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Research Article

The Impact of Aggressive Driving Behavior on Driver-Injury Severity at Highway-Rail Grade Crossings Accidents

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The effect of aggressive driving behavior on driver's injury severity is analyzed by considering a comprehensive set of variables at highway-rail grade crossings in the US. In doing so, we are able to use a mixed logit modelling approach; the study explores the determinants of driver-injury severity with and without aggressive driving behaviors at highway-rail grade crossings. Significant differences exist between drivers' injury severity with and without aggressive driving behaviors at highway-rail grade crossings. The level of injury for younger male drivers increases a lot if they are with aggressive driving behavior. In addition, driving during peak-hour is found to be a statistically significant predictor of high level injury severity with aggressive driving behavior. Moreover, environmental factors are also found to be statistically significant. The increased level of injury severity accidents happened for drivers with aggressive driving behavior in the morning peak (6-9 am), and the probability of fatality increases in both snow and fog condition. Driving in open space area is also found to be a significant factor of high level injury severity with aggressive driving behaviors. Bad weather conditions are found to increase the probability of drivers' high level injury severity for drivers with aggressive driving behaviors.

1. Introduction

Traffic accidents are a very important safety issue in the United States. For example, six million accidents were reported to the police in 2016 which involved 37461 fatalities [1]. Aggressive driving behaviors have been identified as a significant factor in traffic accidents [2]. Haleem and Gan [3] presented that aggressive driver manoeuvres contributed to more severe injuries. Aggressive driving behaviors were found to be involved in more than 55% of all fatal accidents [4]. A critical area of traffic safety research involves highway-rail grade crossing accidents, as vehicle-train collisions are one of the most dangerous traffic accidents in terms of fatalities, injuries, and property damage due to the average 4,000 to 1 weight ratio of trains to motor vehicles [5]. There were 25,945 highway-rail crossing accidents in the United States recent ten years' data between 2002 and 2011 in the FRA (Federal Railroad Administration) database (Highway-Rail Grade Crossing Accident/Incident & US DOT Crossing Inventory Form).

Shinar [6] defined aggressive driving as the operation of a motor vehicle in a manner that endangers or is likely to endanger persons or property. The classification of driving behavior is based on FRA's original variable named "motorist" which included varied actions: (a) drove around or through the gate; (b) stopped and then proceeded; (c) did not stop; (d) stopped on crossing; (e) other. In our research, the actions "drove around or through the gate", "did not stop", and "stopped on crossing" are selected as aggressive driving behaviors. "Stopped and then proceeded" is selected as appropriate driving behaviors. As shown in Figure 1 for highway-rail grade crossing accidents, drivers with injury or fatality at highway-rail crossing accidents occurred more frequently in cases of aggressive driving than in cases without aggressive driving.

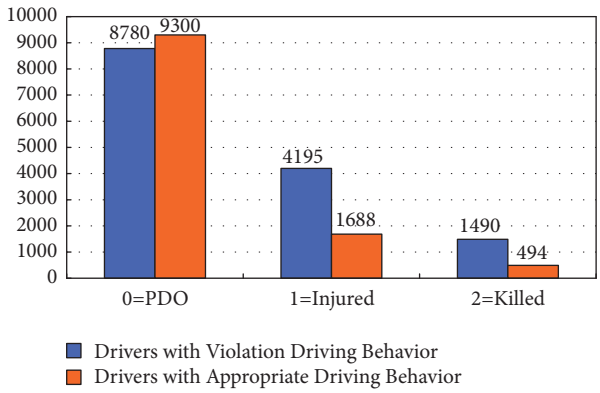

Figure 1: Highway-rail grade crossing accidents by driving behaviors.

Driver behavior at railway level crossings was modelled by Tey et al. [7] using mixed regression models. The analysis results show that active control devices produced much higher levels of driver compliance than passive control conditions. Another study by Tey et al. [8] revealed driver's responses at railway level crossings. This study describes and compares the driver response results from both field survey and driving simulator. Driving simulator is an important tool to analyze driving behaviors [9]. The conclusions show that different types of warning systems produce driver's behaviors at highway-rail grade crossings. According to previous research by Vanlaar et al. [10], there is a wide variety of behaviors which can be considered as aggressive driving behaviors. The data in this study was collected in a representative poll of 1,201 Canadian motor vehicle drivers. The results from a logistic regression model indicate that young male drivers are more likely to exhibit aggressive driving behaviors and have a history of traffic violation tickets. In addition, Hamdar et al. [11] provided an aggressive driving propensity calculation index at signalized intersections using structural equation modelling and applied this index to major signalized intersections in Washington DC. Millar [12] considered the influence of public self-consciousness and anger on aggressive driving. Kaysi and Abbany [13] developed binary probit models to analyze driving behavior on minor streets at unsignalized intersections. The most important variables for determining driving behavior were found to be driver age, car performance, and average vehicle speed on the major roads. Shinar and Compton [14] conducted a comprehensive study analyzing the relationship between aggressive driving behaviors with vehicle and driver's characteristics, as well as situational variables. The study collected over 2,000 occurrences of aggressive driving violations out of approximately 7,200 driver observations.

The level of injury study at highway-rail grade crossings has received the interest and attention from researchers [15]. Hao et al. [16–21] developed injury severity models to study the level of injury in different situations (control device types, area types, driver's age, gender, etc.). Guadamuz-Flores and Aguero-Valverde [22] used Full Bayesian Poisson–lognormal approaches to compare the effects of various models, including heterogeneity-only, spatial-only, and heterogeneity–spatial models. The comparison results suggested that spatial correlation at highway-railway crossings should be considered in modelling of crash frequencies. Ghomi et al. [23] applied an ordered probit model, association rules, and classification and regression tree (CART) algorithms to the US Federal Railroad Administration's (FRA) HRGC accident database for the period 2007–2013 to identify VRU injury severity factors at HRGCs. Using six years of nationwide crashes from 2009 to 2014 in the US, Haleem [24] applied both the mixed logit and binary logit models based on the multiple predictors investigation (e.g., temporal crash characteristics, geometry, railroad, traffic, vehicle, and environment). The mixed logit model was found to outperform the binary logit model.

Eluru et al. [25] developed a latent class model to identify factors influencing driver-injury severity in highway-railway crossing accidents. The dataset used is from FRA (Federal Railroad Administration) highway-rail grade crossing data for 14,532 crossings from 1997 to 2006. Miranda-Moreno et al. [26] modelled and estimated each accident victims' injury severity at highway-rail grade crossings using multinomial models. A sample of 1773 crossings in Canada is considered in this study covering period from 1997 to 2004. Hu et al. [27] used a logit model to study important factors for injury severity at highway-rail crossings based on highway-grade crossing collision data from 1995 to 1997 in Taiwan. Zhang et al. [28] used a mixed logit model to conduct the analysis of drivers' route choice. McCollister et al. [29] developed an injury severity model to predict the probability of injury level at highway-rail crossings using FRA data. A logistic regression model was utilized as the methodology to estimate the probability of a fatality at highway-rail grade crossings.

Based on our literature review conducted, few previous studies have been found that investigated the influence of aggressive driving behaviors on driver's injury severity in highway-rail grade crossing accidents. This study aims to estimate the effect of aggressive driving behaviors on driver's injury severity in highway-rail grade crossing accidents in the United States using data from the Federal Railroad Administration (FRA) database covering the recent ten years' data since 2005. Using a mixed logit modelling approach, the study explores the determinants of driver-injury severity both with and without aggressive driving behaviors at highway-rail grade crossings.

2. Method

The methodology used in this research is to develop a mixed logit model to predict the probability of the level of injury in highway-rail grade crossing accidents based on data with three distinct driver-injury severity outcomes of property damage only, injury, and fatality. The traditional ordered models may not be suitable to consider level of injury severity due to restricting considering the influence of explanatory variables on severity outcomes [30]. Another possible consideration is to use random parameter ordered models; however there still exists the aforementioned limitation. The ordered logit and probit models are constrained to find only one

coefficient on each variable and it is in one direction, either towards higher severity or towards lower severity. It is a constraint because it is not inconceivable that a variable can increase both the probability of low and high severity. Also, a variable can tend towards middle severities and away from the low and high severities. However, the mixed logit model can capture heterogeneity through the use of random parameters. Not only that, but the mixed logit model allows explanatory variables to affect the mean of the distribution of the random parameters [31]. As a consequence, it is more reliable to adopt the unordered discrete outcome model to consider level of injury severity. Therefore, mixed logit model is utilized in this research and the following subsections describe the mixed logit model approach, the calculation of elasticity, and the likelihood test.

2.1. Mixed Logit Model. In this study, a mixed logit model (MXL) is used to predict the probability of the three driver-injury severity outcomes at highway-rail grade crossing accidents reported by police to estimate discrete driver-injury severity outcomes [32, 33],

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

where S_{in} is a severity function determining the driver-injury severity category i in highway-rail grade crossing accident n, X_{in} is a vector of independent variables which affect driver-injury severity category i in highway-rail grade crossing accident n, β_i is a vector of estimate parameters for driver-injury severity category i, and ε_{in} is an error term which is assumed to be generalized extreme value distributed. To arrive at the MXLs, random parameters are introduced with (β_i/φ), where φ is a vector of variables of the chosen density function (mean and variance). The resulting mixed logit injury severity probabilities are

$$P_n\left(\frac{i}{\varphi}\right) = \int \frac{e^{\beta_i X_{in}}}{\sum_{\forall I} e^{\beta_i X_{in}}} \tag{2}$$

where $P_n(i/\varphi)$ is the probability of injury severity i conditional on $f(\beta_i/\varphi)$. If the variance in φ is determined to be explicitly different from zero, there will be incident-specific variations of the effect of X on injury severity across each crash observation n, with the density function $f(\beta_i/\varphi)$ used to determine the values of across crashes [34].

Due to the required numerical integration of the logit formula over the random, unobserved parameters, the maximum likelihood estimate of MXL is computationally complex. Thus, estimation methods based on simulation have been used. Research studies by McFadden and Ruud [35] and Geweke et al. [36] provide an in-depth development of simulation-based maximum likelihood methods for estimating MXL.

To evaluate the effect of individual variable estimates on injury severity outcome probabilities, an elasticity can be computed from the partial derivative for each observation n (n subscripting omitted) as

$$E_{X_{ki}}^{P(i/\varphi)} = \frac{\partial P\left(i/\varphi\right)}{\partial X_{ki}} \times \frac{X_{ki}}{P\left(i/\varphi\right)} \tag{3}$$

where $P(i/\varphi)$ is the probability of injury severity outcome i and X_k is the value of variable K. Elasticity values can be roughly interpreted as the percent effect that a 1% change in X_{ki} has on the injury severity outcome probability $P(i/\varphi)$. A pseudoelasticity indicator variable can be calculated to give the percent effect on the injury severity outcome probability of the parameter ranging in value from zero to one.

2.2. Likelihood Ratio Test. To determine whether there are significant differences between parameter estimates for drivers with and without aggressive driving behaviors, a likelihood ratio test was performed [37–40]. The ratio test determines the transferability of aggressive driving behavior model's coefficients developed in the aggressive driving behavior model to the appropriate driving behavior model and whether there is a significant difference between the two groups. The group of the variables is used to develop a joint model for both conditions. The likelihood ratio statistic is

$$LR = -2\left(L_j - L_L - L_U\right) \tag{4}$$

where $J = K_L + K_U - K_j$, K_j, K_L, and K_U are the number of coefficients in the joint model, the aggressive driving behavior model, and the appropriate driving behavior model, respectively, and L_j, L_L, and L_U represent the log-likelihoods at convergence for the joint model, the aggressive driving behavior model, and the appropriate driving behavior model, respectively.

The null hypothesis for (4) is that the restricted model (joint model) does not have a lower log-likelihood compared with the unrestricted models (separate aggressive driving and appropriate driving behavior models), indicating a lack of significant difference between the driving behavior-specific models and the joint model.

The transferability of coefficients from the aggressive driving behavior model to the appropriate driving behavior model was also investigated. For instance, a model is estimated for the appropriate driving behavior. The resulting model is applied to data for the behaviors during aggressive driving situations with all coefficients restricted to the values estimated for the situations without aggressive driving behaviors, yielding the restricted log-likelihood. Then the exact same model specification is set free and coefficients estimated on the data for the aggressive driving condition, yielding the unrestricted log-likelihood L_R. The likelihood ratio statistic is then

$$LR = -2\left(L_R - L_U\right) \tag{5}$$

where LR is χ^2 distributed with degrees of freedom J, where J is the number of restrictions.

The null hypothesis for (5) is that the coefficients are equal for both the aggressive driving and appropriate driving behavior models. If transferability is rejected at a high significance (the significance level is at 0.05), it is statistically determined that the aggressive driving model and appropriate driving behavior model are not equivalent and behaviors with aggressive driving behaviors have an impact on crash severity.

Table 1: Description of Highway-Rail Collision Characteristics.

Description		Drivers with Appropriate Driving Behaviors		Drivers with Aggressive Driving Behaviors	
		Frequency	Percentage	Frequency	Percentage
Dependent Variable					
Driver	0= PDO	9300	81.00%	8780	60.70%
	1= injured	1688	14.70%	4195	29.00%
	2= killed	492	4.30%	1490	10.30%
Independent Variables					
Vehicle Speed	0 (Less than 50mph)	11470	99.90%	13871	95.90%
	1 (more than 50mph)	11	0.10%	593	4.10%
Train Speed	0 (Less than 50mph)	9587	83.50%	12540	86.70%
	1 (more than 50mph)	1894	16.50%	1924	13.30%
Age	0 (More than 25)	10563	92.00%	13235	91.50%
	1 (Less than 25)	953	8.00%	1085	7.50%
Gender	0 (Female)	3146	27.40%	3124	21.60%
	1 (Male)	8335	72.60%	11340	78.40%
Control Device	0(Active Control)	7659	66.7%	8144	56.31%
	1(Passive Control)	3822	33.3%	6320	43.69%
Vehicle Type	1(Sedan)	5235	45.60%	6581	45.50%
	2(Truck)	758	6.60%	1287	8.90%
	3(SUV)	1803	15.70%	2184	15.10%
	4(Pick-up)	1447	12.60%	2705	18.70%
	5(Van)	402	3.50%	663	4.60%
	6(Bus)	34	0.30%	14	0.10%
	7(Other)	1791	15.60%	1041	7.20%
Time Period	0 (Other Time Periods)	8209	71.50%	9893	68.40%
	1(Peak hour including 7:00AM-9:00AM & 4:00PM-6:00PM)	3272	28.50%	4571	31.60%
Weather	1 (Cloudy)	2296	20.00%	2849	19.70%
	2 (Rain)	792	6.90%	897	6.20%
	3 (Fog)	172	1.50%	217	1.50%
	4 (Sleet)	34	0.30%	29	0.20%
	5 (Snow)	321	2.80%	347	2.40%
	6 (Clear)	7864	68.50%	10125	70%
Accident Happened Area	0(other areas)	9403	81.90%	11253	77.80%
	1(open space)	2078	18.10%	3211	22.20%

3. Data

A complete and detailed data collection is essential to make sure to get reliable conclusions. The original dataset obtained from the FRA database is made up of 25,945 highway-rail grade crossing accidents which occurred in the United States recent ten years' data since 2005. Injury severity is the dependent variable in this study which is ranked as 0-property damage only (PDO), 1-injury, and 2-fatality. For the aggressive driving behavior dataset, the distribution of crashes by injury level is as follows: 60.70% PDO, 29.00% injured, and 10.30% fatality. For the appropriate driving behavior group, the distribution of crashes by injury level is as follows: 81.00% PDO, 14.70% injury, and 4.30% fatality. The independent variables in this study include schedule factor, vehicle speed, vehicle type, weather condition, train speed, driver's age and gender, control device type, and area type. Table 1 shows the frequency and percentage distribution of these variables.

4. Model Results and Discussion

Two MXL models are estimated based on driving behavior and a likelihood ratio test was utilized to test if significant differences existed between parameter estimates for these two models. These tests indicate that the hypothesis that

aggressive driving behavior model and appropriate driving behavior model are the same can be rejected at a confidence level exceeding 99.50%. The likelihood ratio tests included a comparison of a combined aggressive driving behavior model/appropriate driving behavior model with separate aggressive driving behavior and appropriate driving behavior models (see (4)) and a comparison of aggressive driving -converged coefficients based on appropriate driving behavior data with appropriate driving behavior-converged coefficients based on aggressive driving behavior data (see (5)). In light of these results, separate models for aggressive driving behavior model and appropriate driving behavior model are developed to capture the differences.

Tables 2 and 3 show the results of the mixed logit estimation. The models included all estimated parameters that are statistically significant. Parameters which produced statistically significant standard errors for their assumed distribution were found to be random and the standard errors for these parameters are show in the tables. The parameters for which estimated standard errors were not statistically different from 0 were found to be fixed and these parameters are denoted as fixed in the tables. For all of the random parameters, the normal distribution was found to provide the best statistical fit.

4.1. Driver's Characteristics. Looking at the effect of driver age, the findings on coefficient estimation results shown in Tables 2 and 3 indicate that younger drivers are more likely to exhibit aggressive driving behavior with a 15.2% increase in the probability of a fatality in Table 2 given that a highway-rail grade crossing accident happened compared to a 6.9% increase for drivers with appropriate driving behaviors in Table 3. Several previous studies provide support for this finding. One reason may be that younger drivers (less than 25) fundamentally underestimate the risk of being involved in a crash [41]. Another study found that there is a substantial difference in driving behaviors across the different age categories [14]. The probability of injury severity for younger drivers with aggressive driving behaviors is extremely higher than older drivers.

Turning to the influence of gender, this study found that male drivers were more likely to express aggressive driving behaviors outwardly with high level injury severity given a highway-rail grade crossing accident happened than females. A previous study found significant physiological differences between the genders and males who endorse an exaggerated male stereotype are more likely to engage in aggressive driving behaviors [42]. Women have a stronger sense of obligation to traffic laws and tend to obey those laws while men tend to overestimate their driving ability and underestimate the risks associated with traffic violations [43–45].

4.2. Vehicle and Train Characteristics. The probability of a fatality increases by 14.8% for drivers with aggressive driving behaviors and by 8.4% for drivers without aggressive driving behaviors when the vehicle driving speed exceeded 50 mph. Consistent with previous studies, it is expected that, as the speeds of vehicles at railroad crossings increase, the injury severity levels in accidents also increase [16]. The impact of vehicle speeds on injury severity may be explained by the fact that higher vehicle speeds will result in the inability of drivers to visually detect an on-coming train, thereby increasing the likelihood of a higher injury severity in the event of a collision [17]. As a result, we can speculate that driving at high speed together with aggressive driving behaviors such as "drove through the gate" and "did not stop" at highway-rail grade crossings is really dangerous for vehicle drivers.

Meanwhile, the injury severity model results in Tables 2 and 3 show that higher train speed increases the probability of a fatality by 7.8% for drivers with aggressive driving behaviors and 3.8% for drivers with appropriate driving behaviors at highway-rail grade crossings. As a consequence, train speed limit reductions could help to moderate injury severity by allowing for more time for last minute maneuvering and braking actions in avoid collisions or lessen their severity [19].

Considering the impact of vehicle type, it is found that SUV and pick-up drivers are more likely to have a higher injury severity when they drive with aggressive violation behaviors. The model results in Table 2 show that the probability of fatality increases by 8.9% for SUV drivers with aggressive driving behaviors and by 8.1% for pick-up drivers with aggressive driving behaviors. This finding is confirmed by a previous study [5], which found that drivers who drive an SUV or a pick-up truck are more likely to be severely injured in accidents during rush hour.

4.3. Environmental/Situational Factors. The increased level of injury severity accidents happened for drivers with aggressive driving behavior in the morning peak (6-9 am). It could be explained as a reflection of the time pressures on drivers to reach their place of employment on time. In highway-rail grade crossing accidents, the probability of fatality during peak hours increased by 15.1% for drivers with aggressive driving behaviors in Table 2 and by 3.5% for drivers with appropriate driving behaviors in Table 3. As indicated by another study, time pressures, when combined with traffic congestion, can cause driver's aggressive driving behaviors [46, 47]. Both time pressures and traffic congestion are common during the peak-hour period which is consistent with previous studies [48].

For weather conditions, the model results in Table 2 show that the probability of fatality increases by 2.5% (snow condition) and 5.5% (fog condition) with driving aggressive driving behavior relative to clear weather condition. Previous research has shown that bad weather makes roads less skid resistant and decreases visibility which results in poorer braking and steering performance and worse impact angles leading to more severe injuries [19]. The results in this study show that foggy conditions particularly increase the probability of a fatality occurring in highway-rail grade crossing accidents for drivers with aggressive driving behaviors as a result of poor visibility.

4.4. Highway-Rail Grade Crossing Attributes. Open space area is found to increase the probability of fatal accidents by 12.3% in Table 2 for drivers with aggressive driving behaviors and by 9.1% in Table 3 for drivers with appropriate driving

Table 2: Mixed Logit Model Estimation Results for Drivers with Aggressive Driving behavior.

Variables Description	Coefficient	Standard Error	t-Statistic	Elasticity		
				Fatality	Injury	PDO
Defined for Fatality						
Constant	5.525(1.632)	0.682(0.371)	13.16(3.56)			
Vehicle & Train Characteristics						
Vehicle Speed>50mph	7.875(0.198)	0.092(0.127)	7.51(2.74)	14.8%	13.2%	-2.8%
Train Speed>50mph	4.383(0.231)	0.127(0.235)	5.63(1.59)	7.8%	4.8%	-5.5%
SUV	2.351(0.052)	0.096(0.192)	5.23(1.86)	8.9%	-4.5%	3.8%
Pick-up	1.529(0.053)	0.321(0.429)	3.15(1.96)	8.1%	-25.2%	2.5%
Driver's Characteristics						
Age lees than 25	2.351(1.321)	0.563(0.375)	7.51(2.54)	15.2%	17.3%	-3.2%
Male, fixed parameter	1.127		5.23	4.4%	5.8%	-2.9%
Environmental/ situational factors						
Peak-hour, fixed parameter	2.641	0.257	5.21	15.1%	16.2%	-5.5%
Weather fog	1.235(0.276)	0.087(0.382)	-3.81(3.91)	5.5%	-4.3%	1.8%
Weather Snow	1.682(0.357)	0.537(0.291)	-5.52(1.69)	2.5%	-1.8%	2.3%
Highway-rail Grade Crossing Attributes						
Passive control, fixed parameter	2.837	0.892	6.83	7.9%	5.9%	-4.3%
Open space area	2.582(0.179)	0.097(0.476)	4.35(3.94)	12.3%	7.6%	-8.3%
Defined for Injury						
Vehicle & Train Characteristics						
Vehicle Speed>50mph	5.252(0.232)	0.137(0.215)	4.96(2.58)	13.7%	11.9%	-3.7%
Train Speed>50mph	4.327(0.384)	0.261(0.198)	5.25(2.63)	6.9%	5.3%	-6.2%
Pick-up	1.286(0.097)	0.375(0.413)	4.86(4.05)	7.2%	-13.2%	3.8%
Driver's Characteristics						
Age lees than 25	1.232(1.273)	0.678(0.421)	6.51(1.24)	13.3%	12.7%	-4.2%
Environmental/ situational factors						
Peak-hour, fixed parameter	2.321		4.52	7.5%	5.3%	-8.2%
Highway-rail Grade Crossing Attributes						
Passive control, fixed parameter	2.257		5.57	3.5%	4.2%	-2.5%
Defined for PDO						
Vehicle & Train Characteristics						
Train Speed>50mph	4.751(0.563)	0.317(0.385)	6.69(2.31)	7.8%	4.1%	-5.3%
SUV	2.751(0.127)	0.291(0.202)	4.96(3.53)	5.3%	2.7%	-3.6%
Driver's Characteristics						
Age lees than 25	1.263(2.081)	0.893(0.563)	4.59(5.87)	10.5%	9.8%	-8.5%
Male, fixed parameter	0.761		6.17	3.9%	5.2%	-1.9%
Environmental/ situational factors						
Weather fog	1.382(0.344)	0.256(0.567)	-5.92(5.76)	4.8%	3.9%	-7.1%
Weather Snow	1.392(0.467)	0.763(0.361)	-4.93(4.51)	3.6%	-1.7%	3.2%
Highway-rail Grade Crossing Attributes						
Passive control, fixed parameter	2.027		5.18	2.9%	3.1%	-5.1%
Open space area	1.121(0.532)	0.345(1.321)	7.53(4.53)	10.5%	6.5%	-7.8%
Model Statistics						
Number of Observations		14464				
Log-likelihood at constants		-1586.17				
Log-likelihood at convergence		-863.25				

Notes: Parentheses indicate standard errors of random parameter estimates.

Table 3: Mixed Logit Model Estimation Results for Drivers with Appropriate Driving Behavior.

Variables Description	Parameter Estimate	Standard Error	t-Statistic	Elasticity		
				Fatality	Injury	PDO
Defined for Fatality						
Constant	-4.761(1.572)	0.1683(0.523)	8.75(2.38)			
Vehicle & Train Characteristics						
Vehicle Speed	3.386(0.015)	0.007(0.012)	3.28(1.56)	8.4%	10.3%	-5.2%
Train Speed	2.563(0.036)	0.062(0.032)	5.62(2.91)	3.8%	3.2%	-2.3%
SUV	1.753(0.028)	0.126(0.328)	4.82(1.78)	7.2%	-8.3%	5.1%
Pick-up	0.952(0.041)	0.203(0.512)	3.38(1.28)	3.5%	-31.2%	1.9%
Driver's Characteristics						
Age lees than 25	1.361(0.008)	0.006(0.026)	6.32(3.52)	6.9%	12.1%	-6.5%
Male, fixed parameter	0.525	0.128	3.82	2.1%	3.6%	-1.7%
Environmental/ situational factors						
Peak-hour, fixed parameter	1.952	0.628	4.02	3.5%	12.3%	-3.7%
Weather fog	0.652(0.192)	0.072(0.031)	5.12(2.37)	3.9%	-5.6%	2.3%
Weather Rain	0.851(0.325)	0.627(0.043)	2.85(1.21)	1.2%	-2.6%	0.8%
Highway-rail Grade Crossing Attributes						
Passive control, fixed parameter	1.572	0.521	6.57	5.2%	3.6%	-2.7%
Open space area	1.378(0.258)	0.063(0.321)	3.31(2.19)	9.1%	5.2%	-3.6%
Defined for Injury						
Vehicle & Train Characteristics						
Vehicle Speed	2.321(0.021)	0.015(0.009)	3.12(2.16)	10.7%	8.4%	-1.9%
SUV	1.521(0.032)	0.071(0.027)	3.61(1.37)	6.5%	-14.9%	1.7%
Driver's Characteristics						
Male, fixed parameter	0.536	0.218	5.32	1.9%	2.5%	-0.9%
Environmental/ situational factors						
Peak-hour, fixed parameter	1.582	0.372	3.86	5.8%	4.2%	-9.1%
Highway-rail Grade Crossing Attributes						
Open space area	1.385(0.327)	0.051(0.273)	5.52(1.39)	7.3%	3.6%	-1.9%
Defined for PDO						
Vehicle & Train Characteristics						
Vehicle Speed	1.251(0.032)	0.029(0.005)	5.12(1.58)	6.2%	4.9%	-5.1%
Train Speed	1.385(0.027)	0.031(0.038)	6.23(2.16)	3.2%	2.7%	-3.2%
Pick-up	0.891(0.018)	0.056(0.043)	3.76(2.32)	2.1%	-17.8%	2.6%
Driver's Characteristics						
Age lees than 25	0.683(0.007)	0.012(0.021)	4.58(3.09)	6.9%	5.6%	-4.7%
Male, fixed parameter	0.352	0.235	3.98	1.7%	2.3%	-2.6%
Environmental/ situational factors						
Peak-hour, fixed parameter	1.305	0.528	4.31	3.7%	2.5%	-7.3%
Weather Rain	0.792(0.217)	0.479(0.218)	0.68(2.51)	2.9%	2.5%	-4.6%
Weather Sleet	0.631(0.129)	0.762(0.327)	5.38(3.62)	1.9%	-0.7%	2.5%
Highway-rail Grade Crossing Attributes						
Passive control, fixed parameter	1.127	0.436	4.58	2.3%	1.8%	-3.1%
Model Statistics						
Number of Observations		11481				
Log-likelihood at constants		-1032.07				
Log-likelihood at convergence		-576.18				

Notes: Parentheses indicate standard errors of random parameter estimates.

behaviors. This can be explained by the fact that drivers may drive more recklessly with aggressive driving behaviors in open space areas compared to high population density areas [49]. In addition, an explanation for this interesting result is that operating speeds in an open space area may tend to be higher than in other areas as open space areas generally have lower traffic densities which increases the likelihood of high level injury severity given an accident happened [48].

For control device types, consistent with previous studies [18, 50], passive control was found positively correlated with high level injury severity for drivers with aggressive driving behaviors which is demonstrated by our research. Passive control devices are found to increase the probability of a fatal accident by 7.9% in Table 2 for drivers with aggressive driving behaviors and by 5.2% in Table 3 for drivers with appropriate driving behaviors.

4.5. Suggestions. According to the above result, many factors could influence aggressive driving behaviors and injury severity. The comprehensive countermeasures should be used to limit the aggressive driving behaviors. Firstly, speed limit measures are necessary to reduce vehicles' speed (less than 50mph) when approaching highway-rail grade crossing, such as the posted speed limit, yield sign, stop sign, and stop line sign. And it is better to also reduce the train's speed when approaching HRGC. Secondly, the warning devices are important to remind drivers keeping vigilant, such as flashing lights, pavement markings, and photo/audio/video enforcement, especially in the morning peak (6-9 am) and adverse weather (fog and snow). Finally, improving the HRGC condition is also important, such as traffic signal, greater sight distance, and grade separation/closure. In addition, for highway-rail grade crossing accident improvement measure, Saccomanno et al. [51] proposed a Bayesian data fusion method could estimate countermeasure effects for reducing collisions at highway-railway grade crossings.

5. Conclusions

This paper explores the injury severity of drivers with aggressive driving behaviors utilizing accident data at US highway-rail grade crossings. The results of this study have implications for those who aim to reduce accidents involving aggressive driving behaviors. The estimation results indicate that driver age and gender as well as environmental, time-of-day, and weather characteristics have a strong effect on the injury severity level in highway-rail grade crossing accidents. Younger drivers, particularly young males, who engage in aggressive driving behavior during peak hours are more likely to suffer more severe injuries. As a result, education and enforcement efforts aimed at younger male drivers could significantly improve safety by reducing aggressive driving behaviors. In addition, accidents in open space areas are more likely to involve aggressive driving behaviors and produce severe driver injuries. Bad weather and peak-hour conditions also increase the likelihood that drivers will experience severe injuries in accidents when they engage in aggressive driving behaviors in these situations. Injuries also tended to be more severe in open space areas with passive control for drivers with aggressive driving behaviors. As a result, the findings offer insights into the effects of drivers with aggressive driving behavior on driver's injury severity at highway-rail grade crossing accidents.

Data Availability

The safety data used to support the findings of this study were supplied by FRA (Federal Railroad Administration) and you can access the data by the following website: https://safetydata.fra.dot.gov/OfficeofSafety/default.aspx.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] N. Kalra and D. Groves, *The Enemy of Good: Estimating the Cost of Waiting for Nearly Perfect Automated Vehicles*, RAND Corporation, 2017.

[2] R. Paleti, N. Eluru, and C. R. Bhat, "Examining the influence of aggressive driving behavior on driver injury severity in traffic crashes," *Accident Analysis & Prevention*, vol. 42, no. 6, pp. 1839–1854, 2010.

[3] K. Haleem and A. Gan, "Contributing factors of crash injury severity at public highway-railroad grade crossings in the U.S.," *Journal of Safety Research*, vol. 53, pp. 23–29, 2015.

[4] X. Du, Y. Shen, R. Chang, and J. Ma, "The exceptionists of Chinese roads: The effect of road situations and ethical positions on driver aggression," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 58, pp. 719–729, 2018.

[5] X. Yan, L. D. Han, S. Richards, and H. Millegan, "Train-vehicle crash risk comparison between before and after stop signs installed at highway-rail grade crossings," *Traffic Injury Prevention*, vol. 11, no. 5, pp. 535–542, 2010.

[6] D. Shinar, "Aggressive driving: The contribution of the drivers and the situation," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 1, no. 2, pp. 137–160, 1998.

[7] L.-S. Tey, G. Wallis, S. Cloete, and L. Ferreira, "Modelling driver behaviour towards innovative warning devices at railway level crossings," *Accident Analysis & Prevention*, vol. 51, pp. 104–111, 2013.

[8] L.-S. Tey, L. Ferreira, and A. Wallace, "Measuring driver responses at railway level crossings," *Accident Analysis & Prevention*, vol. 43, no. 6, pp. 2134–2141, 2011.

[9] W. Yan, W. Xiang, S. C. Wong, X. Yan, Y. C. Li, and W. Hao, "Effects of hands-free cellular phone conversational cognitive

tasks on driving stability based on driving simulation experiment," *Transportation Research Part F: Traffic Psychology & Behaviour*, no. 58, pp. 264–281, 2018.

[10] W. Vanlaar, H. Simpson, D. Mayhew, and R. Robertson, "Aggressive driving: A survey of attitudes, opinions and behaviors," *Journal of Safety Research*, vol. 39, no. 4, pp. 375–381, 2008.

[11] S. H. Hamdar, H. S. Mahmassani, and R. B. Chen, "Aggressiveness propensity index for driving behavior at signalized intersections," *Accident Analysis & Prevention*, vol. 40, no. 1, pp. 315–326, 2008.

[12] M. Millar, "The influence of public self-consciousness and anger on aggressive driving," *Personality and Individual Differences*, vol. 43, no. 8, pp. 2116–2126, 2007.

[13] I. A. Kaysi and A. S. Abbany, "Modeling aggressive driver behavior at unsignalized intersections," *Accident Analysis & Prevention*, vol. 39, no. 4, pp. 671–678, 2007.

[14] D. Shinar and R. Compton, "Aggressive driving: an observational study of driver, vehicle, and situational variables," *Accident Analysis & Prevention*, vol. 36, no. 3, pp. 429–437, 2004.

[15] M. Zhang, A. J. Khattak, J. Liu, and D. Clarke, "A comparative study of rail-pedestrian trespassing crash injury severity between highway-rail grade crossings and non-crossings," *Accident Analysis & Prevention*, no. 117, pp. 427–438, 2018.

[16] W. Hao and J. Daniel, "Severity of injuries to motor vehicle drivers at highway-rail grade crossings in the United States," *Transportation Research Record*, no. 2384, pp. 102–108, 2013.

[17] W. Hao and J. Daniel, "Motor vehicle driver injury severity study under various traffic control at highway-rail grade crossings in the United States," *Journal of Safety Research*, vol. 51, pp. 41–48, 2014.

[18] W. Hao, C. Kamga, and J. Daniel, "The effect of age and gender on motor vehicle driver injury severity at highway-rail grade crossings in the United States," *Journal of Safety Research*, vol. 55, pp. 105–113, 2015.

[19] W. Hao and J. Daniel, "Driver injury severity related to inclement weather at highway–rail grade crossings in the United States," *Traffic Injury Prevention*, vol. 17, no. 1, pp. 31–38, 2016.

[20] W. Hao, C. Kamga, and D. Wan, "The effect of time of day on driver's injury severity at highway-rail grade crossings in the United States," *Journal of Traffic and Transportation Engineering (English Edition)*, vol. 3, no. 1, pp. 37–50, 2016.

[21] W. Hao and C. Kamga, "The effects of lighting on driver's injury severity at highway-rail grade crossings," *Journal of Advanced Transportation*, vol. 50, no. 4, pp. 446–458, 2016.

[22] R. Guadamuz-Flores and J. Aguero-Valverde, "Bayesian Spatial Models of Crash Frequency at Highway–Railway Crossings," *Transportation Research Record*, vol. 2608, no. 1, pp. 27–35, 2017.

[23] H. Ghomi, M. Bagheri, L. Fu, and L. F. Miranda-Moreno, "Analyzing injury severity factors at highway railway grade crossing accidents involving vulnerable road users: A comparative study," *Traffic Injury Prevention*, vol. 17, no. 8, pp. 833–841, 2016.

[24] K. Haleem, "Investigating risk factors of traffic casualties at private highway-railroad grade crossings in the United States," *Accident Analysis & Prevention*, vol. 95, pp. 274–283, 2016.

[25] N. Eluru, M. Bagheri, L. F. Miranda-Moreno, and L. Fu, "A latent class modeling approach for identifying vehicle driver injury severity factors at highway-railway crossings," *Accident Analysis & Prevention*, vol. 47, pp. 119–127, 2012.

[26] L. F. Miranda-Moreno, L. Fu, S. Ukkusuri, and D. Lord, "How to incorporate accident severity and vehicle occupancy into the hot spot identification process?" *Transportation Research Record*, no. 2102, pp. 53–60, 2009.

[27] S.-R. Hu, C.-S. Li, and C.-K. Lee, "Investigation of key factors for accident severity at railroad grade crossings by using a logit model," *Safety Science*, vol. 48, no. 2, pp. 186–194, 2010.

[28] W. B. Zhang, Y. Qi, Y. Yan, J. J. Tang, and Y. H. Wang, "A method of and traveller behavior analysis under multimodal traffic condition," *Transportation Research Part D: Transport & Environment*, no. 52, pp. 139–155, 2017.

[29] G. M. McCollister and C. C. Pflaum, "A model to predict the probability of highway rail crossing accidents," *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, vol. 221, no. 3, pp. 321–329, 2007.

[30] S. Yasmin and N. Eluru, "Evaluating alternate discrete outcome frameworks for modeling crash injury severity," *Accident Analysis & Prevention*, vol. 59, pp. 506–521, 2013.

[31] J.-K. Kim, G. F. Ulfarsson, S. Kim, and V. N. Shankar, "Driver-injury severity in single-vehicle crashes in California: a mixed logit analysis of heterogeneity due to age and gender," *Accident Analysis & Prevention*, vol. 50, pp. 1073–1081, 2013.

[32] Z. Feng, J. Zhan, C. Ma et al., "Is cognitive intervention or forgiveness intervention more effective for the reduction of driving anger in Chinese bus drivers?" *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 55, pp. 101–113, 2018.

[33] W. Zhang, Z. Hu, Z. Feng, C. Ma, K. Wang, and X. Zhang, "Investigating factors influencing drivers' speed selection behavior under reduced visibility conditions," *Traffic Injury Prevention*, vol. 19, no. 5, pp. 488–494, 2018.

[34] D. McFadden and K. Train, "Mixed MNL models for discrete response," *Journal of Applied Econometrics*, vol. 15, no. 5, pp. 447–470, 2000.

[35] D. McFadden and P. A. Ruud, "Estimation by simulation," *Review of Economics and Statistics*, vol. 76, no. 4, pp. 591–608, 1994.

[36] J. Geweke, M. Keane, and D. Runkle, "Alternative computational approaches to inference in the multinomial probit model," *Review of Economics and Statistics*, vol. 76, no. 4, pp. 609–632, 1994.

[37] G. F. Ulfarsson and F. L. Mannering, "Differences in male and female injury severities in sport-utility vehicle, minivan, pickup and passenger car accidents," *Accident Analysis & Prevention*, vol. 36, no. 2, pp. 135–147, 2004.

[38] J. Tang, J. Liang, S. Zhang, H. Huang, and F. Liu, "Inferring driving trajectories based on probabilistic model from large scale taxi GPS data," *Physica A: Statistical Mechanics and its Applications*, vol. 506, pp. 566–577, 2018.

[39] Y. Yan, S. Zhang, J. Tang, and X. Wang, "Understanding characteristics in multivariate traffic flow time series from complex network structure," *Physica A: Statistical Mechanics and its Applications*, vol. 477, pp. 149–160, 2017.

[40] J. Tang, S. Zhang, X. Chen, F. Liu, and Y. Zou, "Taxi trips distribution modeling based on Entropy-Maximizing theory: A case study in Harbin city—China," *Physica A: Statistical Mechanics and its Applications*, vol. 493, pp. 430–443, 2018.

[41] S. Islam and F. Mannering, "Driver aging and its effect on male and female single-vehicle accident injuries: Some additional evidence," *Journal of Safety Research*, vol. 37, no. 3, pp. 267–276, 2006.

[42] R. Lawton and A. Nutter, "A comparison of reported levels and expression of anger in everyday and driving situations," *British Journal of Psychology*, vol. 93, no. 3, pp. 407–423, 2002.

[43] B. Krahé and I. Fenske, "Predicting Aggressive Driving Behavior: The Role of Macho Personality, Age, and Power of Car," *Aggressive Behavior*, vol. 28, no. 1, pp. 21–29, 2002.

[44] K. Jiang, F. Ling, Z. Feng et al., "Effects of mobile phone distraction on pedestrians' crossing behavior and visual attention allocation at a signalized intersection: An outdoor experimental study," *Accident Analysis & Prevention*, vol. 115, pp. 170–177, 2018.

[45] N. Lyu, L. Xie, C. Wu, Q. Fu, and C. Deng, "Driver's cognitive workload and driving performance under traffic sign information exposure in complex environments: A case study of the highways in China," *International Journal of Environmental Research and Public Health*, vol. 14, no. 2, article no. 203, 2017.

[46] D. Parker, T. Lajunen, and H. Summala, "Anger and aggression among drivers in three European countries," *Accident Analysis & Prevention*, vol. 34, no. 2, pp. 229–235, 2002.

[47] L. Buckley and M. S. Foss, "Protective factors associated with young passenger intervening in risky driving situations," *Journal of Safety Research*, vol. 43, no. 5-6, pp. 351–356, 2012.

[48] C. Ma, R. He, W. Zhang, and X. Ma, "Path optimization of taxi carpooling," *PLoS ONE*, vol. 13, no. 8, pp. 1–15, 2018.

[49] K. H. Beck, M. Q. Wang, and M. M. Mitchell, "Concerns, dispositions and behaviors of aggressive drivers: What do self-identified aggressive drivers believe about traffic safety?" *Journal of Safety Research*, vol. 37, no. 2, pp. 159–165, 2006.

[50] C. Ma, W. Hao, A. Wang, and H. Zhao, "Developing a Coordinated Signal Control System for Urban Ring Road under the Vehicle-infrastructure Connected Environment," *IEEE Access*, vol. 6, pp. 52471–52478, 2018.

[51] F. F. Saccomanno, P. Y.-J. Park, and L. Fu, "Estimating countermeasure effects for reducing collisions at highway-railway grade crossings," *Accident Analysis & Prevention*, vol. 39, no. 2, pp. 406–416, 2007.