



Examining injury severity in truck-involved collisions using a cumulative link mixed model

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ABSTRACT

Background: Trucks play a vital role in promoting regional freight transportation and economic development, but truck-involved collisions often have more severe consequences and create greater losses for society.

Research purpose: This study examined the relationships between injury severity and various explanatory factors in truck-involved collisions to identify preventive countermeasures for safety improvement.

Data: Los Angeles' collision records from 2010 to 2018 were analyzed.

Method: A cumulative link mixed model was applied, where the heterogeneities among drivers were highlighted.

Result: Our findings confirmed that various driving mistakes, such as speeding, improper driving, and drinking alcohol, contributed to severe injuries. Male drivers were more likely to be severely injured, while female occupants were more likely to be severely injured. The use of safety equipment always helped mitigate injury severity. Collisions at night on dark roads with no streetlights and collisions on slippery road surfaces had higher risks of causing severe injuries. In addition, collisions on ramps were more likely to result in severe injuries. Drivers in old trucks were also at a higher risk of suffering from severe injuries.

Conclusions: Freight companies are encouraged to monitor drivers' performance using remote cameras. Policy-wise, local agencies should regulate improper driving behavior and safety equipment use for truck drivers. Improving lighting conditions, periodically testing the skid resistance of road surfaces, adjusting speed limits, and applying weigh-in-motion technologies may greatly help mitigate injury severity. Old trucks should be brought in for frequent tests or abandoned after many years of usage.

1. Introduction

With the development of modern shipping and logistics, most companies now engage in overseas manufacturing and global trade. The freight industry has similarly been greatly reshaped with a growing demand for consumer goods (Hesse, 2007; Yuan, 2018a). More recently, with advancements in smartphone technology, online retail has exploded, and its logistics network has expanded

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significantly as well. Many online retailers, like Amazon, have doubled or tripled shipping capacity over the past decade. The ongoing outbreak of Covid-19 has also illustrated the weaknesses regarding worldwide delivery needs. Fleet managers, dispatchers, and drivers often struggle to find the best way to serve their communities. The freight industry faces extreme challenges but also embraces rich opportunities. To provide more frequent and time-sensitive deliveries, major gateway cities must adapt to high volumes of freight transportation (Cidell, 2011; Yuan, 2018b). Increased heavy truck traffic adds a burden to the road system and increases the risk of collisions (McDonald et al., 2019; Rosenbloom, 2009). According to the US Bureau of Transportation Statistics, the total tonnage transported by trucks in 2017 was 11.52 billion tons, adding up to a value of \$12.421 trillion in the US (Anon, 2017). However, trucks have high collision risks due to their high volume, large vehicle size, heavy weight, and other operational characteristics. Injuries from truck-involved collisions are more likely to be severe or fatal (Ch Anastasopoulos and Mannering, 2011), and result in millions of dollars in financial losses. Truck drivers are involved in more severe collisions than drivers of any other type of vehicle. In the year of 2017, the total number of fatal vehicle injuries in the US was 34,247, with truck-involved fatalities making up 11,029 of those, according to the Traffic Safety Facts reported by the US National Transportation Safety Board (2016–2017; NHTSA, 2017). Essentially, nearly 1/3 of fatal collisions involved trucks. Examining truck-involved collisions, identifying factors that contribute to severe injuries, proposing preventive measures for collision risk mitigation, and improving road safety are thus of great importance.

Injury severity has been studied for decades by both engineering and health scholars and professionals. However, several unique features of truck-involved collisions and injuries have not been closely examined in prior literature. First, in collisions involving multiple victims, there are autocorrelations between the victims' injury outcomes, and such autocorrelations are rarely controlled for. Second, the kinetic energy of a truck (due to its larger mass) often leads to more severe injuries for victims in cars or other smaller vehicles. Unlike collisions between passenger vehicles, occupants sitting in smaller cars are more vulnerable to severe injuries in truck-involved collisions. In prior literature, studies examining the relationship between kinetic energy and collision outcomes treated vehicle weight and speed change as two independent variables (Conroy et al., 2008; Lee et al., 2010). The direct effect of kinetic energy has barely been studied. Additionally, many studies were centered on the principle of forgiveness. This principle dictates that road users are responsible for causing accidents and countermeasures should therefore be aimed at changing drivers' behavior (Lemp et al., 2011; Teoh et al., 2017; Zhu and Srinivasan, 2011a, b). Several scholars (Larsson et al., 2010; Wegman, 2017) conceptualized the safety system approach. Under this framework, factors contributing to the occurrence of collisions are treated as a complex system. It is not only the people, but also the road, the environment, the collision, and the car that jointly contribute to road collisions and injuries. This approach was applied to conceptualize our model in this study.

Developing a comprehensive model that captures all observable factors for injury severity is challenging for many reasons, such as missing variables, missing values, rare events, and an inadequate number of observations. The California Statewide Integrated Traffic Records System (SWITRS) has a rich data set of traffic records and enabled us to specifically investigate truck-involved collisions. To account for group heterogeneities among drivers, this study employed a Cumulative Link Mixed Model (CLMM) to identify factors that explain the injury severity in truck-involved collisions and capture autocorrelations among drivers by incorporating random effects.

2. Literature review

Prior studies examining truck-involved collisions have emphasized different groups of factors when analyzing injury severity. These factors can be classified into the following categories: (1) socio-demographic profiles, such as age and sex, (2) behavioral factors, such as alcohol use, distraction, improper driving, unsafe driving speed, and the misuse of safety equipment, (3) temporal factors, such as collision time, season, and day of the week, (4) environmental factors, such as weather and street lighting conditions, (5) road conditions, such as roadway geometry, road damage, road surfaces, and road obstructions, (6) collision characteristics, such as collision type, and (7) vehicle characteristics, such as a truck's length, weight, and years of usage.

Among these factors, truck drivers' socio-demographic characteristics, behavioral characteristics, and vehicle characteristics are correlated with the injury severity of occupants in truck-involved collisions. Frequently discussed factors include truck drivers being distracted or intoxicated, the misuse of safety equipment, and a truck's weight and size. Truck drivers' higher degrees of distraction and intoxication have been directly linked with more severe injuries (Khorashadi et al., 2005; Lemp et al., 2011; Teoh et al., 2017; Zhu and Srinivasan, 2011a, b). Interestingly, a positive relationship was identified between the number of truck trailers and the fatality rate, but the length and the weight of trucks both suggested negative correlations with the fatality rate (Bedard et al., 2002; Lemp et al., 2011). Meanwhile, injuries caused by improper driving behavior such as speeding were far less severe when safety equipment was used (Zhu and Srinivasan, 2011b). Studies have not paid much attention to victims' characteristics, with only a few studies suggested that males tend to be more severely injured than females in truck-involved collisions (Uddin and Huynh, 2017).

In terms of temporal factors, several studies indicated that victims were more severely injured in collisions that occurred at night (Osman et al., 2016; Pahukula et al., 2015). Injuries were less severe during the summer months, probably due to there being longer daytime and better road conditions (Pahukula et al., 2015).

Environmental factors were correlated with injury severity (Ahmed et al., 2018; Lemp et al., 2011; Lyman and Braver, 2003; Naik et al., 2016; Uddin and Huynh, 2017; Wang and Shi, 2013; Zou et al., 2017). Bad weather conditions, including fog, ice, and snow, showed positive relationships with severe injuries. In terms of lighting conditions, areas with no street lights had more severe collisions (Uddin and Huynh, 2017). Road surface conditions were also found to be related to injury severity. On dry road surfaces, the risks of collision and severe injury were greatly reduced, and vice versa (Ahmed et al., 2018). When road surfaces were covered by ice, the probability of death in truck-involved collisions was greatly increased (Lemp et al., 2011).

In terms of collision types and location characteristics, injuries caused by head-on collisions tended to be more severe. Injuries caused by truck-involved collisions at state and interstate highways' intersections were also more severe (Zhu and Srinivasan, 2011a).

Specifically, truck-involved collisions on state and interstate highways were 2.3 and 4.5 times more likely to be severe injuries, respectively (Osman et al., 2016).

For methodology, various discrete choice models have been used to examine injury severity in truck-involved collisions, such as the multinomial logit (MNL) model and the nested logit (NL) model. Some studies treated injury severity as an ordered categorical variable and employed an ordered logit (OL) model or a generalized ordered logit (GOL) model, as shown in Table 1. With increased modeling capacity, recent studies have tried to include random parameters to capture individual heterogeneities (Al-Bdairi and Hernandez, 2017; Naik et al., 2016; Zou et al., 2017). Different approaches with a focus on individual or group heterogeneities that capture autocorrelations among multiple occupants are expected.

3. Research Design

3.1. Methodology

This paper employed the cumulative link mixed model (CLMM), also known as the ordered response mixed model, which is an extension of the cumulative link model (CLM). The CLM is also referred to as the ordered logit (OL) model or the proportional odds (PPO) model. The advantage of employing a CLMM lies in its inclusion of random effects to model group heterogeneities. In this study, a default assumption is that drivers of the same sex and age, performing similar driving behavior, are likely to result in similar injury severity outcomes for all occupants in truck-involved collisions. The failure of capturing this feature may overstate the injury severity in truck-involved collisions. The general form of the CLMM is denoted as Eqs. (1–2).

$$G^{-1}[P(Y_i \leq j)] = a_j - (Z_{t[i]} \mu_t + X_i \beta) \quad (1)$$

$$\mu_t \sim N(0, \sigma_t^2) \quad (2)$$

where Y_i denotes the injury severity that takes values from 1 to J , X_i represents the vector of fixed effects, β is the vector of coefficients for each regressor, a_j is the threshold for level j , $j = 1, \dots, J$ for an ordinal variable with J levels, G^{-1} is the link function, and μ_t represents the vector of coefficients corresponding to the group-level predictors $Z_{t[i]}$ for observation i in group t . This model has the added assumption that random effects are normally distributed and centered at zero. The CLMM was estimated with the R 'ordinal' package (Christensen, 2019).

3.2. Data

The collision data were documented in the US Statewide Integrated Traffic Records System (SWITRS). This study employed the truck-involved collision data from January 2010 to December 2018 from the city of Los Angeles (LA), California. LA was selected for analysis for three reasons. First, LA is a famous harbor city with high freight demand. As such, trucks play an important role in the local economy. Second, LA has a high traffic volume, correlating with a higher rate of truck-involved collisions. Third, the SWITRS is a well-reported collision data system, which serves as the basis for an insightful analysis of injury severity in truck-involved collisions.

The response variable, injury severity, had five levels, including property damage only, possible injury, evident injury, severe injury, and fatal injury. When processing the raw data, any collision involving a truck or large vehicle was selected, while collisions between or among other types of vehicles were filtered out, which resulted in a sample of 24,514 observations. However, the data had many missing values. After removing cases with missing values, the final sample was reduced to 21,258 observations. A descriptive summary of the response variable is given in Table 2. The percentages of injury types were largely consistent between the original and final samples, indicating that using the final sample for analysis would not introduce any serious sampling bias. Due to fatally injured victims not being able to provide information, some observations of fatal injuries were removed from the final sample, which may

Table 1
Methods examining injury severity in truck-involved collisions.

Authors	Model
Khattak et al. (2003)	Binary Probit and ordered Probit
Khorashadi et al. (2005)	Multinomial logit
Chen and Chen (2011)	Mixed logit
Lemp et al. (2011)	Ordered Probit and heteroskedastic ordered Probit
Zhu and Srinivasan (2011a)	Ordered Probit
Zhu and Srinivasan (2011b)	Mixed ordered Probit
Islam and Hernandez (2013)	Random parameter ordered Probit
Pahukula et al. (2015)	Random parameter logit
Naik et al. (2016)	Random parameter ordered logit and mixed logit
Osman et al. (2016)	Multinomial logit, nested logit, ordered logit, and generalized ordered logit
Al-Bdairi and Hernandez (2017)	Ordered random parameter Probit
Uddin and Huynh (2017)	Mixed logit
Zou et al. (2017)	Random parameter ordered Probit and spatial generalized ordered Probit
Ahmed et al. (2018)	Bayesian logit

Table 2

The number and the percentage of each injury type.

Injury	Property damage only	Possible injury	Evident injury	Severe injury	Fatal
Original sample (24,514 cases)	5,297 (21.61%)	13,689 (55.84%)	4,336 (17.69%)	831 (3.39%)	361 (1.47%)
Final sample (21,258 cases)	4,453 (20.95%)	12,113 (56.98%)	3,818 (17.96%)	678 (3.19%)	196 (0.92%)

incur some biases. In this study, over half of the fatally injured observations were kept in the final sample, accounting for 0.92% of the total number of injuries. The other levels, including property damage only, possible injury, evident injury, and severe injury, accounted for 20.95%, 56.98%, 17.96%, and 3.19% respectively in the final sample.

3.3. Variable selection

A collision is often caused by many parties. In this study, any vehicle involved in a collision was treated as a party, and each party had one driver and possibly multiple passengers. Moreover, both drivers and passengers were considered as occupants. Following the safety system approach (Larsson et al., 2010), all selected variables were grouped as factors of human behavior, natural and road environment, collision and vehicle attributes. In detail, this model included the individual profiles of drivers and other occupants, behavioral factors, temporal factors, environmental factors, location characteristics, collision characteristics, and vehicle characteristics. Fig. 1 presents the conceptual model framework, which followed the safety system approach and was built based on existing studies (Apronti et al., 2019; Lemp et al., 2011; Zhu and Srinivasan, 2011a, b) and data availability.

3.4. Data processing

The data cleaning process involved several steps. The first step was to handle the missing values. For example, vehicles' lengths and weights were largely missing in the data. Although their importance in explaining injury severity has been widely recognized, these two variables were excluded from the final sample. The vehicle size was included as a substitute for this information. The second step was to work with rare events. For behavioral factors, drug use was excluded because seriously intoxicated truck drivers were rarely present in the data. These rare observations can be picked out for more microscopic case studies but should not be included in the final model. To simplify analysis and to obtain the maximum amount of information with useful implications for real-world practices, some attributes that had similar indications were merged. For instance, among the various driving behavior-related factors, following too closely, driving on the wrong side of the road, improper passing, unsafe lane changing, and improper turning were merged into a variable titled improper driving. Similarly, rain, snow and fog were combined into the variable of bad weather. Wet, snowy, icy, and slippery road surfaces were merged into slippery road surfaces. Roadway damage, obstructions on roadways, and narrow roadways were merged into poor road conditions. A descriptive analysis of selected variables is shown in Table 3.

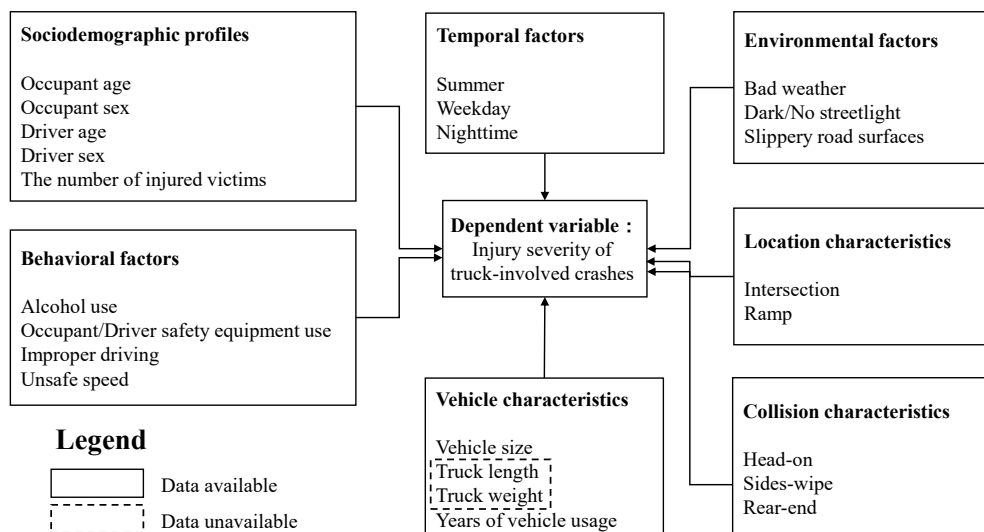
**Fig. 1.** Modeling conceptual framework.

Table 3
Variable descriptions and data summary.

Variables	Mean	S.D.	Min.	Max.	Percent of '1'	Description
Human Factors						
Demographic profiles						
Driver	–	–	–	–	57.54%	Driver 1; else 0
Driver age	39.95	14.72	16.00	80.00	–	Driver's age, from 16 to 80
Driver sex	–	–	–	–	59.82%	Male 1; else 0
Occupant age	36.55	17.49	1.00	99.00	–	The occupant's age, from 16 to 104
Occupant sex	–	–	–	–	56.69%	Male 1; else 0
Number of injured occupants	1.91	2.03	0.00	34.00	–	The number of occupants
Behavioral factors						
Alcohol use	–	–	–	–	7.26%	If the driver used alcohol 1; else 0
Driver safety equipment use	–	–	–	–	57.83%	If the driver used safety equipment 1; else 0
Improper driving	–	–	–	–	36.51%	If the driver didn't drive properly 1; else 0
Unsafe speed	–	–	–	–	39.05%	If the speed was too fast or too slow 1; else 0
Occupant safety equipment use	–	–	–	–	56.75%	If the occupant used safety equipment 1; else 0
Natural and Road Environment Factors						
Temporal factors						
Summer	–	–	–	–	11.25%	June, July, and August, 1; else 0
Weekday	–	–	–	–	83.59%	If the collision occurred during weekdays 1; else 0
Nighttime	–	–	–	–	25.92%	If the collision occurred during nighttime (06:00 p.m.-06:00 a.m.) 1; else 0
Environmental factors						
Bad weather	–	–	–	–	3.11%	Bad weather days, including rain, snow, fog weathers, 1; else 0
Dark/No streetlight	–	–	–	–	5.46%	No streetlight or non-functioning lights 1; else 0
Slippery road surfaces	–	–	–	–	6.06%	If road surface condition is wet or slippery 1; else 0
Location characteristics						
Intersection	–	–	–	–	15.72%	If the collision occurred at an intersection 1; else 0
Ramp	–	–	–	–	4.67%	If the collision occurred on a ramp 1; else 0
Collision characteristics						
Head-on	–	–	–	–	3.54%	If the collision is head-on 1; else 0
Side-swipe	–	–	–	–	26.84%	If the collision is side-swipe 1; else 0
Rear-end	–	–	–	–	44.48%	If the collision is rear-end 1; else 0
Vehicle Characteristics						
Years of vehicle usage	9.12	6.79	0.00	58.00	–	The difference between the model year and the year of collision
Vehicle size	2.47	0.83	1.00	4.00	–	Motorcycle or scooter 1, passenger car 2, light truck or emergency car 3, large truck or large vehicle (bus) 4

4. Results

4.1. Descriptive analysis

Among the 21,258 injury cases, property damage accounted for 20.95%, possible injuries accounted for 56.98%, evident injuries accounted for 17.96%, severe injuries accounted for 3.19%, and fatal injuries only accounted for 0.92%. For explanatory variables, the number of drivers accounted for 57.54% of all occupants, the mean age of drivers was 39.95, and the percentage of male drivers was 59.82%. The mean age of all occupants was 36.55, and the percentage of male occupants was 56.69%. Although the maximum number of injured occupants per collision was 34, the mean of injured occupants per collision was 1.91. In many cases, drivers made errors when driving, including alcohol use, improper driving, and driving at unsafe speeds, which accounted for 7.26%, 36.51%, and 39.05% respectively. It is worth noticing that the percent of drivers and the percent of all occupants using safety equipment were at the same level, accounting for 57.83% and 56.75% respectively. This indicates that the use of safety equipment needs to be promoted. For temporal factors, about 12% of the collisions occurred during the summer, about 26% of the collisions occurred at night, and about 84% of the collisions occurred on weekdays. In addition, collisions occurred less frequently at intersections, only accounting for 15.72%. Collisions more often occurred at ramps. In terms of collision characteristics, collisions were more often rear-end or side-swipe collisions, and the percentage of head-on collisions was quite low. These three types of collisions accounted for 44.48%, 26.84%, and 3.54% respectively. Furthermore, older trucks did present a greater level of collision risks. For the final sample, trucks had been used for an average of 9.12 years, with the oldest one being used for 58 years.

4.2. Inferential analysis

The CLMM was used to examine relationships between various explanatory factors and injury severity in truck-involved collisions. The modeling outcome is shown in Table 4. This study specifically includes drivers' socio-demographic factors and driving behavioral factors as random effects to capture group heterogeneities to account for intra-class correlations created by drivers.

The four thresholds between different injury types, including the threshold between property damage only and possible injury, the threshold between possible injury and evident injury, the threshold between evident injury and severe injury, and the threshold between severe injury and fatal injury were all significant. In addition, only the threshold between property damage only and possible injury was negative, which indicates that the injury outcomes in truck-involved collisions were unlikely to be just property damage, and brings more attention to mitigating the negative consequences on our society.

Among human factors, both demographic profiles and behavioral characteristics suggest important findings. For demographic factors, the driver's sex and occupant's age had a positive effect on injury severity, suggesting that male drivers and older occupants were more likely to be severely injured. In comparison, older drivers and male occupants were less likely to be severely injured. When compared with passengers, drivers were more likely to be severely injured. For driving behavioral factors, some variables showed significant correlations with injury severity. The use of safety equipment helped mitigate injury severity for both drivers and other occupants. Drivers driving improperly or drunk both indicated positive relationships with severe injuries.

Among various environment-related factors, summer and nighttime variables showed positively significant correlations with injury severity. Dark/no streetlight showed a positive relationship with injury severity while slippery road surfaces showed a negative relationship with injury severity. As for collision location, the injury outcomes of collisions occurring at intersections were less severe, while the injury outcomes of collisions occurring on ramps were more severe.

In terms of collision types, the injury outcomes of side-swipe and rear-end collisions tended to be less severe, while the injury outcomes of head-on collisions did not have a significant effect in this study.

Table 4
Results of the cumulative link mixed model.

Threshold Coefficients						
Category	Estimate	S.D.	Z-value			
Between property damage only and possible injury	−1.29	0.10	−12.42			
Between possible injury and evident injury	2.52	0.11	23.61			
Between evident injury and severe injury	4.67	0.11	42.17			
Between severe injury and fatal	6.26	0.13	49.09			
Independent Variables Coefficients						
Category	Variable	Estimate	P-value			
Fixed Effects						
Human Factors						
Demographic Profiles	Driver	2.65***	0.00			
	Driver age	−0.01***	0.00			
	Driver sex	0.56***	0.00			
	Occupant age	0.01***	0.00			
	Occupant sex	−0.22***	0.00			
	The number of injured occupants	0.16***	0.00			
Behavioral Factors	Alcohol use	1.07***	0.00			
	Driver safety equipment use	−0.27***	0.00			
	Improper driving	0.10	0.05			
	Unsafe speed	−0.10	0.35			
	Occupant safety equipment use	−0.54***	0.00			
Natural and Road Environment Factors						
Temporal Factors	Summer	0.19***	0.00			
	Weekday	0.06	0.13			
	Nighttime	0.17***	0.00			
Environmental Factors	Bad weather	−0.0008	0.99			
	Dark/No streetlight	0.34***	0.00			
	Slippery road surfaces	−0.16*	0.05			
Location Characteristics	Intersection	−0.12*	0.01			
	Ramp	0.34***	0.00			
Collision Characteristics						
Collision Characteristics	Head on	0.06	0.47			
	Side swipe	−0.63***	0.00			
	Rear end	−0.61***	0.00			
Vehicle Characteristics						
Vehicle Characteristics	Years of vehicle usage	0.02***	0.00			
	Vehicle size	−0.43***	0.00			
Interaction Effects	Vehicle size: Unsafe speed	0.12**	0.001			
Random Effects						
Groups	Variable	Variance	S.D.	Intra-class	Correlation	
Driver sex: Driver age	Intercept	0.04	0.20	−	−	−
	Improper driving	0.06	0.25	−0.70	−	−
	Unsafe speed	0.08	0.29	−0.82	0.71	−
	Alcohol use	0.10	0.32	−0.49	0.52	0.43
Log-likelihood = −18,933.60	AIC = 37,945.20	n = 21,258				

Significance codes: '***' 0.001; '**' 0.01; '*' 0.05; '.' 0.1

In terms of vehicle characteristics, years of vehicle usage showed a positive relationship with injury severity. This study specifically placed a focus on interpreting the effect of trucks' kinetic energy on other vehicles. As shown, unsafe speeds seemed to not have any significant effect on the injury severity, while vehicle size had a negative relationship with injury severity. This indicates that occupants on trucks were unlikely to be severely injured, but property damage on trucks was still possible. It is worth highlighting that the interaction effect of vehicle size and unsafe speed showed a positive effect on injury severity.

Taking advantage of the CLMM, this study split the sample into multiple groups based on drivers' age and sex and included drivers' behavioral factors as random effects to account for intra-class correlations within the clusters. Among the three included random effects, alcohol use presented great variations across different driver groups, followed by unsafe speeds, and then improper driving. The high intra-class correlation indicated that drivers who had improper driving behavior were also likely to drive at unsafe speeds.

5. Discussion

This study examined the effects of various factors on injury severity in truck-involved collisions. According to our results for the threshold coefficients, truck-involved collisions deserve more attention because injury outcomes in such collisions are unlikely to only cause property damage. As shown in Table 4, most of the selected explanatory variables were significant, suggesting that preventive countermeasures can be designed around significant indicators. Most of our findings were consistent with prior studies (Al-Bdairi and Hernandez, 2017; Lemp et al., 2011; Naik et al., 2016; Uddin and Huynh, 2017; Zhu and Srinivasan, 2011a, b). The variables we utilized included alcohol use, safety equipment use, improper driving, nighttime, dark/no streetlight, and vehicle size, all of which were consistent with prior research.

Among the selected human factors, truck drivers who drove improperly and drank alcohol were more susceptible to severe injuries (Al-Bdairi and Hernandez, 2017; Zhu and Srinivasan, 2011a, b). It is worth mentioning that the use of safety equipment greatly mitigated injury severity for both drivers and other occupants. These findings highlight the importance of safety education to prevent human fatalities. Regarding socio-demographic factors, if the driver was older or a female, collision injuries tended to be less severe. In contrast, if the occupant was older or a female, the injuries tended to be more severe. Generally, females are more cautious than males when driving, and young drivers tend to drive more aggressively. Drivers who have records of reckless or improper driving should attend training programs for critical road safety topics, especially for young, male drivers. Furthermore, the number of injured occupants was positively correlated with injury severity. This is sensible as when more people are injured, the more likely there are severe injuries.

When it comes to the natural environment factors and road conditions, slippery road surfaces and the season of summer contradicted existing literature (Islam and Hernandez, 2013; Pahukula et al., 2015). However, for the slippery road surfaces, several other studies have suggested similar findings (Ahmed et al., 2018; Lemp et al., 2011). To clarify, LA is located in the south of the US and the temperature is generally high throughout the year. Snowy weather, cold winters and slippery road surfaces are rare in LA. LA has dry road surfaces for most of the year. When road surfaces are wet and slippery, truck drivers become more cautious when driving, hence reducing the injury severity on wet and slippery road surfaces. This may partially explain why the findings are not consistent with prior studies examined in other cities. On the other hand, negative consequences related to extremely hot weather could impact the performance of drivers in LA (Naik et al., 2016). For example, individuals drive more aggressively on hot days. Reflections on asphalt road surfaces can temporarily damage eyesight and increase collision risks. These alternative explanations need to be further examined in future research. However, such a contradictory finding sounds reasonable and could be applicable to cities with similar climates. For truck-involved collisions happening at nighttime and in the dark without street lighting, injuries were far more severe (Uddin and Huynh, 2017). All in all, manufacturers should continually improve techniques for both electronic stability control and tire design to prevent vehicle wheel skidding. Local authorities should check road surfaces and lighting systems periodically and add anti-skid materials and street lights in collision hotspots.

As for location characteristics, our results indicate that collisions occurring at intersections tended to be less severe, but those on ramps were more severe. Generally, vehicles slow down when approaching intersections, which greatly reduces the likelihood of collisions and severe injuries. However, when driving on ramps, most drivers are accelerating, failing to notice vehicles coming from other directions, which may result in collisions and severe injuries. This finding indicates the importance of adding signs and signals and regulating driving behavior on ramps. As for collision types, prior studies have investigated vertical collisions, such as head-on and rear-end collisions (Zhu and Srinivasan, 2011a), and the results of our research for rear-end collisions are fully consistent. Another collision type, namely side-swipe collisions, was included in this study. As expected, the injury severity in side-swipe truck-involved collisions was less severe.

In addition, compared with previous studies, this study had some interesting findings. We noticed that the longer a truck was used for, the higher likelihood of it being involved in collisions with severe injuries. Therefore, local authorities should closely supervise annual vehicle inspection in order to maintain the quality of on-road vehicles. This study also examined the injury outcomes triggered by the kinetic energy transferred from trucks to passenger vehicles, which represents a unique feature of truck-involved collisions when compared with collisions between regular passenger vehicles. As shown, occupants sitting in larger vehicles were less likely to be severely injured, while occupants in smaller vehicles were more vulnerable to severe injuries. Additionally, driving at unsafe speeds had an insignificant effect, which is quite different from prior road safety research regarding passenger car collisions. These findings suggest different takeaways for both vehicle manufacturers and local authorities. For vehicle manufacturers, more investments should be made in vehicle collision buffering systems to offset the kinetic energy transferred in collisions. Local authorities are encouraged to adopt dynamic weighing technology in order to better detect and reduce the number of overweight and overloaded trucks on the road. In densely populated urban environments, a shift from heavy and large trucks to light transport vehicles is also strongly encouraged.

6. Conclusions

Trucks play a vital role in promoting regional freight transportation and economic development, but injuries from truck-involved collisions can create great losses for society. Currently, the ongoing coronavirus pandemic results in many changes in shopping that people are getting used to, such as ordering foods and goods online. Even after the vaccine is successfully developed and things are back to the new normal, shopping habits may be changed permanently. The urban freight system faces an expanded volume of online sales, and shipping companies should make large investments to increase their workforce and improve their operational safety. Such a trend confirms the research significance of this study. Therefore, it is important to examine the relationships between injury severity in truck-involved collisions and various explanatory factors to identify evidence-based preventive measures to mitigate negative consequences. This study employed the data from the SWITRS for LA to develop a CLMM. Following the safety system approach, this study incorporated human factors, natural road environment factors, collision characteristics, and vehicle characteristics. This study also examined considerable random effects of explanatory variables to capture group heterogeneities and intra-class correlations.

For the human factors, the findings of this study confirm that various driving errors contribute to severe injuries, such as speeding, improper driving, and drinking alcohol. Male drivers were more likely to be involved in severe collisions, but female occupants were more likely to be severely injured. It is important to recognize the intra-class correlation between improper driving and unsafe speeds. Drivers who drive improperly are very likely to be those who drive at unsafe speeds. The use of safety equipment always mitigated injury severity. Hence, monitoring truck drivers' performance helps regulate improper driving behavior and prevent reckless driving. Education, enforcement, and engineering tools all play important roles in preventing human mistakes and improving road safety.

For environmental factors and vehicle characteristics, driving at night and driving on dark roads with no streetlights led to higher risks of collisions and severe injuries. Streetlights are important for drivers to identify pedestrians and other vehicles in dark or inclement weather conditions. Improving lighting conditions on main corridors of traffic may greatly help reduce the number of collisions. Meanwhile, regulating speeds contributes to the reduction of kinetic energy, which then helps mitigate injury severity. Another component relating to kinetic energy is vehicle weight. To mitigate injury severity, we encourage authorities to apply weigh-in-motion technologies to reduce the number of overweight and overloaded trucks on the road. Switching from large, heavy trucks to light delivery vehicles is strongly encouraged in dense urban environments. Most states have drunk driving laws to prevent driving with a blood alcohol content (BAC) greater than 0.08%. Many trucks are owned by companies or fleets that have alcohollocks in them to prevent drivers from drinking and driving. Therefore, alcohol use is rare among truck drivers. Additional safety countermeasures can be enforced on ramps. For example, lowering speed limits, installing cameras, and improving the visibility of signals and signs on ramps. Local and state agencies should periodically test the skid resistance of road surfaces. Lastly, the expiration of very old trucks should be considered. More frequent tests should be required for old trucks to ensure that they operate safely on roadways.

Lastly, it is worth mentioning one limitation of the police-reported collision data, where the severity of injury is usually a quick decision that is made at the scene. According to the prior research, the severity of the victims' injuries can be underestimated or overestimated based on police officer's subjective measures (Amoros et al., 2007; McDonald et al., 2009). Data improvement by integrating the police-reported collision records and hospital-recorded injuries will contribute to build a more complete data system, and support a more accurate understanding of issues in road safety.

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CRedit authorship contribution statement

Mingyang Chen: Formal analysis, Data curation, Writing - original draft, Data analysis, Manuscript Draft. **Peng Chen:** Data curation, Research Design, Advise, Manuscript Revise, Data Access. **Xu Gao:** Methodology, Methodological Support. **Chao Yang:** Advise.

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