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Severity Analysis of Large-Truck Wrong-Way Driving Crashes in the State of Florida

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Abstract: Wrong-way driving (WWD) crashes lead to severe injuries and fatalities, especially when a large truck is involved. This study investigates the factors associated with crash-injury severity in large-truck WWD crashes in Florida. Various driver, roadway, weather, and traffic characteristics were explored as explanatory variables through a random parameter ordered logit model. The study also accounted for heterogeneity by identifying random parameters in the model and introducing interaction effects as potential sources of such heterogeneity. The findings indicate that not using a seatbelt, driving under the influence of drugs, and a driving speed of 50–74 mph were more likely to result in fatal crashes. On the contrary, female drivers, private roadways, and sideswipe collisions showed negative impacts on crash-injury severity. The model identified two random parameters, including a speed of 25–49 mph and early-morning crashes. The interaction effects showed that when driving at a speed of 25–49 mph, young drivers (under 20 years old) and middle-aged drivers (36–50 years old) were the sources of heterogeneity, decreasing crash-injury severity. Understanding the contributing factors of large-truck WWD crashes can help policymakers develop safety countermeasures to reduce the associated injury severity and improve truck safety.

Keywords: large truck; wrong-way driving; heterogeneity

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1. Introduction

Wrong-way driving (WWD) crashes take place when a vehicle travels in the opposite direction of the traffic flow. The outcome of such crashes is more severe than other types of crashes, as they usually result in head-on or sideswipe-opposite-direction crashes. According to National Transportation Safety Board Special Investigation Report, on average, 360 people have been killed every year in WWD crashes, which comprise about 2.8% of all fatal crashes on divided roads [1]. WWD crashes could happen for various reasons, such as driver confusion, poor geometric design, insufficient lighting, and alcohol or drug use [2–5]. Human error and occupational issues were other important factors that influence the likelihood of crash occurrence and injury severity. For example, sleep disorder, fatigue, and anxiety among professional drivers are highly associated with crash occurrence [6,7]. Although WWD crashes are relatively infrequent, the high probability of resulting in a fatal or incapacitating injury makes them one of the most severe crashes in the United States.

In the state of Florida, 386 WWD crashes occurred between 2007 and 2011, making it the third most dangerous state for wrong-way driving crashes in the U.S. [8]. The majority (71%) of these crashes occurred in dark-lighting conditions, and approximately half of the drivers were physically impaired. Given the high fatality rate of WWD crashes, many studies have investigated WWD crashes in terms of their characteristics and contributing factors [4,5,9]. When there is a large truck involved in WWD crashes, the consequences become even more severe. In this study, large trucks are defined as trucks with a gross vehicle weight rating (GVWR) larger than 10,000 lbs or 5 tons. Large trucks generally result in more severe outcomes due to their larger gross weight and dimensions; consequently, large-truck WWDs are expected to have more substantial financial and social impacts.

Utilizing appropriate methods to determine the contributing factors of crash-injury severity would lead to accurate and reliable results, as well as effective strategies and countermeasures to improve safety. Due to multiple access points in arterial facilities, providing countermeasure for reducing wrong-way driving crashes is challenging [10]. One critical concept in crash-injury severity analysis is heterogeneity. The literature showed that under different conditions, the impact of explanatory factors might vary between observations, which could impact the accuracy and reliability of model results [3,11–13]. Therefore, to better understand the nature of large-truck WWD crashes, this study investigated the effect of various underlying factors, including roadway, driver, weather, and motor vehicle-related factors, as well as the role of heterogeneity on the severity of this type of crashes. The study used a random parameter ordered logit model (RPOL) to analyze large-truck WWD crashes in Florida in a ten-year span (between 2007 and 2016), hoping to shed light on the contributing factors to the injury severity of these crashes. Given the high fatality rate of WWD crashes, many studies have investigated WWD crashes in terms of their characteristics and contributing factors [4,5,9]. In particular, many studies have used discrete choice models to investigate the injury severity of WWD crashes [3,14]. However, the application of these models in analyzing large truck WWD crashes has not yet been performed. The results from this study may help develop more specific and effective countermeasures that could help reduce the severity and occurrence of WWD crashes involving large trucks. This would help reduce crashes and enhance safety, which could bring significant societal and economic benefits.

The next section summarizes the current literature on WWD crashes. The following section presents the data used in this study, followed by a description of the methodology applied. The model results are reported and discussed in the following section. The last section presents discussions, conclusions, and potential policy implications, as well as potential directions for future work.

2. Literature Review

Several studies have been conducted to understand the contributing factors of WWD crashes. In view of empirical studies on the injury severity of WWD crashes, Kemel (2015) applied logistic regression to assess the contributing factors of WWD crashes [15]. The results indicated that WWD crashes were expected to be more likely during night hours and on non-freeway roads compared to other crashes. Moreover, drivers who drive on the wrong side of the wrong way tended to be older, intoxicated, and local drivers. Additionally, drivers engaged in WWD crashes probably drive older vehicles and passenger cars without passengers.

Pour-Rouholamin and Zhou (2016) investigated the influence of various factors on WWD crashes using three different types of models, including the ordered logit model, generalized ordered logit model, and partial proportional odds model [14]. For Illinois and Alabama crash data, it was found that driver's condition (intoxication), not using a seatbelt, driving during midnight, airbag deployment, driving in rural areas, dark lighting conditions, and head-on crashes had significant positive impacts on crash severity. On the other hand, older drivers, afternoons, and wet surface conditions were correlated with lower injury severity. Another study in Florida focusing on WWD crashes showed similar results [5]. The study showed that older and male drivers, high blood alcohol concentration, out-of-state drivers, driver's defects (i.e., poor eyesight, fatigue, sleepiness, etc.), no seatbelt use, higher average annual daily traffic (AADT), arterial facility, dark lighting condition, rural roads, weekends, and nighttime had positive impacts on WWD fatal crashes.

Recognizing the role of heterogeneity, Jalayer et al. (2018) used a random parameter ordered probit model to determine the factors contributing to WWD crash-injury severity and the presence of heterogeneity [3]. Crash data in Alabama and Illinois were explored. The results showed that dark lighting conditions, no seatbelt use, airbag deployment, pickup and SUV vehicles, and older vehicles were associated with more severe crashes. On the other hand, urban roadways, wet surface conditions, and older drivers were associated with lower crash-injury severity. Moreover, winter season, less than three vehicles being involved in the crash, and urban roadways were found as variables with random effects across the observations.

Atiquzzaman and Zhou (2018) used a logistic regression model called Firth's penalized likelihood to predict the occurrence of WWD crashes in Alabama [16]. The study used wrong-way-entry datasets at the exit ramps of diamond interchanges. They found that low AADT of exit ramps and high crossing AADT increased the probability of crash occurrence, while signalized exit ramps decreased the probability of WWD crashes. Using the same model, Pour-Rouholamin et al. (2015) conducted a comprehensive assessment of the severity of WWD crashes on interstate highways in Alabama [17]. The results showed that older drivers, night and evening periods, DUI (driving under the influence), driver impairment, and older vehicles increased the probability of fatal crashes.

Alluri et al. (2019) performed a crash hotspot analysis in the Geographic Information System (GIS) with five-year WWD crash datasets in Florida [10]. Ten potential WWD crash hotspots were identified using a spatial clustering method. Once the crash hotspot for non-limited access facility was identified, several roadway geometric and demographic contributing factors were analyzed. The results revealed that one-way streets, signalized and stop-controlled intersections, the absence of warning signs, older drivers, and driver impairment played significant roles in the occurrence of WWD crashes.

Other studies developed machine learning methods to investigate WWD crashes. Das et al. (2018a) applied multiple correspondence analyses to determine the clusters that best described the injury severity of WWD crashes [9]. They found sixteen significant clusters, including locations with higher posted speed, rural areas, divided facilities, no lighting at night, roadways with no controls, physical barriers, proper signage, and drivers older than 75 years. Using the same method on crash data from Alabama and Illinois, Jalayer et al. (2018b) found that DUI driving, older drivers, poor lighting, and weather conditions best predict WWD crashes [4]. Similarly, Das et al. (2018b) found that driver impairment is a critical factor in WWD crashes using the vertical data mining method called the ECLAT algorithm on crash data from Louisiana [2]. A decision tree model was used in a more recent study to identify the pattern of factors associated with WWD crashes [18]. The study used 1890 crashes that occurred on arterial roads between the years 2012 and 2016 in Florida. The results showed that front-to-front collisions, days of the week, speed, light condition, age of the driver, and impairment made significant contributions to the injury severity of WWD crashes.

Table 1 presents a summary of existing studies focusing on WWD crashes. It shows that driver impairment, poor lighting conditions, and other driver and roadway characteristics contributed to WWD crash severity levels. However, no study has specifically investigated large-truck WWD crashes. Given the higher fatality rate associated with large trucks, recognizing the contributing factors of large-truck WWD crashes could help to understand these crashes and develop more practical countermeasures to improve safety.

Table 1. Summary of Literature on WWD Crashes.

Author	Year	Location	Sample Size	Methodology	Major Findings
Nafis et al., 2021 [18]	2021	Florida	1890	Random Forest and Decision Tree	Positive impact: front-to-front collision, days of the week, speed, light condition, age of the driver, and driver impairment.
Alluri et al., (2019) [10]	2019	Florida	702	Crash Hotspot Analysis	Positive impact: one-way street, signalized intersection, stop-controlled intersection, traffic control device, driver age, and impairment.

Table 1. *Cont.*

Author	Year	Location	Sample Size	Methodology	Major Findings
Das et al. (2018a) [9]	2018	Louisiana	1873	Multiple Correspondence Analysis	Positive impact: higher posted speed locations, rural area, no lighting, divided facility, roadway without control access, physical barrier and proper signage, and drivers older than 75 years.
Das et al. (2018b) [2]	2018	Louisiana	1419	Association Rules Mining	Positive impact: driver impairment, male drivers, off-peak hours, two-lane undivided roads, head-on crashes, impaired drivers, improper pavement markings, insufficient signs, and night.
Jalayer et al. (2018a) [3]	2018	Alabama and Illinois	398	A random parameter ordered probit model	Positive impact: dark lighting conditions, no seatbelt use, airbag deployed, pickup or SUV vehicles, and older vehicles. Negative impact: Urban roadways, wet surface conditions, and older drivers decreased crash-injury severity.
Jalayer et al. (2018b) [4]	2018	Alabama and Illinois	398	Multiple Correspondence Analysis	Positive impact: Driving under the influence of alcohol, old derivers, poor lighting, and non-clear weather conditions
Ponnaluri V (2016) [19]	2016	Florida	3821	Binomial logistic models	Positive impact: Older and male driver, blood alcohol concentration, out-of-state driver, driver defect, no seatbelt use, higher AADT, arterial facility, dark lighting condition, rural road, weekend, nighttime.
Ponnaluri V (2018) [5]	2018	Florida	3823	Binomial logistic models	Positive impact: Alcohol, driver impairment, night, weekend, inadequate lighting, low traffic, rural geography.
Zhou et al. (2015) [20]	2015	Illinois	632	Descriptive statistics	Positive impact: Weekend, urban area, passenger car, drug use, alcohol use, midnight-5 am
Pour-Rouholamin et al. (2015) [17]	2015	Alabama	1456	Firth's penalized-likelihood logit model	Positive impact: older driver, night and evening time, a driver under the influence (DUI), physical impairment, and older vehicles
Pour-Rouholamin and Zhou (2016) [14]	2016	Alabama and Illinois	398	ordered logit, proportional odds, generalized ordered logit	Positive impact: Driver condition (i.e., intoxication), seatbelt not used, midnight, airbag deployed, rural areas, dark lighting condition, and head-on crashes Negative impact: older drivers, afternoon time periods, and wet surface conditions
Baratian et al. (2014) [21]	2014	USA		Descriptive statistics	Positive impact: Crash location, driver gender, age, and impairment
Sandt et al. (2015) [22]	2015	Florida	400	Survey	Positive impact: State Road 408 and Florida's Turnpike
Kemel E (2015) [15]	2015	France	266	Logistic Regression	Positive impact: night hours, non-freeway roads, older, intoxicated, and local drivers, older vehicles, and passenger cars without passengers.
Atiquzzaman and Zhou (2018) [16]	2018	Alabama and Illinois	128 exit ramps	Firth's penalized-likelihood logit	Positive impact: Low exit ramp AADT and high crossing AADT. Negative impact: Signalized exit ramps.

3. Data

This study used data obtained from the Signal Four Analytics database [23]. WWD crashes that occurred between 2007 and 2016 and involved at least one large truck were extracted from the database. The data were further filtered to extract crashes where the large truck was the responsible vehicle (i.e., entered the wrong side of the roadway), which allows the analysis to focus on the large truck that caused WWD crashes. The final dataset contains information for 479 large-truck WWD crashes. The data include comprehensive information on the driver, vehicle, roadway, crash, weather, and lighting characteristics. In this database, injury severity indicates the injury severity of people involved in the crash, not necessarily the truck driver [24].

Table 2 provides a summary of the crash characteristics. The driver characteristics presented in Table 2 are related to the truck drivers (at-fault drivers). As observed, the overall fatality rate was remarkably high (25%), indicating the severe nature of large-truck WWD crashes. Interstate roadways (58%) had the highest fatality rate among the roadway types, probably due to higher driving speed on these roadways. Moreover, more fatal crashes happened when the posted speed limit was 50 to 75 (mph), and no seatbelt was used. Drivers older than 75 years showed the highest rate of fatalities (41%). As expected, almost half of the crashes (47%) led to a fatal outcome when the truck driver was under the influence of medications, drugs, or alcohol. In terms of time periods, late night, evening, and early morning were more likely to see fatal WWD crashes, due to poor lighting conditions and driver fatigue or impairment.

Table 2. Crash Data Characteristics.

	Property Damage Only		**Injury**		**Fatality**		**Total**
Variable Description	Frequency	Share	Frequency	Share	Frequency	Share	
Crash Severity	241	50%	119	25%	119	25%	479
Road Surface Condition							
Dry	216	50%	105	24%	110	26%	431
Wet	21	49%	13	30%	9	21%	43
Mud, Dirt, Gravel	2	100%	0	0%	0	0%	2
Other	2	67%	1	33%	0	0%	3
Type of Shoulder							
Paved	48	33%	45	31%	51	36%	144
Unpaved	80	44%	46	25%	55	31%	181
Curb	113	73%	28	18%	13	9%	154
Road System Identifier							
Interstate	8	24%	6	18%	19	58%	33
U.S.	10	21%	13	28%	24	51%	47
State	32	29%	39	36%	39	35%	110
County	35	42%	25	30%	23	28%	83
Local	105	73%	29	20%	10	7%	144
Turnpike/Toll	2	20%	4	40%	4	40%	10
Private road, Parking Lot	46	96%	2	4%	0	0%	48
Other	3	75%	1	25%	0	0%	4
Type of Intersection							
Not at Intersection	160	44%	92	26%	108	30%	360
Four-Way Intersection	42	70%	14	23%	4	7%	60

Table 2. *Cont.*

	Property Damage Only		Injury		Fatality		Total
T-Intersection	24	60%	11	28%	5	12%	40
Y-Intersection	3	60%	0	0%	2	40%	5
Roundabout	1	100%	0	0%	0	0%	1
Other	11	85%	2	15%	0	0%	13
Speed limit (mph)							
0–24	158	77%	36	18%	10	5%	204
25–49	46	37%	42	34%	37	29%	125
50–74	11	11%	27	27%	61	62%	99
75–120	14	58%	6	25%	4	17%	24
unknown	12	44%	8	30%	7	26%	27
Airbag Deployed							
Not Deployed	129	70%	39	21%	17	9%	185
Deployed Front	11	10%	27	24%	73	66%	111
Deployed Side	1	50%	1	50%	0	0%	2
Deployed Other	0	0%	1	100%	0	0%	1
Deployed Combination	1	7%	7	46%	7	47%	15
Unknown	51	57%	26	29%	12	14%	89
Restraint System							
None Used	7	13%	17	31%	30	56%	54
Shoulder and Lap Belt	207	56%	88	24%	74	20%	369
Shoulder Belt Used Only	2	40%	1	20%	2	40%	5
Lap Belt Used Only	0	0%	1	100%	0	0%	1
Used Type Unknown	1	100%	0	0%	0	0%	1
Other	2	25%	0	0%	6	75%	8
Unknown	19	56%	9	26%	6	18%	34
Driver Age							
16 to 20 years old	12	46%	11	42%	3	12%	26
21 to 35 years old	57	39%	36	25%	53	36%	146
36 to 50 years old	80	60%	28	21%	25	19%	133
51 to 75 years old	59	50%	31	26%	29	24%	119
More than 75 years old	9	41%	4	18%	9	41%	22
Unknown	24	73%	9	27%	0	0%	33
Driver Condition							
Normal	143	62%	49	21%	40	17%	232
Asleep	8	40%	7	35%	5	25%	20
Physical Impairment	0	0%	2	50%	2	50%	4
Other Non-Performance	1	8%	4	33%	7	58%	12
Under Medication/Drug/ Alcohol Influence	10	23%	13	30%	20	47%	43
Unknown	79	47%	44	26%	45	27%	168
Gender							

Table 2. *Cont.*

	Property Damage Only		Injury		Fatality		Total
Male	174	49%	89	25%	90	26%	353
Female	48	48%	23	23%	29	29%	100
Unknown	19	73%	7	7%	0	0%	26
Vision Obstruction							
Vision Not Obscured	225	50%	103	23%	118	27%	446
Weather/Fog/Smoke/Glare	4	57%	3	43%	0	0%	7
Parked or Stopped Vehicle/Load	3	75%	1	25%	0	0%	4
Signs/Billboards/Trees/Bushes	1	33%	2	67%	0	0%	3
Unknown	8	42%	10	53%	1	5%	19
Alcohol-Related							
No	224	55%	97	24%	84	21%	405
Yes	17	23%	22	30%	35	47%	74
Drug-Related							
No	239	52%	116	25%	104	23%	459
Yes	2	10%	3	15%	15	75%	20
Crash Location							
Major Roadways	197	47%	110	26%	116	27%	423
Non-major Roadways	44	79%	9	16%	3	5%	56
Manner of Collision							
Front to Rear	8	62%	1	8%	4	30%	13
Front to Front (Base)	20	18%	30	27%	63	55%	113
Angle	35	49%	25	35%	12	16%	72
Sideswipe, same direction	32	84%	6	16%	0	0%	38
Sideswipe, Opposite Direction	39	60%	11	17%	15	23%	65
Rear to Side	2	100%	0	0%	0	0%	2
Rear to Rear	2	100%	0	0%	0	0%	2
Other	25	63%	9	22%	6	15%	40
Unknown	78	58%	37	28%	19	14%	134
Crash Time							
Early Morning (5–9 am)	30	33%	33	36%	29	31%	92
AM (9–12 am)	53	54%	20	20%	26	26%	99
Midday (12–3 pm)	98	61%	39	24%	24	15%	161
PM (3–6 pm)	28	46%	16	26%	17	28%	61
Evening (6–9 pm)	15	54%	4	14%	9	32%	28
Late Night (9 pm–5 am)	17	45%	7	18%	14	37%	38

4. Methodology

Various modeling techniques have been employed in the literature to investigate the crash severity of WWD crashes. The logistic regression model [15], binomial logistic models [5], firth's Penalized Likelihood model [16], ordered logit models, and proportional odds models [14] are among the traditional methods that have been applied by previous studies. Recently, a few machine learning and data mining methods have been used to understand the nature of WWD crashes [2,4,9]. However, one limitation of these methods is that they do not permit the researchers to perform significance tests among various clusters.

Considering the ordered nature of crash-injury severity and the potential randomness of variables across observations, this study applied a random parameter ordered logit (RPOL) model structure. Three levels of injury severity were considered, including no injury/property damage only (PDO), minor injury, and severe injury and fatality. It is assumed that the error term is independent and identically distributed. The severity outcome can be specified as follows:

$$Y_{nk}^{*} = X_n \beta_{nk} + \epsilon_{kn} \tag{1}$$

Here,
Y_{nk}^{*} = Latent function with severity level k and observation n
X_n = Vector of independent variables
β_{nk} = Vector of random coefficients
ϵ_{kn} = Error term

The presence of heterogeneity is determined by random parameters. Assuming that the random parameter coefficient follows a normal distribution, the magnitude of the coefficient is divided into a fixed-effect and a random effect. To explain what factors may have contributed to the heterogeneity, interaction terms were introduced to the model. The interaction effect improves the performance of the model and identifies potential sources of variations. In this study, we evaluated various variables as potential interaction effects, including driver age and gender, driver condition at the time of the crash, driver distraction, vehicle speed, and road type.

To better understand the contribution of each explanatory variable, average pseudo elasticity was applied to determine the impact of contributing factors on the injury severity of the crashes. Average pseudo elasticity indicates the difference in the likelihood of injury severity when the value of an indicator variable is switched from 0 to 1 [25].

In this study, the performance of the model with the interaction effect and the model without the interaction effect are compared using the following equations:

$$\mathrm{LL} = -2\left[\mathrm{LogL}\left(\beta_{(\mathrm{main-effects-model})}\right) - \mathrm{LogL}\left(\beta_{(\mathrm{interaction-model})}\right)\right] \tag{2}$$

The value of log-likelihood (LL) is compared to the chi-square value χ^2_{DF}, where the degree of freedom (*DF*) is defined as the difference in the number of significant contributing factors. If the value of LL is higher than the value of χ^2_{DF}, it can be stated that the performance of the model with interaction effects is better compared to the model without the interaction effects.

5. Model Results

Table 3 presents the results of two RPOL models, one with only the main effects, and one with the interaction effects. Table 4 shows the results of average pseudo-elasticity for the model with interaction effects. In terms of model performance, the log-likelihood ratio test indicated that the interaction effect model showed better performance than the main effect model at the 5% significance level.

$$\mathrm{LL} = -2(-324.1 + 317) = 14.2 \; > \; \chi^2_{DF=3} = 7.81$$

5.1. Roadway Attributes

Several roadway attributes showed significant impacts on large-truck WWD crash-injury severity. The results showed that injury severity increased on state and county roadways compared to local roads, while curb shoulders, private roadways, and roadways with more than four lanes had negative impacts on injury severity. Based on average pseudo-elasticity values, the probability of fatal crashes on private roadways and parking lots decreased by 19.30%. One possible reason could be the lower speed on these roadways.

On the contrary, state roadways increased the likelihood of fatal crashes by 9.10%, which could be related to the higher driving speed or design speed on these roadways. Additionally, roadways with more than four lanes increased the probability of fatal crashes by 9.55%, which also could be related to higher driving speed in the roadways with a larger number of lanes.

Table 3. Results of Random Parameter Ordered Logit Models.

Category	Name	Attributes	Without Interaction Effects		With Interaction Effects	
			Coeff.	z-Value	Coeff.	z-Value
	Constant	Constant FI (Injury and Fatality)	2.55	8.84	2.49	8.67
		Constant PI (PDO and Injury)	−0.73	−2.68	−0.74	−2.75
Roadway	Type of Shoulder	Curb	−1.07	−3.22	−1.05	−3.25
	Road System Identifier	Private Road, Parking Lot	−1.75	−2.24	−1.79	−2.28
		County Road	0.95	2.68	1.12	3.13
		State Road	1.23	3.77	1.15	3.62
	Type of Intersection	Four−way	−1.44	−3.33	−1.37	−3.26
	Total Lanes	More than four lanes	1.12	3.44	1.06	3.38
Vehicle	Airbag Deployed	Combination	1.30	1.83	1.21	1.77
		Front Only	2.44	5.73	2.39	5.88
Driver	Suspected of Drug Use	Yes	1.45	1.92	1.25	1.77
	Gender	Female	−0.75	−2.15	−0.81	−2.43
	Speed limit	50 to 74 (mph)	2.04	5.29	2.03	5.36
	Restraint System	None Used−Motor Vehicle Occupant	1.82	4.26	1.79	4.31
Environment	Vision Obstruction	Inclement Weather, Fog, Glare	−3.28	1.76	−3.5	−2.04
Crash	Manner of Collision	Sideswipe Same Direction	−1.94	−2.91	−1.79	−2.28
		Sideswipe Opposite Direction	−0.69	−1.74	−0.69	−1.78
Random Parameters	Speed_25 to 49 (miles per hour)	Mean	0.64	1.80	1.37	3.56
		Standard Deviation	2.08	3.67	1.64	2.66
	Crash Time_Early Morning	Mean	−0.88	−2.39	−0.68	−1.84
		Standard Deviation	1.26	2.18	1.06	1.85
Interaction Effects	Speed_25 to 49 (miles per hour)	Driver Age−Under 20 yrs.	-	-	−1.88	−2.16
		Driver Age−36 to 50 yrs.	-	-	−1.83	−2.63
	Crash Time_Early Morning	Road System Identifier−County Road	-	-	−1.74	−1.83
	Number of observations		479		479	
	Log-Likelihood		−324.1		−317	

5.2. Vehicle Attributes

Front airbag deployment and combined airbag deployment had positive impacts on crash-injury severity. Accordingly, for front and combined airbag deployment, the likelihood of WWD fatality and injury increased by 19.80% and 12.30%, respectively.

Table 4. Average Pseudo Elasticity.

Category	Name	Attributes	PDO	Injury	Fatality
Roadway	Type of Shoulder	Curb	10.80%	−2.66%	−8.10%
	Road System Identifier	Private Road, Parking Lot	25.56%	−6.31%	−19.30%
		County Road	−10.60%	2.61%	7.96%
		State Road	−12.10%	2.98%	9.10%
	Type of Intersection	Four-way	16.18%	−3.99%	−12.20%
	Total lanes	More Than four Lanes	−12.68%	3.13%	9.55%
Vehicle	Airbag Deployed	Combination	−16.33%	4.00%	12.30%
		Front Only	−26.20%	6.50%	19.80%
Driver	Suspected of Drug Use	Yes	−13.10%	3.23%	9.87%
	Gender	Female	8.90%	−2.20%	−6.70%
	Speed limit (miles per hour)	25–49	−9.98%	2.46%	7.50%
		50–74	−24.90%	6.15%	18.80%
	Restraint System	None Used-Motor Vehicle Occupant	−21.52%	5.30%	16.20%
Environment	Vision Obstruction	Inclement Weather, Fog, Glare	30.66%	−7.60%	−23.10%
Crash	Manner of Collision	Sideswipe Same Direction	20.50%	−5.00%	−15.40%
		Sideswipe Opposite Direction	7.04%	−1.74%	−5.30%
Temporal	Crash Time	Early Morning	8.80%	−2.17%	−6.60%

5.3. Truck Driver Attributes

Among driver-related attributes, the results showed that drug use, speed limit, female drivers, and not using a seat belt had significant impacts on the crash-injury severity. Alcohol use was tested as a potential explanatory variable, but its impact was not significant at the 90% significance level.

Truck drivers under the influence of drugs had a high positive impact on injury severity, increasing the chance of fatal and injury outcomes by 9.87% and 3.23%, respectively. Similar findings were reported in previous studies [5,26]. Driver's speed had a positive impact on the injury severity of crashes. As expected, the results indicated that the higher speed significantly increased the probability of fatal crashes, which is consistent with previous studies [27]. Female truck drivers were less likely to be associated with severe crash-injury severity. Table 4 shows that when the driver was a female, the chances of fatality and injury decreased by 6.70% and 2.20%, respectively. This might be because females drive these trucks less compared to the male drivers.

Seatbelt usage was another significant factor positively associated with large-truck WWD crash-injury severity. The results indicated that when a seatbelt was not used, the probability of fatal crashes increased by 16.20%. Therefore, it can be inferred that seatbelt usage is an efficient way to reduce the severity of WWD crashes, which is similar to the findings of the literature [4,28].

5.4. Temporal Attributes

In terms of temporal effects, the model results showed that it was 6.60% less likely to have a fatal outcome when the crash occurred in the early morning (5 to 9 am), which might be due to the lower traffic volume in this time period.

5.5. Environmental Attributes

Driver's vision obstructed by inclement weather, fog, and glare had a significant impact on the WWD crashes. The results showed that driver vision has a negative impact on the injury severity of crashes. The negative association could be because the truck drivers tend to drive more cautiously when the weather is not in favorable conditions.

5.6. Crash Attributes

In terms of collision manner, both sideswipe types (same direction and opposite direction) had a negative impact on crash-injury severity. The likelihood of a fatal outcome decreased by 15.40% and 5.3%, respectively, when it was a same-direction sideswipe and opposite-direction sideswipe, compared to other types of crashes. The results are consistent with findings from the literature, indicating that non-head-on collisions tended to have lower injury-severity outcomes than head-on crashes [29,30].

5.7. Heterogeneity

The mean and standard deviation of two variables, including speed and the early-morning period, were significant at the 95% significance level, suggesting the presence of heterogeneity. In addition, both random parameters had very large standard deviations, implying that these parameters can have positive or negative impacts on crash-injury severity [11]. Thus, looking only at the coefficient's mean value and sign might not provide reliable results, as both are likely to change due to large standard deviations. We tested various variables for interaction effects with the two random parameters to identify potential sources of the heterogeneity. The results of the model with the interaction effect in Table 3 show that truck drivers' age had a significant interaction effect with moderate driving speed (25–49 mph). Specifically, young drivers (younger than 20 years old) and middle-aged drivers (between 36–50 years old) were less likely to result in severe WWD crashes when they drove at this speed compared to truck drivers in other age groups. In terms of early-morning crashes, county roads showed a negative interaction effect, decreasing crash-injury severity. This suggests that although county roads were associated with higher injury levels for WWD crashes compared to local roads, they posed less severe outcomes when the crash occurred in the early morning period. The reason behind this might be since that in the early morning, there is less traffic on county roads.

6. Discussion and Conclusions

This study investigated the impact of various contributing factors on large-truck WWD crashes using a ten-year period crash dataset in Florida. A wide range of variables was explored as random parameters to account for the presence of heterogeneity. To further investigate the sources of heterogeneity, interaction effects were also introduced to the model. The main objective of this research was to conduct a thorough investigation of the contributing factors associated with WWD crashes caused by large trucks. Figure 1 presents the marginal effects of each contributing factor.

The model results show that the severity of fatalities or injuries due to crashes increases when the speed is between 50 and 74 mph, when only the front airbag is installed, and when no seatbelt is used in the large-truck vehicle. Furthermore, the chance of WWD fatal crashes increases to a large extent when the truck driver is under the influence of drugs. These findings support the results presented in Valen et al. [26]. According to the study, one of the significant risks of traffic crashes is associated with drug- or alcohol-impaired driving. The study also found that driving on drugs was significantly associated with speeding, non-use of seat belts, and not having a driver's license.

On the other hand, vision obstruction due to inclement weather, private roads, or parking lots, four-way intersections, sideswipe collision types, the presence of curb shoulders, and female drivers are associated with less injury severity in large-truck WWD crashes. Although private roads or parking lots, sideswipe collision types, the presence of curb shoulders, and drivers' vision obstruction lead to more property damage crashes. These findings could be useful for setting up safety guidelines for large trucks such as providing warning signs and markings for drivers focusing on specific road categories, geometries, and environmental conditions.

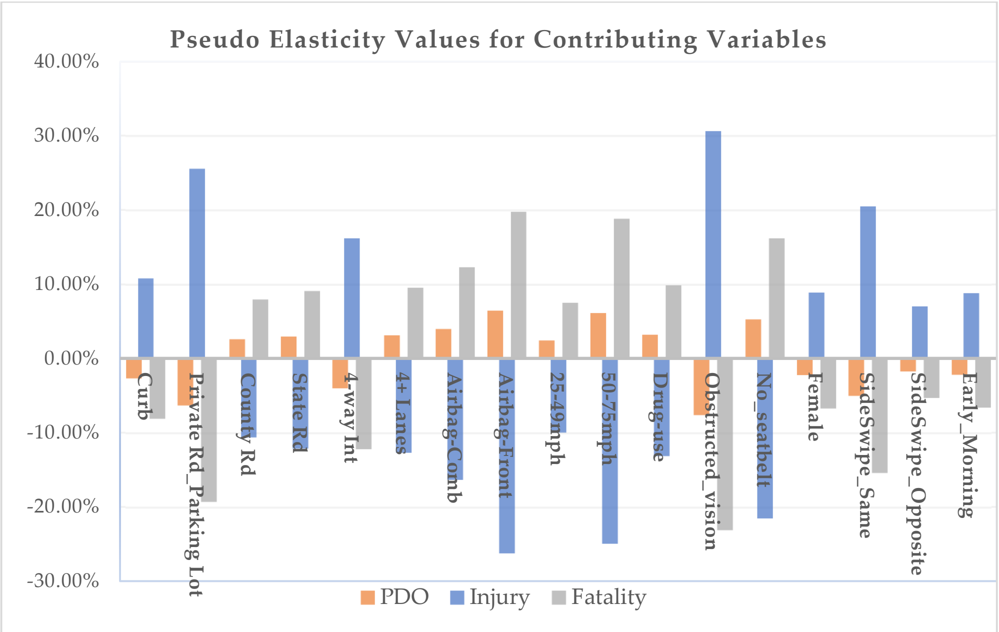

Figure 1. Marginal effects of factors contributing to large-truck WWD crash.

Among the various tested factors, a speed of 25–49 mph and the early-morning period showed heterogeneous effects on the injury severity of large-truck WWD crashes. The truck drivers' age and the roadway type were identified as the potential sources of heterogeneity. Accounting for heterogeneity and incorporating the interaction effects significantly improved the model performance. This provides a better estimation of the impacts of contributing factors and helps to develop more effective safety countermeasures.

Compared to the existing literature focusing on general WWD crashes, this study shows similar results for large-truck WWD crashes. It suggests that higher speed, older and male drivers, driving under the influence of a drug, no seatbelt use, higher AADT, or the number of lanes were the common factors that lead to higher crash-injury severity. Lighting conditions, weather conditions, and alcohol use did not show significant impacts in this study. Interestingly, vision obstruction due to inclement weather was associated with lower levels of crash-injury severity. This might be attributed to the more cautious driving behavior of truck drivers under adverse weather conditions. It could also be due to the small sample size. Further investigation is needed in this area.

The above findings provide useful insight into the parameters that contribute to the crash-injury severity of large-truck WWD crashes. This knowledge can help policymakers and authorities develop safety countermeasures to reduce WWD crashes and improve truck safety. Identifying heterogeneity and investigating its potential sources could also provide the groundwork for a better understanding of the potential factors that influence crash-injury severity. Another key factor in terms of driver's characteristics in large truck safety is the sleep and mental state of the drivers. Although these parameters are hard to assess, studies show that driver's sleep, mental stress, shift work, poor job organization, lack of facility, and job strain have a significant impact on truck drivers' unsafe and risk-taking behavior on the road [7,31,32]. As a result, they are more likely to be involved in crashes.

Based on the findings of this research, countermeasures can be recommended to reduce the severity of large-truck WWD crashes and enhance safety on roads. For example, the use of seat belts should be highly enforced for large-truck drivers through enforcement strategies or educational programs. The recommended enforcement strategies to increase seatbelt use could include increasing penalties for violations and increasing police efforts in unsafe areas. Furthermore, our results show that drug use significantly increased the severity of large-truck WWD crashes. Specific educational programs on the dangers of drug use and driving, especially for truck drivers, can be beneficial for enhancing safety.

Existing strategies related to educating alcohol-related drivers need to be modified since the characteristics of drug-impaired drivers are different from those of alcohol-impaired drivers [33]. Campaigns can help promote the messages to young drivers and specific age groups of drivers regarding the serious risks associated with specific drug use and driving on the road. For example, medications that cause drowsiness or impairment should clearly indicate this with their doses. Enhancing educational and safety awareness programs through social media can be useful for reducing crashes since encouraging seatbelt use and prohibiting drug or alcohol use can decrease crash-injury severity. Due to the severe nature of WWD crashes on non-limited access facilities, adequate street lighting and wrong-way signage on one-way facilities should be provided to help mitigate wrong-way driving-related crashes.

The study has some limitations that can be further investigated in future work. The sample size was small, resulting in zero or no observations for some categories. Thus, the authors could not explore many important variables. Future work can be conducted to investigate large datasets of wrong-way driving crashes. To assess the spatial stability of the model estimates, the model could be applied to other geographic regions. Additionally, these data cover a 10-year period, and this long period may introduce the issue of temporal instability, thus impacting the reliability of the model. Future studies can focus on addressing the temporal heterogeneity issues.

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