statistics.

Variable	Category	Count	Percentage/Mean
Crash severity	PDO	98,702	62.55%
	Minor injury	49,771	31.54%
	Severe injury	9327	5.91%
Crash type	Fixed object	13,399	8.49%
	Head-on	3813	2.42%
	Overturned	1156	0.73%
	Other	10,479	6.64%
	Rear end	52,953	33.56%
	Sideswipe	17,471	11.07%
	Angle	58,529	37.09%
Traffic signal	Yes	40,998	25.98%
	No	116,802	74.02%
Weather condition	No adverse condition	137,196	86.94%
	Adverse condition	20,604	13.06%
Roadway alignment	Straight	142,472	90.29%
	Curve	15,328	9.71%
Roadway type	Two-way divided	91,375	57.91%
	Two-way undivided	62,206	39.42%
	One-way	4219	2.67%
Work zone	No	153,567	97.32%
	Yes	4233	2.68%
Alcohol	Yes	3483	2.21%
	No	154,317	97.79%
Belted	No	4271	2.71%
	Yes	153,529	97.29%
Bike	Yes	915	0.58%
	No	156,885	99.42%
Distracted	Yes	28,054	17.78%
	No	129,746	82.22%
Drowsy	Yes	2733	1.73%
	No	155,067	98.27%
Drugs	Yes	716	0.45%
	No	157,084	99.55%

Table 1. *Cont.*

Variable	Category	Count	Percentage/Mean
Pedestrian	Yes No	1605 156,195	1.02% 98.98%
Speed violation	Yes No	20,211 137,589	12.81% 87.19%
Area type	Urban Rural	121,884 35,916	77.24% 22.76%
Animal	Yes No	5060 152,740	3.21% 96.79%
Posted speed (mph)	-	157,800	41.93
Weekend	Yes No	32,622 125,178	20.67% 79.33%

3. Methodology

3.1. Ordinal Logistic Regression (OLR)

OLR is a generalization of the binary logistic regression model in the case of multiple categories. As such, OLR was used to model the ordinal categories of a given response variable with multiple categories. Ordinal logistic regression modeling is useful in estimating the odds being either equal to or below a specific response-variable level [28]. For instance, if the levels of ordinal outcomes are denoted as j, then the number of predictions that are made by the OLR model is given as $(j-1)$. Each of these predictions estimates the probability of the odds being either equal to the jth level or below it in consideration of the outcome variable. Such odds equal to or below the jth level constitute the cumulative odds. At this juncture, the working assumption is that there are similar odds ratios across all categories for each predictor. This assumption is noted as the parallel lines or the proportional odds assumption. The proportional odds (PO) model is expressed in the logit form, as given by Equation (1) [31]:

$$\operatorname{logit}\left[\pi_j(x)\right] = \ln\left(\frac{\pi_j(x)}{1-\pi_j(x)}\right) = \alpha_j + \left(-\beta_1 X_1 - \beta_2 X_2 - \ldots - \beta_{\mathrm{p}} X_{\mathrm{p}}\right) \tag{1}$$

where $\pi_j(x) = P\left(Y \leq j \mid x_1, x_2, \ldots, x_{\mathrm{p}}\right)$, which gives the probability of being equal to or below the j level for any given set of predictors, j is a discrete index $\{1, 2, \ldots, j-1\}$, α_j is the cutoff point, and $\beta_1, \beta_2, \ldots, \beta_{\mathrm{p}}$ are the logit coefficients. In order to calculate the ln(odds) of being equal to or below the jth level, Equation (1) can be rewritten as given by Equation (2):

$$\begin{aligned} \operatorname{logit}\left[P\left(Y \leq j \mid x_1, x_2, \ldots, x_{\mathrm{p}}\right)\right] &= \left(\frac{P\left(Y \leq j \mid x_1, x_2, \ldots, x_{\mathrm{p}}\right)}{P\left(Y > j \mid x_1, x_2, \ldots, x_{\mathrm{p}}\right)}\right) \\ &= \alpha_j + \left(-\beta_1 X_1 - \beta_2 X_2 - \ldots - \beta_{\mathrm{p}} X_{\mathrm{p}}\right) \end{aligned} \tag{2}$$

For the ordinal response variable, it is plausible to consider the PO as a number of simultaneously estimated binary logistic regression models. There is a dichotomization of the outcome variables of the binary models from the ordinal outcome variable that compares outcomes at or below the category ($Y \leq$ cat. j) or above the category ($Y >$ cat. j). Thus, the odds of being equal to or below the category, coded as 1, versus the odds of being above the category, coded as 0, can be estimated using binary logistic regression. The estimated logit coefficients are reported to be equal despite the logistic models having different intercepts. This means that across the categories, the odds are proportional or the regression lines are parallel. Consequently, for every predictor variable, only one regression coefficient needs estimating, as opposed to estimating multiple coefficients.

3.2. Multilevel Ordinal Logistic Regression (M-OLR)

The data format used in hierarchical structured data, multilevel data, and nested data is such that observations at a lower level are nested within one, or more, higher level. Examples of this approach are the nesting of patients within hospitals in medical science, the nesting of voters within districts in political science, and the nesting of families within communities in sociology. Thus, there is a deliberate violation of the assumption of independence, since a greater level of homogeneity is observed in the same groups, as opposed to when observing different groups. The level 1 equation for the multilevel PO model is given by Equation (3) [31]:

$$\begin{aligned} \text{logit}\left[\pi_{kij}(Y \le k)\right] &= \ln\left(\frac{\pi\left(Y_{ij} \le k \mid x_1, x_2, \ldots, x_p\right)}{\pi\left(Y_{ij} > k \mid x_1, x_2, \ldots, x_p\right)}\right) \\ &= \alpha_k + \left(-\beta_{1j}X_{1ij} - \beta_{2j}X_{2ij} - \cdots - \beta_{pj}X_{pij}\right) \end{aligned} \tag{3}$$

In this case, the link function is provided as $\text{logit}\left[\pi_{kij}(Y \le k)\right]$. The purpose of the link function is to transform the original ordinal response variable Y for the ith individual in the jth cluster into the logit, the transformed outcome, or the log odds of the cumulative probability of being equal to or below a particular category k. On the other hand, the middle section is termed the log odds. At this point, the cumulative odds of being equal to or below a specific category equate to the probability ratio of being equal to or below a category to being above that category. Finally, the linear combination of the predictor variables whereby every logit coefficient is associated with cluster j is provided on the right side of the equation. In this case, the cutoff points are given as α_k, while the predictor variables for the ith individual within the jth cluster are given as X_{1ij}, X_{2ij}, ... , X_{pij}. Finally, the logit coefficients of the predictors within the jth cluster are provided as β_{1j}, β_{2j}, ... , β_{pj}.

The crash predictors to the level 1 equation are included in the random intercept model, where the intercept is permitted to randomly change across various physical jurisdictions. For the M-OLR model, the logit link for the cumulative probability of being at or below a particular category k for the ith crash predictor in the jth physical jurisdiction is provided as logit (π_{kij}). Concisely, the components of the level 1 equation (i.e., Equation (3)) are the crash severity, or the ordinal response variable, and the crash predictors.

In the level 2 equation, γ_{00} is the overall logit or log odds of being at or below a specific crash severity across physical jurisdictions, and u_{0j} is an error term at the physical jurisdiction level. The relationships are given by Equation (4):

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + u_{0j} \\ \beta_{1j} &= \gamma_{10} \\ \beta_{2j} &= \gamma_{20} \\ &\vdots \\ &\vdots \\ \beta_{pj} &= \gamma_{p0} \end{aligned} \tag{4}$$

While the level 2 equation is noted to have random intercepts, the crash predictors are constrained and the slopes are fixed.

4. Results and Discussion

4.1. Model Comparison

The crash-severity levels were modeled using the OLR model and the M-OLR model, since spatial heterogeneity has an impact of influencing the severity of the injury that is realized in traffic accidents [26]. Multilevel ordinal logistic regression (M-OLR) modeling was utilized to account for the cluster-specific effect. The comparison statistics between the two models are presented in Table 2. The results show that the likelihood-ratio statistics for the OLR and M-OLR models were 15,561 and 15,696, respectively. Both models were statistically significant at a 99% confidence interval level. These results indicate that both models were useful for explaining the crash severity. However, note that the M-ORL model yields a better fit, as the likelihood-ratio statistics comparing the OLR and M-OLR models were found to be 4650.6, with 1 df and a p-value of <0.001. Moreover, the M-OLR model is preferable, as it was found to yield a significantly lower AIC (240,091) and BIC (240,360) than the OLR method, whose corresponding AIC and BIC data were 244,740 and 244,999, respectively.

Table 2. Model comparison statistics.

Model	LL (β)	LL (0)	Degree of Freedom	Likelihood Ratio Statistics	AIC	BIC
Ordinal logistic regression (OLR) model	−122,344	−130,124	24	15,561	244,740	244,999
Multilevel ordinal logistic regression (M-OLR) model	−120,018	−127,866	24	15,696	240,091	240,360

4.2. Results of the Crash-Severity Model

An M-OLR model was developed to investigate the influencing factors on crash-severity level. The estimated model parameters are presented in Table 3. Eighteen variables were found to significantly influence (at a 95% confidence level) crash severity among elderly drivers. These variables included the crash type, traffic signal, weather condition, roadway alignment, roadway type, work zone, alcohol use, belt usage, bike involvement, distraction, drowsiness, drug usage, pedestrian involvement, speed violation, area type, animal involvement, posted speed, and time of the week (i.e., whether the incident occurred on a weekend). The model estimates and odds ratios (ORs) confirmed that the crash severity was influenced when compared with a baseline (i.e., reference) category. A positive estimate and an OR of more than 1 indicate that the category affects the crash-severity level more than the reference category and vice versa.

The estimated model parameters for both head-on and overturned crashes were found to be positive (i.e., 0.942 and 0.836, respectively) with ORs larger than 1 (i.e., 2.57 and 2.31, respectively). This finding confirms the higher severity of head-on and overturned crashes for the elderly compared to the angle (side) crash type. This outcome is likely attributed to transferring the full kinetic energy of the crash through the front of both vehicles or the vehicle involved in the overturn. A similar result was obtained for the fixed-object crashes. In contrast, both the rear-end and sideswipe crashes displayed negative parameter estimates (i.e., −0.170 and −0.892, respectively) with ORs less than 1 (i.e., 0.84 and 0.41, respectively), indicating the lower severity of these crashes for elderly drivers compared to the angle-crash type.

For the traffic signal variable, the model estimate indicates that crash locations with traffic signals negatively impact the crash-severity level (OR = 1.25). This result can be attributed to risk compensation [32], where a higher dependence of road users on traffic signals can reduce their level of attention to the surrounding environment. Moreover, the crash severity on curved roads is higher than when driving on straight roads, where the odds were found to be 0.88. This outcome can be attributed to the higher probability of noncompliance and the reduced visibility and ability to control vehicles or bikes on curved roads compared to straight roads. Similar results were obtained in an earlier study [24]. With respect to roadway type, the model estimate indicates that crashes occurring on two-way roadways are likely to be more severe than those on one-way roadways, with an OR of 1.28.

Table 3. Multilevel ordinal logistic model results.

Variable	Category	Estimate	SE	Z-Stat	p-Value	Odda Ratio	95% CI (Odds)	
							Lower	Upper
Crash type	Fixed object	0.2837	0.021	13.24	< 0.001	1.33	1.27	1.39
	Head-on	0.9426	0.033	28.16	< 0.001	2.57	2.40	2.74
	Overturned	0.8358	0.060	13.99	< 0.001	2.31	2.05	2.59
	Rear end	−0.1696	0.013	−12.82	< 0.001	0.84	0.82	0.87
	Sideswipe	−0.8917	0.021	−42.43	< 0.001	0.41	0.39	0.43
	Angle *							
Traffic signal	Yes No *	0.2248	0.013	17.34	< 0.001	1.25	1.22	1.28
Weather condition	No adverse condition Adverse condition *	0.1601	0.016	9.95	<0.001	1.17	1.14	1.21
Roadway alignment	Straight Curve *	−0.1246	0.019	−6.539	<0.001	0.88	0.85	0.92
Roadway type	Two-way divided	0.2493	0.036	6.98	<0.001	1.28	1.20	1.38
	Two-way undivided	0.2438	0.036	6.80	<0.001	1.28	1.19	1.37
	One-way *							
Work zone	No Yes *	0.2187	0.035	6.33	<0.001	1.24	1.16	1.33
Alcohol	Yes No *	0.4487	0.035	12.76	<0.001	1.57	1.46	1.68
Belted	No Yes *	1.8704	0.032	58.92	<0.001	6.49	6.10	6.91
Bike	Yes No *	2.4919	0.062	40.41	<0.001	12.08	10.71	13.64
Distracted	Yes No *	0.079	0.014	5.494	<0.001	1.08	1.05	1.11
Drowsy	Yes No *	0.1313	0.041	3.208	0.0013	1.14	1.05	1.24
Drugs	Yes No *	0.4028	0.076	5.332	<0.001	1.50	1.29	1.74
Pedestrian	Yes No *	2.8737	0.055	52.661	<0.001	17.70	15.91	19.70
Speed violation	Yes No *	0.2145	0.016	13.090	<0.001	1.24	1.20	1.28
Area type	Urban Rural *	−0.1809	0.023	−7.880	<0.001	0.83	0.80	0.87
Animal	Yes No *	−1.4831	0.052	−28.610	<0.001	0.23	0.21	0.25
Posted speed	-	0.0076	0.001	12.526	<0.001	1.01	1.01	1.10
Weekend	Yes No *	0.0536	0.013	4.059	<0.001	1.06	1.03	1.08
Intercept	PDO | minor injury	1.1308	0.060	18.93	<0.001	3.682	3.23	4.20
	Minor injury | severe and fatal injury	3.5962	0.061	59.16	<0.001	45.679	39.97	52.20
Intercept variance	Physical jurisdiction	0.1798	0.424					
Log − likelihood at convergence	−120,018							
Log − likelihood at zero	−127,866							
AIC	240,091							
Likelihood ratio	15,696							
Number of observations	157,800							

* Reference category.

Furthermore, crashes that involve drunk drivers or those under the influence of drugs are likely to be more severe than those involving unimpaired drivers, with ORs of 1.57 and 1.5, respectively. This finding is due to the impact of alcohol and drugs on diminished brain functions associated with thinking, reasoning, and muscle coordination, which are essential for controlling a vehicle. Similarly, distracted and drowsy drivers are associated with more severe crashes than undistracted and nondrowsy drivers, with ORs of 1.08 and 1.14, respectively. This increasingly important finding can be attributed to the impact of phone usage on the cognitive functions of road users. Indeed, a growing body of literature is emphasizing how dual tasking (e.g., mobile phone use or texting while driving) competes for cognitive resources, which may lead to prioritizing the former over the latter, thereby increasing the risk of vehicular accidents [33]. Research also shows that drowsy drivers tend to display longer reaction times, reduced judgment and muscle coordination, and more frequent lane-departure events compared to nondrowsy drivers [34].

For unbelted drivers and passengers, the model estimate indicates that the consequences of crashes involving unbelted drivers are likely to be more severe than those involving belted drivers and passengers, with an OR of 6.49. This finding is almost certainly due to the increased likelihood of severe head and chest trauma resulting from slamming into the dashboard or windscreen (or even being ejected from the car) compared to belted drivers and passengers. For traffic crashes that involve vulnerable road users (e.g., bikes or pedestrians), the model estimates indicate that the likelihood of severe crashes is higher for crashes that involve these vulnerable road users compared to those that do not, with ORs of 12.08 and 17.70, respectively. This increased risk is associated with the higher likelihood of traumatic brain or musculoskeletal injuries in such crashes.

With respect to the traffic environment, the model estimate indicates that crash severity on high-speed facilities (e.g., highways) is higher than those taking place on low-speed facilities (e.g., local roads), with an OR of 1.01 for an increase in speed of 1 mph. This finding can be attributed to higher crash speeds at higher driving speeds, which leads to more severe crashes. Moreover, driving at higher speeds gives the driver less time to react in the case of an emergency, and likely requires a greater braking distance. Moreover, the model estimate indicates that speed violations would likely lead to more severe crashes, with an OR of 1.24. We can attribute this finding to higher noncompliance with the rules of the road. Previous studies have shown that higher noncompliance with road-design requirements is associated with more severe crashes [17,35–37].

When considering weather conditions, the model estimates indicate that crashes occurring in clear weather (i.e., in the absence of rain, snow, fog, etc.) are likely to be more severe than those taking place under adverse weather conditions, with an OR of 1.17. This finding can be attributed to risk compensation, where in adverse weather conditions road users perceive higher risk and are likely become more cautious of their surroundings, while maintaining lower driving speeds. Similar results were obtained in previous studies [27,38,39]. Moreover, for traffic crashes that occurred in work zones, the model estimate indicates that the likelihood of severe crashes in work zones was lower in comparison to those occurring on regular roads, with an OR of 1.24—likely due to lower driving speeds required within work zones. Similar results were obtained in [40].

For crashes that involve animals, the model estimate indicates that vehicle–animal crashes are more likely to result in PDO and less likely to result in severe driver injury or fatality. Similar results were obtained in [41]. Moreover, the model estimates indicate that crashes occurring in urban areas tend to be less severe than those occurring in more rural areas, with an OR of 0.83. This may be attributed to different vehicle proportions in rural areas compared to urban areas, where large vehicles (e.g., trucks) often navigate in rural areas. This result is consistent with previous studies [27,42]. Additionally, the model estimates indicate that crashes that occur at weekends are likely to be more severe than crashes that occur during weekdays, with an odds ratio of 1.06. This can be attributed to differences in drivers' traveling purposes and behaviors on weekends compared to weekdays. Similar results were reported in [43].

5. Conclusions

This study investigated the influence of several contributing factors on the crash-severity level for elderly drivers. Crash-severity levels were classified into three categories: PDO, minor injuries, and severe and fatal injuries. On-site crash-severity levels were obtained for the Commonwealth of Virginia over an eight-year period (2014 to 2021). A multilevel ordinal logistic regression model was utilized to account for the spatial heterogeneity (i.e., cluster heterogeneity) across different physical jurisdictions. To the authors' knowledge, the current study is the first to use multilevel modeling to quantify the factors affecting crash severity among elderly drivers. Numerous variables were used to explain the variance in crash severity, including crash type, site type and attributes, time characteristics, and driver behavioral attributes.

The results confirmed that head-on and overturned crashes are likely to be more severe than other crash types (e.g., rear-end and sideswipe crashes). Our findings also indicate that crashes occurring on two-way roadways are likely to be more severe than those on single-lane roadways. Moreover, distracted, drowsy, or drunk drivers are associated with more severe crashes than undistracted, nondrowsy, or sober drivers. The consequences of crashes involving unbelted drivers are likely to be more severe than those experienced by belted drivers and passengers. Furthermore, the severity of crashes when driving at higher speeds or on highways with higher speed limits is likely to be greater in comparison to driving at lower speeds or on roads with lower speed limits. Findings from this study also confirmed that although injury and death are possible when a driver collides with an animal, such events are more likely to lead to PDO rather than severe driver injury.

This study has several limitations. The dataset used in this study applied only to older drivers within the Commonwealth of Virginia. Although the findings detailed herein are likely to be generalizable to other states in the United States, a comparative study using other datasets from different geographic locations would add to the literature on older drivers and the challenges that they face.

Future research should investigate the influence of SEDs of the drivers of crash-severity level (e.g., sex, driver age). In addition, the impact of other factors that are related to vehicle characteristics (e.g., size), vehicle type, and road geometric variables, such as lane width, can be considered in future work. Furthermore, investigating the influence of "driving" an autonomous vehicle on crash severity is becoming an increasingly important topic for all drivers, but merits particular attention for the elderly, given their age-related physical and cognitive deficits. Moreover, this study employed a statistical approach for modeling the crash severity of elderly drivers. As such, considering other modeling approaches, such as deep neural networks that might capture nonlinearity in the data, should also be considered in future research.

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