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Risk Factors Associated with Crash Injury Severity Involving Trucks

Srinivas S. Pulugurtha
University of North Carolina at Charlotte

Sarvani Duvvuri
University of North Carolina at Charlotte

Sonu Mathew
University of North Carolina at Charlotte

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Risk Factors Associated with Crash Injury Severity Involving Trucks

Sarvani Duvvuri, PhD
Srinivas S. Pulugurtha, PhD, PE, FASCE
Sonu Mathew, PhD

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Report 21-23

Risk Factors Associated with Crash Injury Severity Involving Trucks

Sarvani Duvvuri, Ph.D.

Srinivas S. Pulugurtha, Ph.D., PE, F.ASCE

Sonu Mathew, Ph.D.

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16. Abstract

Nearly 499,000 motor vehicle crashes involving trucks were reported across the United States in 2018, out of which 22% resulted in fatalities and injuries. Given the growing economy and demand for trucking in the future, it is crucial to identify the risk factors to understand where, when, and why the likelihood of getting involved in a severe or moderate injury crash with a truck is higher. This research, therefore, focuses on capturing and exploring risk factors associated with surrounding land use and demographic characteristics in addition to crash, driver, and on-network characteristics by modeling injury severity of crashes involving trucks. Crash data for Mecklenburg County in North Carolina from 2013 to 2017 was used to develop partial proportionality odds model and identify risk factors influencing injury severity of crashes involving trucks. The findings from this research indicate that dark lighting condition, inclement weather condition, the presence of double yellow or no-passing zone, road sections with speed limit >40 mph and curves, and driver fatigue, impairment, and inattention have a significant influence on injury severity of crashes involving trucks. These outcomes indicate the need for effective geometric design and improved visibility to reduce the injury severity of crashes involving trucks. The likelihood of getting involved in a crash with a truck is also high in areas with high employment, government, light commercial, and light industrial land uses. The findings can be used to proactively plan and prioritize the allocation of resources to improve safety of transportation system users in these areas.

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Mineta Transportation Institute
College of Business
San José State University
San José, CA 95192-0219

Tel: (408) 924-7560
Fax: (408) 924-7565
Email: mineta-institute@sjsu.edu

transweb.sjsu.edu/research/2117

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Executive Summary

Trucks are heavy vehicles with larger weight and greater difficulty in maneuverability than passenger cars. These characteristics of trucks make them susceptible to severe operational and safety challenges. Past studies emphasize the challenges associated with maneuverability, large braking distances, vehicle size, and weight characteristics as critical factors that influence trucks and the surrounding safety performance of the traffic stream. According to the National Highway Traffic Safety Administration, 111,415 crashes (22%) out of a total 499,000 truck crashes in 2018 resulted in severe injuries and fatalities.

Despite the ongoing global pandemic, the "2020 Freight Transportation Forecast" report projected a 36% increase in freight volume by 2031. An increase in the number of trucks carrying out freight and commercial trips on highways affects the safety of roads due to trucks' complex interactions with other vehicles. Hence, identifying potential risk factors associated with various injury levels of truck crashes enables practitioners and planners to better allocate resources for overall truck safety improvement on highways.

One of the essential parameters of truck traffic patterns is the influence of surrounding area characteristics such as land use and demographics. Past research on truck crash analysis lacks the evaluation of a comprehensive dataset involving such surrounding area characteristics. The present research addresses this gap by incorporating land use and demographic data along with the crash, driver, and road characteristics into the truck crash safety analysis. The objective of this research is to identify potential crash risk factors associated with varying levels of truck crash injury severity.

Mecklenburg County in the state of North Carolina was chosen as the study area for this research. Motor vehicle crash data from the Highway Safety Information System for the years 2013–2017 was used for analysis and modeling. Several vehicle types—single-unit trucks (2- or 3-axle, 6-tire or more), truck-trailers/tractors, fire/emergency vehicles, and other heavy vehicles/trucks—were categorized as trucks in this research. Data like land use (parcel-level) and demographic estimates at the traffic analysis zone level were collected from the Charlotte Regional Transportation Planning Organization. A 0.50-mile circular buffer around the crashes was used to capture the land use and demographic characteristics.

A partial proportionality odds model was developed for computing the potential risk factors associated with various truck crash injury severity levels. Backward elimination was performed to identify the independent variables for which at least one category is significant at a 90% confidence level. Various crash, road, lighting, weather, land use, and demographic characteristics influence the truck crash injury severity.

The results of this research indicate that the presence of curvature on the road (level, hillcrest, or bottom grade) is positively associated with severe and moderate injury truck crashes, which can be attributed to the difficulty of maneuvering trucks, especially on roads with the presence of horizontal or vertical curves. The presence of snow, smoke, and fog is positively associated with the truck crash injury severity, which is attributed to poor visibility while driving. This research also indicates that driver impairment, disregarding signs or signals, and not being compliant with the safe speed have a positive association with severe and moderate injury truck crashes.

Commercial, industrial, and resource land uses are positively associated with severe and moderate injury truck crashes, attributed to the substantial trucking activity (both in-house shipments and external trips). The presence of office land use is negatively associated with moderate and severe injury truck crashes, which is related to the lower trucking activity rates in areas such as business parks. Demographic characteristics also significantly affect the severe and moderate injury truck crashes. As the estimated number of employees in an area increase, the likelihood of severe injury truck crashes also increases. The presence of areas with employee estimates of 1000 to 1500 are associated with severe injury truck crashes compared to the areas with employee estimates of 500 or less.

The findings from this research indicate the need for effective geometric design and practices to improve visibility conditions and reduce the risk of severe and moderate injury truck crashes. Potential countermeasures such as the use of variable speed limits signs or dynamic message signs to harmonize the speed of the stream for safer vehicle maneuvering can be considered to reduce risk and enhance safety. Additionally, advanced driver warning, crash avoidance systems, and truck traffic signal priority could be explored in high-risk areas (near commercial and industrial land uses). In addition, relevant truck safety enforcement and education could reduce the associated risks.

1. Introduction

Difficult maneuverability, large braking distances, enormous vehicle size, and weight characteristics are some of the critical factors that influence trucks' overall safety performance in a traffic stream (IIHS 2019). Crashes involving trucks are also more severe in nature than those involving smaller vehicles. More than 499,000 motor vehicle crashes involving trucks were reported in 2018 in the United States, and 22% of these crashes (111,415) resulted in fatalities and injuries (NHTS 2019). In particular, 4,119 fatalities due to truck crashes were recorded (in 2019) across the United States, indicating a 31% increase compared to 2009 (IIHS 2019). The average truck fatal and injury crash costs exceed $3.6 million and $200 thousand, respectively (includes medical emergency costs, market productivity loss, insurance, workplace costs loss, legal costs, congestion costs and property damage costs) (NHTSA 2019).

Trucking is a vital component of the freight industry due to its impact on the nation's economy. Trucking transports nearly 80% of the total commodities (such as raw materials, food, medicine, etc.) and 70% of the total freight tonnage over land in the United States (US Transport 2019; Dorf 2019). The American Trucking Association's 2020 "Freight Transportation Forecast" report estimated a 36% increase in freight volume by 2031 despite the limited freight and trucking operation challenges of the ongoing global pandemic. Hence, the anticipated revenue for the year 2031 is expected to be $1.435 trillion (ATA 2020).

The significant amount of freight and commercial trucking activity on highways results in complex interactions with other vehicles and raises safety concerns. These concerns are often associated with (but not limited to) size, weight, vehicle design (higher ground clearance), braking performance, and other safety/operating characteristics of trucks. Growth in truck traffic is expected to further increase the number of crashes involving trucks unless risk factors are identified and remedial solutions are proactively implemented. Hence, there is a need to model, examine, and identify the risk factors influencing truck crash injury severity levels to prioritize critical areas where relevant countermeasures can be selected and implemented.

Trucking trips and their travel activity depend on surrounding area characteristics like land use development and the corresponding demographic patterns (Pulugurtha and Pasupuleti 2013; USDOT 2020). Identifying parameters specific to such characteristics enables researchers and practitioners to understand the underlying patterns associated with truck crashes and prioritize areas for truck safety improvement. Including such parameters in the research framework will also help planners to design transportation systems efficiently and enhance overall safety.

1.1 Problem Statement

With the increasing demand for freight (and, hence, truck trips), highways are susceptible to critical safety issues if measures are not proactively implemented. These safety challenges result in loss of lives, property, and economy. Various agencies at federal and state levels are proactively implementing measures to mitigate motorized as well as non-motorized crashes and improve overall road safety through multiple policies. The Fixing America's Surface Transportation (FAST) Act (Section 1116) and Highway Safety Improvement Program (HSIP) (legislated under Section 148 of Title 23) were implemented to improve operational performance, reduce traffic fatalities and injuries, and use an extensive data-driven and strategic approach. Policies and programs such as FAST Act encourage and enable researchers, practitioners and engineers to use extensive and multiple data driven analytical approaches to improve traffic safety parameters.

A comprehensive amount of research exists in the field of traffic safety and crash analysis. However, most of the studies associated with traffic safety have emphasized crash frequency estimation, risk factor analysis, and safety parameters of passenger cars or mixed traffic stream conditions. Relatively fewer studies on truck safety analysis exist. Hence, an investigation is needed for trucks/heavy vehicles, considering their growing demand and trucks' importance to the nation's economy.

Area characteristics remain one of the critical parameters that influence truck trip and volume patterns. Trends in the frequency of trucks involved in motor vehicle crashes in a region are influenced by surrounding land use development, population, and area type (Pulugurtha and Pasupuleti 2013; USDOT 2020). Existing studies on truck crashes have considered truck crash parameters and the potential influence of road, vehicle, occupant, driver, and weather conditions on crash injury severity. However, the influence of area characteristics such as the surrounding land use development and demographics that may potentially influence truck crash patterns have not been considered in the past. Hence, there is a need to account for both off-network (land use and demographic/socioeconomic) and on-network (road) characteristics along with the crash and driver parameters. Such an analysis will help identify where the likelihood of getting involved in truck crashes is higher and why.

1.2 Objective of the Research

The objective of this research is to investigate and identify potential crash risk factors at varying levels of truck crash injury severity by considering driver, crash, weather, on-network, and off-network characteristics. The findings from this research will help identify where and why the likelihood of getting involved in a truck crash is higher. In addition to locating potential areas for resource allocation, it will also assist with selecting suitable countermeasures to mitigate crashes involving trucks.

1.3 Organization of the Report

The remainder of the report comprises six chapters. Chapter II summarizes past research on truck crashes, with a focus on identifying risk factors. Relevant discrete choice model applications and other statistical methods for truck crash analysis are identified and presented. Chapter III describes the study area and the data collection and processing methods, also introducing the descriptive statistics of the final database used in this research. Chapter IV presents a discussion of the methodological framework used for this research. Chapter V presents the results from the truck crash analysis and our interpretation. Chapter VI discusses the conclusions from this research and the scope for future research.

2. Literature Review

This chapter presents an overview of past research associated with truck crash costs, safety analysis, and risk factor identification with an emphasis on the modeling approaches used in the past. Further, additional discussions related to the association of land use and demographic characteristics in the safety analysis are presented.

2.1 Truck Crash Cost

Large truck crashes are highly distinguishable due to their patterns of crash fatalities and associated costs. In general, large trucks pose additional risk to surrounding vehicles when it comes to crash injury severity (Evans and Frick 1993). A study by Zaloshnja and Miller (2004) indicated that trucks with a weight rating of more than 10,000 pounds have an average cost of $59,153 USD (in 2000). This estimate increases if multiple vehicles are involved in a crash, in which case the average cost is estimated at $88,483 USD (in 2000). The crash costs for 1,000 truck miles were estimated to be $157 for single-unit trucks, $131 for single combination trucks, and $63 for multiple combination trucks (Zaloshnja and Miller 2004). Further, crashes involving trucks with one or two trailers cost the most at $289,549 per crash (Zaloshnja and Miller 2004). These computations were performed by considering medical-related costs, emergency services, property damage, lost productivity, and monetized value of human-related injury or fatality (Zaloshnja and Miller 2004). With added inflation and economic value, the present estimates for the truck crashes are expected to higher than the estimated numbers by Zaloshnja and Miller (2004).

2.2 Risk Factors Associated with Truck Crash Injury Severity

Truck crash injury severity is governed by characteristics such as truck vehicle properties, driver characteristics, road characteristics, light conditions, weather, and the surrounding network. Past literature on truck crash analysis has considered a majority of the aforementioned characteristics in seeking to identify underlying crash patterns and risk factors.

Prior literature has found driver parameters such as fatigue, impairment, and distraction to influence the truck crash occurrence and the corresponding injury severity. Driving longer distances during a trip is one of the critical challenges for truck drivers, resulting in fatigue or drowsiness, and it is one of the primary reasons for fatigue-related crashes (Golob, Recker, and Leonard 1987). Zhu and Srinivasan (2011a) observed that driver familiarity, distraction, alcohol use, and other emotional factors significantly influence the truck crash injury severity. In addition, driver experience has a significant role in the truck crash injury severity. Zheng et al. (2018) analyzed the relationship between truck crash severity and crash characteristics, driver information, and vehicle registration data. Their study results showed that newly registered drivers were found to have a higher risk of getting involved in a truck crash.

In addition, the temporal aspects, weather characteristics, and lighting conditions have a significant influence on the injury severity of crashes involving trucks (Pahukula, Hernandez, and Unnikrishnan 2015; Naik et al. 2016; Uddin and Huynh 2017; Behnood and Mannering 2019; Behnood and Al-Bdairi 2020). In the research by Naik et al. (2016), factors such as wind speed, rain, and higher temperature of the area were observed to be associated with severe and injury-causing crashes involving a single truck. Uddin and Huynh (2017) studied the severity of truck crashes, and the results indicate that the presence of an animal or object and the speed limit of the facility are positively associated with crashes on rural roads in dark conditions. Likewise, the presence of a curve is positively associated with crashes on urban roads in dark conditions (Uddin and Huynh 2017). In addition, temporal factors such as day of the week also has a positive association with crashes on urban roads in dark conditions (Uddin and Huynh 2017).

Past research indicates that vehicle properties (truck trailers and weight properties, in this case) also significantly affect the truck crash severity patterns: Lemp et al. (2011) evaluated the effect of driver, environmental, and vehicle characteristics on severity of truck crashes and observed that trucks with no trailer are positively associated with severe injury when compared to other types of trucks.

Road characteristics such as the type of road, curvature, and grade may also affect drivers' maneuvers and, hence, the crash occurrence and severity parameters. Chang and Mannering (1999) computed and compared risk factors associated with truck and non-truck-related crashes. Their results indicate that the speed limit, left-turning maneuvers, and crash type are associated with truck-related crashes. Anderson and Hernandez (2017) investigated crash rates involving trucks using random-parameter Tobit regression and latent class Tobit regression methods which consider the unobserved heterogeneity in the crash data. The traffic volume, road characteristics, and traffic control devices were observed to significantly affect truck crash rates (Anderson and Hernandez 2017).

The type of crash, vehicles involved, and at-fault/not-at-fault parameters have an important role in the injury severity of truck crashes. Golob et al. (1987) analyzed the relationships between truck crash characteristics and collision type on freeways. Their results indicate that the hit object collisions, broadside collisions, and single-vehicle collisions are associated with the high severity of the crashes (Golob, Recker, and Leonard 1987). Chen et al. (2015) used a hierarchical Bayesian random intercept model to evaluate truck crashes in rural areas. Their results indicate that road grade, number of vehicles in a crash, vehicle damage, vehicle actions, driver age, seatbelt use, and driver impairment are significantly associated with injuries and fatalities involving trucks (Chen et al. 2015). To understand the at-fault or not-at-fault characteristics of the drivers, Shao et al. (2020) developed two different models and presented the difference in crash risk factors of injury severity in rear-end truck crashes. The varying influence of driver characteristics, lighting conditions, temporal aspects, and seasonal factors for car-strike-truck and truck-strike-car crashes emphasize the significance of both passenger car driver behavior and truck driver behavior. The key differences between the two models include driver age, trailers, driver impairment, and road characteristics.

2.3 Influence of the Surrounding Land Use, Demographic and Network Characteristics

Apart from the local parameters (such as the crash location, temporal and on-network characteristics), surrounding off-network characteristics (such as land use and demographics) also influence the overall traffic safety performance (Harkey 1999; Pulugurtha, Duddu, and Kotagiri 2013; Moridpour, Mazloumi, and Mesbah 2015; Zou, Wang, and Zhang 2017). Considering the concentrations of truck traffic, it becomes essential to acknowledge the influence of spatial characteristics such as the surrounding location and network characteristics. Zou et al. (2017) modeled the crash severity of single and multiple vehicles using ordered probit model, accounting for spatial location and temporal parameters. Their results indicate that the single-vehicle truck crashes in the afternoon and at night tend to be less severe, while the multi-vehicle crashes at those times are more severe (Zou, Wang, and Zhang 2017).

The land use characteristics influence the interactions between the drivers under different conditions (Harkey 1999). A few researchers in the past have examined the influence of land use type on the interactions between the drivers under different conditions. Kim et al. (2006) examined the role of population, socioeconomic data, employment data, and economic activity levels on motor vehicle crashes. Their results indicate that vehicle-to-vehicle crashes were related to high employment while bicycle crashes were related to economic developments. Commercial areas, schools, and areas of high employment were significantly associated with higher numbers of crashes (Kim, Brunner, and Yamashita 1953). Similarly, Islam and Hernandez (2013) studied the crash injury outcomes of trucks on highways considering the surrounding network and area type parameter (urban/rural area type based on population). Their results indicated a 49.6% and 25.2% likelihood of fatal and injury crashes in rural areas, whereas a negative association (lower likelihood) was observed between incapacitating injuries and urban areas. Likewise, driver parameters (such as driver experience), traffic characteristics, road geometry, area type, weather, and lighting conditions were observed to play a significant role in injury severity (Islam and Hernandez 2013).

2.4 Modeling Approaches for Truck Crash Injury Analysis

Past literature reporting truck crash injury severity analyses include the use of statistical models such as fixed/random effect logit, probit, and nested logit, as well as machine learning approaches such as gradient boosting models. Table 1 summarizes selected studies and the methodological approach and models used along with the associated dependent variable.

Table 1. Summary of Selected Truck Crash Research

Author(s) and Year	Model Used	Study Objective	Dependent Variable
Chang and Mannering, 1999	Nested logit model	Examine the relationships between vehicle occupancy and corresponding level of severity and between truck- and non-truck-involved accidents	Injury severity level
Lemp et al., 2011	Standard and heteroscedastic ordered probit models	Analysis of large truck crash injury severity	Maximum injury severity suffered by any vehicle occupant and maximum vehicle-level injury
Zhu and Srinivasan, 2011b	Ordered probit model	Factors influencing truck crash injury severity	Injury severity level
Islam and Hernandez, 2013	Mixed logit model	Factors influencing heavy vehicle crash injury severity	Injury severity level (binary explanatory)
Chen et al., 2015	Hierarchical Bayesian random intercept model	Identify interaction effects in rural road truck crashes	Injury severity level
Naik et al., 2016	Random parameter mixed multinomial logit model	Impacts of weather characteristics on single-vehicle truck crash injury	Injury severity level
Anderson and Hernandez, 2017	Random parameter Tobit regression and latent class Tobit regression	Model heavy vehicle crash rates	Crash rate
Uddin and Huynh, 2017	Mixed logit models	Factors influencing truck crash injury severity under various lighting conditions and area characteristics	Injury severity level
Uddin and Huynh, 2018	Fixed and random parameter ordered probit models	Factors influencing injury severity of crashes involving trucks transporting hazardous materials	Injury severity level of occupants
Zheng et al. 2018	Gradient boosting (data mining) model	Factors contributing to commercial truck crash injury severity	Injury severity level
Behnood and Mannering, 2019	Random parameters logit model	Influence of temporal factors on injury severity of large truck crashes	Injury severity level
Shao et al., 2020	Random parameter ordered probit analysis	Injury severity analysis of rear-end collisions considering two categories: car-strike-truck and truck-strike-car crashes	Injury severity level
Alrejjal et al., 2021	Correlated random parameters binary logit model	Injury severity analysis of single-truck rollover crashes on interstate curves	Occurrence of a truck rollover crash
Hosseinzadeh et al., 2021	Support vector machine and random parameter logit model	Injury severity analysis of crashes involving large trucks	Injury severity of a truck crash (fatal and non-fatal)

Some of the most important parameters which differ across the studies summarized in Table 1 are the type of model considered, study objective (or area of focus), and dependent variable considered for modeling. A majority of the research emphasizes the importance of temporal, road, lighting, weather, vehicle, occupant, and driver characteristics influencing the likelihood of severe injury.

2.5 Limitations of Past Research

The truck movement across a city is majorly dictated by the location of warehouses and distribution centers. The travel routes and destinations of truck trips are influenced by on-network (road) and off-network (land use and demographic) characteristics. Past literature on truck crash analysis has considered location-specific road inventory data, temporal aspects, weather data, driver characteristics, and occupant-related characteristics to identify risk factors using a wide range of statistical approaches. However, a limited number of studies on truck crashes have accounted for off-network characteristics, such as the area type (Islam and Hernandez 2013), land use, or demographic parameters. Not many studies in the past have examined the influence of both off-network and on-network characteristics on truck crash injury severity. This research incorporates comprehensive land use, demographic, and on-network characteristics to model and examine the influence of various factors on truck crash injury severity.

3. Study Area and Data

This chapter provides an overview of the study area, data, and data processing techniques. Descriptive statistics are also presented in this chapter.

3.1 Data Collection

Mecklenburg County in the state of North Carolina was chosen as the study area for this research. Crash data, land use data, and demographic/socioeconomic data were analyzed. The data collection involved acquiring data from open sources or through requests submitted to state, regional, and local agencies.

The crash data for North Carolina for the years 2013–2017 were obtained from the Highway Safety Information System (HSIS). The raw crash data were obtained in three subfiles: crash, vehicle, and road. Crashes are typically represented using the case number, and the vehicle subfile contains records of the multiple vehicles involved with the associated case number. Hence, the raw files were combined prior to the other data cleaning and filtering processes.

The recent land use data (shapefile) were obtained for Mecklenburg County from the county's open data source, and the set included parcel-level information such as area, heated area, and other variables. A total of 115 categories with a designated land use code was present in the raw data. The demographic/socioeconomic data were also obtained in a geospatial format (shapefile) at the traffic analysis zone (TAZ) level from the Charlotte Regional Transportation Planning Organization (CRTPO). Typically, the estimates are provided based on the model year. The most recent data, for the year 2015, was assessed for the study. The population estimates, number of household units, and the number of people employed in the TAZ were used for modeling.

3.2 Data Processing and Filtering

Initial processing involved joining the data files, filtering (if needed), and extracting selected variables. Crash data, land use data, and demographic/socioeconomic data required initial processing of the data before other operations were performed.

The combined crash dataset (with all subfiles joined) contains a unique case number allocated to each crash with vehicle information provided in separate rows. A total of 917,110 vehicle records show data pertaining to motor vehicle crash information from 2013 to 2017, out of which 106,190 vehicles were involved in motor vehicle crashes in Mecklenburg County. Vehicles falling in the categories of single-unit truck (2- or 3-axle, 6-tire or more), trailer/tractor, fire/emergency vehicles, and other heavy vehicles/trucks were categorized as trucks in this research. Data and records associated with trucks were extracted and used for the analysis.

A total of 5,589 trucks were involved in motor vehicle crashes in Mecklenburg County. While the trucks account for nearly 5% of the total vehicles involved in crashes in Mecklenburg County, there is a need to address this portion of crashes due to the increasing trend from 2013 to 2017. The number of trucks involved in crashes almost doubled during these years. Figure 1 indicates the frequency of the trucks involved in crashes from the raw crash database sorted by year.

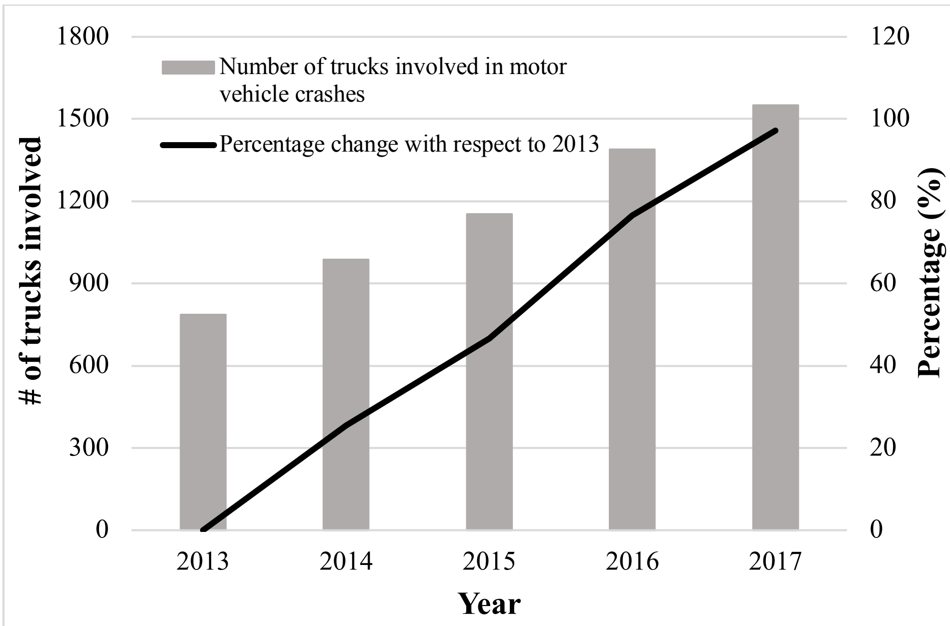

Figure 1. Truck Crash Frequency by Year in Mecklenburg County

Data cleaning and filtering is an essential step in the analysis due to its potential to skew the results if not appropriately conducted. Data filtering consisted of the elimination of records with null values for the variables considered in this research. Most of the variables present in the crash data are categorical. To prepare the data for analysis, the other variables were converted to categorical. Such variables include driver age and posted speed limit.

The crash injury severity in the raw database was categorized into five levels: fatal crash, injury type A, injury type B, injury type C, and no injury (property damage only [PDO]). They were aggregated to three levels for this research: severe injury (fatal and injury type A), moderate injury (injury type B and injury type C), and PDO (no injury).

The filtered dataset consisted of 5,260 truck records in the crash database (for the years 2013–2017). Figure 2 shows the locations of crashes (in the form of points) in the filtered dataset.

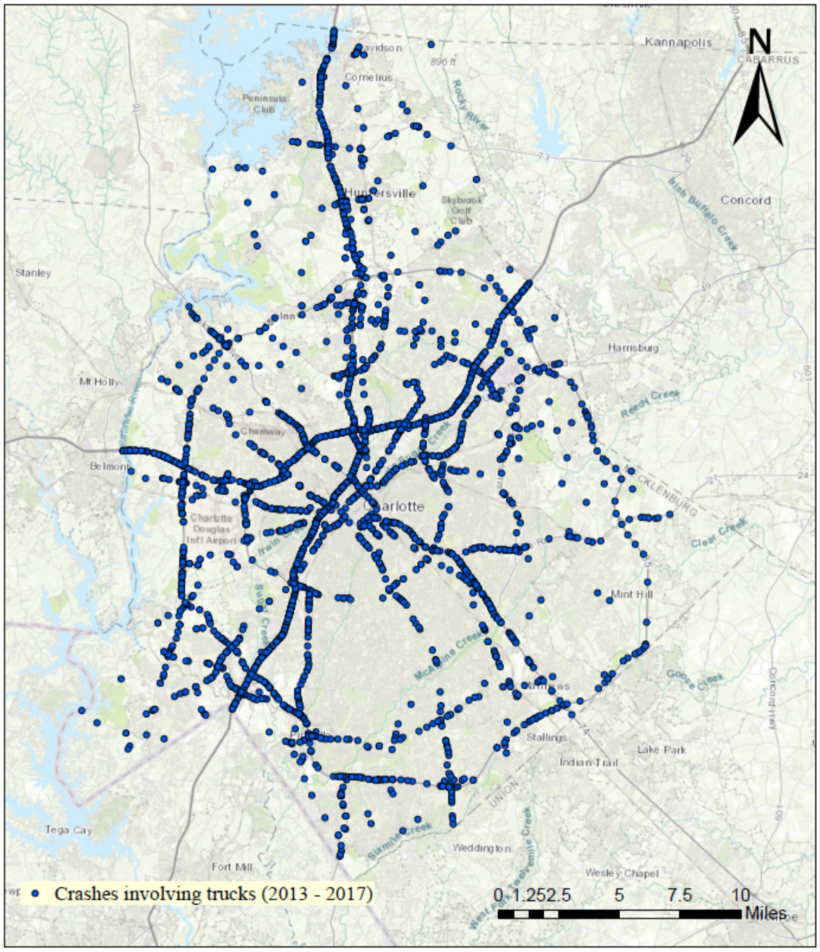

Figure 2. Spatial Distribution of Truck Crashes Used for Modeling

The frequency distribution of the variables in the filtered and processed crash data was checked before modeling. Tables 2–4 represent the frequency distribution of the crash data and corresponding location, driver, and road characteristics.

Table 2 summarizes the frequency distribution of crash and crash location characteristics. Variables such as the crash severity, contributing factors to the crash, crash type, in addition to temporal aspects (time of the day and day of the week) and surrounding location aspects (light/weather conditions and location/area type) are summarized in Table 2.

Table 3 summarizes the driver characteristics associated with the truck crash records. Variables include driver age, gender, and physical condition (including states such as fatigue and impairment).

Table 4 shows the frequency distribution of the road characteristics of the associated truck crash records. A wide range of parameters such as the configuration, grade and curvature, classification (jurisdiction), surface condition, speed limit, access, and control characteristics of the roads are summarized in the table.

Table 2. Frequency Distribution of Crash and Crash Location Characteristics

Variable	Category	Frequency (in #)	Percentage (in %)
Severity	Fatal + type A injury	47	0.89
	Type B + type C injury	1,285	24.43
	Property damage only (PDO)	3,928	74.68
Contributing factor of the crash	No contributing factors	2,702	51.37
	Disregarding signs or signals	35	0.67
	Exceeded safe speed / speed limit or fail to reduce speed	768	14.60
	Improper turn or right turn on red	119	2.26
	Crossed centerline, improper lane change, or use of an improper lane	584	11.10
	Overcorrected, oversteered, or improper passing	74	1.41
	Improper backing, failing to yield to the right of way, or driver inattention	647	12.30
	Improper backing or parking	87	1.65
	Operating too closely, aggressive driving, or alcohol use	73	1.39
	Visibility constraints, weather constraints, or defective equipment	171	3.25
Crash type	Ran off road	82	1.56
	Jackknife, overturn/rollover	128	2.43
	Animal or movable object	190	3.61
	Parked vehicle or fixed object	146	2.78
	Rear end collision	1,694	32.21
	Left/right turn crashes	344	6.54
	Head-on collision	39	0.74
	Sideswipe, angle, or backing up	2,560	48.67
	Other	77	1.46
Day of the week	Sunday	160	3.04
	Monday	903	17.17
	Tuesday	993	18.88
	Wednesday	947	18.00
	Thursday	940	17.87
	Friday	993	18.88
	Saturday	324	6.16
Time of the day	12:00 AM – 03:00 AM	150	2.85
	03:00 AM – 06:00 AM	179	3.40
	06:00 AM – 09:00 AM	986	18.75
	09:00 AM – 12:00 PM	1,006	19.13
	12:00 PM – 03:00 PM	1,081	20.55
	03:00 PM – 06:00 PM	1,138	21.63
	06:00 PM – 09:00 PM	479	9.11
	09:00 PM – 12:00 PM	241	4.58

Variable	Category	Frequency (in #)	Percentage (in %)
Trailer type	No trailer	2,876	54.68
	Boat, camper, horse, utility, house trailer, or towed vehicle	178	3.38
	Tanker or other non-semi trailer	205	3.90
	Enclosed van, flatbed, or other semi trailer	1,559	29.64
	Flatbed, platform, or double trailer	442	8.40
Weather condition	Apparently normal	4,069	77.36
	Cloudy	767	14.58
	Rain	375	7.13
	Snow, fog, smoke, smog, sleet, or hail raining	49	0.93
Light condition	Daylight	4,225	80.32
	Dusk, dawn, or dark unlighted road	449	8.54
	Lighted road (dark)	586	11.14
Location type	No feature	4,159	79.07
	Presence of bridge, bridge approach, or underpass	81	1.54
	Driveway or alleyway intersection	37	0.70
	Four-way, T or Y intersection, or railroad	602	11.44
	Ramp area, divided highway, or median crossing	373	7.09
	Other	8	0.15
Area type	Urban	5,199	98.84
	Rural	61	1.16

Table 3. Frequency Distribution of Driver Characteristics

Variable	Category	Frequency (in #)	Percentage (in %)
Driver gender	Male	5,046	95.93
	Female	214	4.07
Driver age	≤ 29 years	750	14.26
	30 – 39 years	1,104	20.99
	40 – 49 years	1,545	29.37
	50 – 59 years	1,359	25.84
	≥ 60 years	502	9.54
Physical condition of the driver	Normal	5,216	99.16
	Fatigue, impairment, or medical condition	44	0.84

Table 4. Frequency Distribution of Road Characteristics

Variable	Category	Frequency (in #)	Percentage (in %)
Road configuration	One-way, not divided	268	5.10
	Two-way, not divided	981	18.65
	Two-way, divided, unprotected median	1,023	19.45
	Two-way, divided, positive median barrier	2,988	56.81
Road characteristic	Straight-levelled road	4,528	86.08
	Straight-hillcrest/bottom	127	2.41
	Straight-grade	384	7.30
	Curve-levelled/grade/hillcrest	221	4.20
Road classification	Interstate	2,570	48.86
	US route	187	3.56
	NC route or state secondary route	322	6.12
	Local street, driveway, public/private area	2,181	41.46
Road surface condition	Dry	4,565	86.79
	Wet	626	11.90
	Presence of water/snow/ice/other kinds of dust	69	1.31
Functional class of road	Principal arterial – interstate	2,739	52.07
	Principal arterial – other	1,427	27.13
	Minor arterial	836	15.89
	Major collector	144	2.74
	Local	114	2.17
Speed limit class	≤ 35 mph	897	17.05
	40 – 45 mph	1,606	30.53
	50 – 55 mph	1,171	22.26
	≥ 60 mph	1,586	30.15
Traffic control present at the location	No control present	3,741	71.12
	Presence of stop/yield sign	253	4.81
	Presence of stop and go signal	1,175	22.34
	Flashing signs (with/without stop)	27	0.51
	Railroad-crossing-related signs/signals	3	0.06
	Double yellow or no passing	39	0.74
	Presence of human control or warning signs	22	0.42
Work zone area	Yes	517	9.83
	No	4,743	90.17
Access	No access	2,013	34.74
	Full access	3,307	57.08
	Partial access	474	8.18

The raw land use database for Mecklenburg County included 115 unique land use categories reaggregated into 18 selected categories. The final land use categories considered for modeling and analysis are summarized in Table 5. The land use data for each year was filtered using the built year column present in the dataset. For example, the data for year 2013 has parcels with land use data with the built year of 2013 or before. This filtering technique was performed to ensure that the year of crash occurrence aligns with the land use parcel built year.

Table 5. Description of Land Use Variables

Land Use Variable	Description
Agriculture	Land use parcels such as farms, commercial forestry, pasture, tree farms, etc.
College	School and college/university parcels; both public and private-owned institutions
Government	Land use parcels owned by state or municipal authorities
Institutional	Parcels where services are provided for the community, such as daycare, church, etc.
Medical	Hospitals, pharmacy, and medical-based parcels
Light commercial	Community-based services such as fast food centers, commercial stores (such as laundry), service stations, etc.
Heavy commercial	Commercial land use parcels such as shopping malls, furniture stores, etc.
Light industrial	Light-manufacturing-based industries and warehouse-based land use parcels
Heavy industrial	Involves industry-based land use parcels involving small manufacturing services, wastewater treatment plans, etc.
Single-family	Residential: fully detached, semi-detached, a row house or a townhome
Multi-family	Residential: condominium houses, multi-dwelling residential units, apartment buildings, and mobile home parks
Office	Land use parcels mainly for administrative, office, or business parks
Recreational	Land use parcels such as a bowling alley, theatre, golf course, etc.
Resource	Resource land use parcels include wetlands, creeks, etc.
Retail	Parcels allocated for retail purposes; include convenience/department store, supermarket, etc.
Transportation	Parcels such as trucking rest areas, right of way, or transportation/parking services
Unknown	Unknown parcels
Vacant	No land use category is allocated

The population, employment, and household estimates were extracted from the TAZ-level dataset from CRTPO. The population density and employment density values were computed from the raw dataset using equations 1 and 2.

$$TAZ\ population\ density = \frac{Number\ of\ people\ in\ the\ TAZ}{Area\ of\ the\ TAZ\ (in\ square\ miles)} \quad (1)$$

$$TAZ\ employment\ density = \frac{Number\ of\ people\ employed\ in\ the\ TAZ}{Area\ of\ the\ TAZ\ (in\ square\ miles)} \quad (2)$$

3.3 Data Joining and Analysis

Buffers are a spatial toolset to capture the proximal area of an entity; the buffer around an entity creates a border with a specified buffer width indicating the area of influence. Buffers around the crash points were generated to capture the surrounding land use and demographic/socioeconomic characteristics. Buffer width for a crash is highly crucial to capture the influence of the surrounding characteristics. Past literature related to the influence of the surrounding characteristics was analyzed where a buffer width of 0.50-mile was found to be appropriate to evaluate crashes and develop truck crash prediction models (Pulugurtha and Pasupuleti 2013; Pasupuleti and Pulugurtha 2013). Therefore, a 0.50-mile buffer width was used for this research. These buffer areas are separately intersected with the land use and demographic/socioeconomic shapefile data to capture these characteristics. Figures 3 and 4 show the area of influence along with the overlapped features. The figures indicate that the buffers overlap in multiple TAZs and land use parcels.

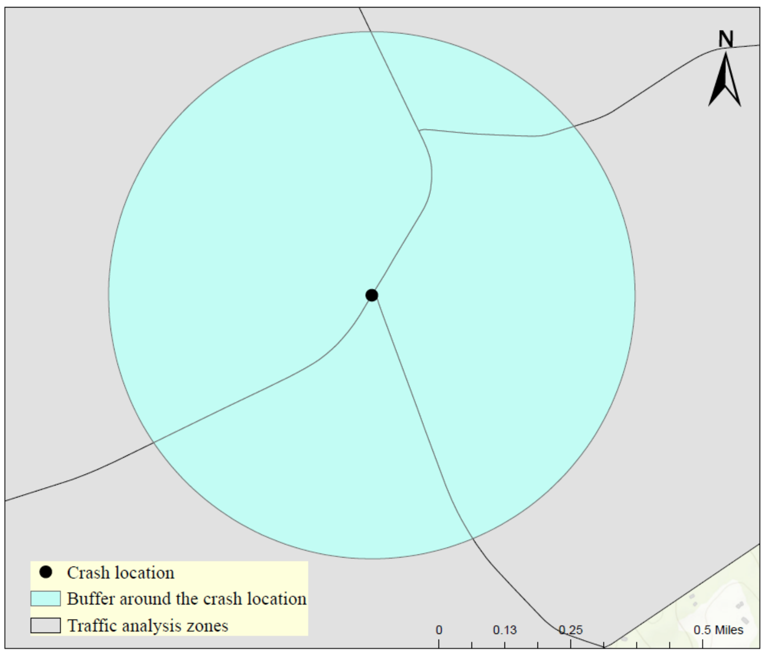

Figure 3. Intersected Characteristics Over the Buffer Area with TAZ Data

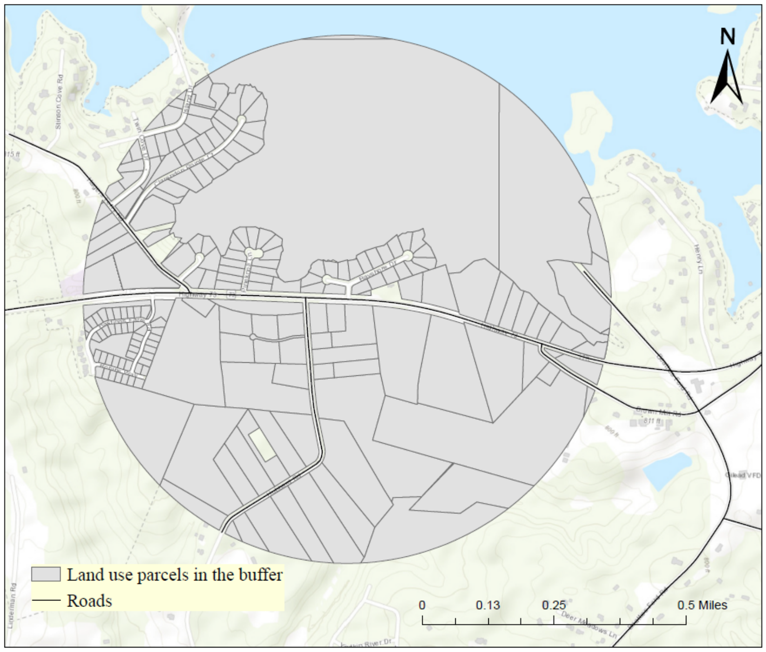

Figure 4. Intersected Characteristics Over the Buffer Area with Land Use Data

The area of each land use category within each buffer (around each crash location) is computed as percentages and appended to the corresponding crash record. Based on the percentage value of each land use category, a total of five categories were defined to quantify each land use category (0%, ≤ 25%, >25% and ≤ 50%, >50% and ≤ 75%, >75%). These land use variables are used in the model as categorical variables. Based on the type of land use, the total number of categories is reduced accordingly. For example, very few samples have vacant land use with the >75% category. Hence, fewer categories of the variable are allotted. Table 6 summarizes the frequency distribution of the categorical land use variables.

Table 6. Frequency Distribution of Land Use Variables

Variable	Category	Frequency (in #)	Percentage (in %)
Agriculture	0%	4,915	93.44
	≤ 25%	321	6.10
	>25% and ≤ 50%	24	0.46
College	0%	3,608	68.59
	≤ 25%	1,472	27.98
	>25% and ≤ 50%	136	2.59
	>50%	44	0.84
Government	0%	4,404	83.73
	≤ 25%	834	15.86
	>25%	22	0.42
Light commercial	0%	746	14.18
	≤ 25%	3,517	66.86
	>25% and ≤ 50%	856	16.27
	>50% and ≤ 75%	119	2.26
	>75%	22	0.42
Heavy commercial	0%	2,675	50.86
	≤ 25%	2,512	47.76
	>25%	73	1.39
Light industrial	0%	1,312	24.94
	≤ 25%	2,008	38.17
	>25% and ≤ 50%	1,059	20.13
	>50% and ≤ 75%	520	9.89
	>75%	361	6.86
Heavy industrial	0%	5,030	95.63
	≤ 25%	119	2.26
	>25% and ≤ 50%	59	1.12
	>50%	52	0.99
Medical	0%	4,815	91.54
	≤ 25%	427	8.12
	>25%	18	0.34
Institutional	0%	1,468	27.91
	≤ 25%	3,734	70.99
	>25%	58	1.10
Office	0%	1,776	33.76
	≤ 25%	3,241	61.62
	>25% and ≤ 50%	201	3.82
	>50%	42	0.80
Single-family residential	0%	292	5.55

Variable	Category	Frequency (in #)	Percentage (in %)
	≤ 25%	2,328	44.26
	>25% and ≤ 50%	1,403	26.67
	>50% and ≤ 75%	788	14.98
	>75%	449	8.54
Multi-family residential	0%	1,321	25.11
	≤ 25%	3,140	59.70
	>25% and ≤ 50%	590	11.22
	>50%	209	3.97
Recreational	0%	4,069	77.36
	≤ 25%	1,083	20.59
	>25% and ≤ 50%	77	1.46
	>50%	31	0.59
Resource	0%	2,077	39.49
	≤ 25%	3,146	59.81
	>25% and ≤ 50%	25	0.48
	>50%	12	0.23
Retail	0%	4,366	83.00
	≤ 25%	870	16.54
	>25%	24	0.46
Transportation	0%	5,039	95.80
	>0%	221	4.20
Unknown	0%	1,235	23.48
	≤ 25%	3,941	74.92
	>25% and ≤ 50%	47	0.89
	>50% and ≤ 75%	37	0.70
Vacant	0%	3,482	66.20
	>0%	1,778	33.80

The population density, employment density, and number of household units are computed using weighted average techniques to estimate the values for each buffer (equations 3 and 4).

$$PD_i = \frac{\sum_j A_{j,i} \times PD_j}{A_i} \tag{3}$$

where PD_i is the population (or employment) density of the buffer i, $A_{j,i}$ is the area of the TAZ j in the buffer i, PD_j is the population (or employment) density of the TAZ j, and A_i is the total area of the buffer i.

$$P_i = \sum_j \frac{A_{j,i}}{A_j} \times P_j \tag{4}$$

where P_i is the population/employment estimates or number of household units of the buffer i, $A_{j,i}$ is the area of the TAZ j in the buffer i, P_j is the population/employment estimate or number of household units of the TAZ j, and A_j is the total area of the TAZ j.

The values from the buffer analysis are used to convert the demographic/socioeconomic characteristics to categorical variables. Each category is chosen based on the allocated thresholds. Table 7 summarizes the frequency distribution of the demographic/socioeconomic variables considered in this research.

Table 7. Frequency Distribution of Demographic Variables

Variable	Category	Frequency (in #)	Percentage (in %)
Population estimates	≤ 500	3,350	63.69
	>500 and ≤ 1000	1,224	23.27
	>1000 and ≤ 1500	547	10.40
	>1500	139	2.64
Number of households	≤ 500	4,928	93.69
	>500 and ≤ 1000	327	6.22
	>1000	5	0.10
Employment estimates	≤ 500	2,833	53.86
	>500 and ≤ 1000	1,373	26.10
	>1000 and ≤ 1500	575	10.93
	>1500	479	9.11
Population density (i.e., population per square mile)	≤ 1000	2,658	50.53
	>1000 and ≤ 2000	1,495	28.42
	>2000 and ≤ 3000	753	14.32
	>3000 and ≤ 4000	220	4.18
	>4000	134	2.55
Employment density (i.e., total number of people employed per square mile)	≤ 1000	2,212	42.05
	>1000 and ≤ 2000	1,289	24.51
	>2000 and ≤ 3000	842	16.01
	>3000 and ≤ 4000	407	7.74
	>4000	510	9.70

4. Methodology

This chapter presents the methodology adopted to identify the risk factors associated with truck crash injury severity.

Discrete choice modeling was chosen to study the potential influence of selected independent variables on the truck crash injury severity. The crash severity is considered as an ordered dependent variable due to its ranking in terms of injury severity. The ordered probit or logit models assume that the independent variables have the same influence on the dependent variable irrespective of the severity level, which might not be true (Savolainen et al. 2011; Eluru and Yasmin 2015). On the other hand, the multinomial model completely ignores the ordinal nature of the crashes (Savolainen et al. 2011; Eluru and Yasmin 2015). Based on the past literature synthesis on crash injury modeling, some researchers have opted for the proportional odds model to overcome the assumptions mentioned in the case of ordered probit/logit and multinomial models (Savolainen et al. 2011; Eluru and Yasmin 2015; Washington, Karlaftis, and Mannering 2003). Specifically, studies on truck crash severity analyses have used a proportional odds model to identify the risk factors (Wang and Prato 2019; Song and Fan 2020).

The proportionality odds assumption states that the influence of an independent variable is similar for all dependent variable categories. To assess the applicability of that approach to the developed dataset, the proportional odds test was performed. The null hypothesis states that all the independent variables have equal slopes across the dependent variable categories. The obtained p-value was less than 0.05, resulting in the rejection of the stated null hypothesis. Hence, the non-proportional odds test was conducted to examine, for each variable, whether it has an equal or unequal slope. Based on the obtained p-values, unequal slopes were allocated for the variables, prompting a rejection of the null hypothesis (that all the independent variables have unequal slopes). The partial proportional odds model was then developed using an equal or unequal slope option for each independent variable.

The next steps proceeded following Williams (2006). A partial proportional odds model with ordinal dependent variable Y_i as the injury severity level of crash i (with $i \geq 1$) and X_j as independent variables is represented using Equation (5). The model has (i-1) intercepts with j slopes. The model prediction is called the “expected logit.” These logits are used to calculate cumulative probabilities using Equation (6).

$$\ln(Y_i) = logit\ [\pi(x)] = \ln\left(\frac{\pi(x)}{1-\pi(x)}\right) = \beta_0 + (\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_j X_j) \quad (5)$$

$$P(Y \geq i) = \frac{e^{\beta_0 + (\beta_1 X_1 + \cdots + \beta_j X_j)}}{1 + e^{\beta_0 + (\beta_1 X_1 + \cdots + \beta_j X_j)}} = \frac{e^{\ln(Y_i)}}{1 + e^{\ln(Y_i)}} \quad (6)$$

where the function $\pi(x)$ indicates the probability of a resulting outcome (injury severity level, in this case), β_0 is the constant, and $\beta_1, \beta_2, \ldots, \beta_j$ are the coefficients, which are the unknown parameters corresponding to independent variables $X_1, X_2, \ldots, X_j$ (Williams 2006).

The model uses a reference category through which the results are interpreted. Reference category is typically used to represent ideal conditions (for example, clear weather conditions – with respect to the weather conditions). The reference category for each independent variable is compared with the results of other categories of the same independent variable for interpretation. The reference categories were chosen and modeled based on the frequency distribution and a detailed inspection of variables. The PDO (or no injury) severity is considered as the reference category for the dependent variable in this research.

5. Results and Discussion

This chapter presents the results of the partial proportional odds model.

All the independent variables considered for modeling are categorical in the final dataset. They were included to evaluate the potential crash risk factors using the proportional odds test. Backward elimination was performed manually to identify the independent variables which are significant at least at a 90% confidence level. The independent variables are included in the model if at least one category is significant at a 90% confidence level. Table 8 summarizes the influence of the selected independent variables using the Wald Chi-square value and the p-value.

Table 8. Wald Chi-Square and P-Values of the Variables in the Final Model

Variable	Degrees of Freedom	Wald Chi-Square	P-Value
Time of the day	7	11.37	0.12
Day of the week	12	22.03	0.04
Crash type	16	198.76	<0.0001
Weather condition	3	2.57	0.46
Light conditions	4	24.80	<0.0001
Road characteristics	6	11.29	0.08
Road class	6	14.68	0.02
Traffic control present at the location	12	16.76	0.16
Contributing factor	9	25.59	0.00
Trailer type	8	14.21	0.08
Physical condition of the driver	2	14.92	0.00
Speed limit	6	12.49	0.05
Functional class of the road	8	14.88	0.06
Government land use	2	5.12	0.08
Light commercial land use	8	24.83	0.00
Light industrial land use	4	6.67	0.15
Office land use	6	12.23	0.06
Resource land use	3	9.99	0.02
Number of household units	2	7.18	0.03
Employment estimates	6	13.94	0.03

Table 9 summarizes the estimates and corresponding odds ratio for each category. The odds ratio is defined as the likelihood that the event will occur for the dependent variable category with respect to their reference category (Williams 2006). The reference category is mentioned in parentheses in the header column (i.e., the leftmost column). Separate estimates are provided for severe and moderate injury, for each category, with unequal slope parameters. Similarly, a single merged cell is used for severe and moderate injury with equal slope parameters for each category.

Hence, equal slope value indicates that the variable category has a similar effect on the injury severity of crashes involving trucks. Similarly, an unequal slope indicates varying effects of variable category on the injury severity of crashes involving trucks.

Table 9. Estimates and Odds Ratios for Models by Crash Injury Severity

Variable (Reference category)	Category	Estimate: Severe injury	Estimate: Moderate injury	Odds Ratio: Severe injury	Odds Ratio: Moderate injury
Intercept		-19.94	-1.34**	-	-
Time of the day (09:00 AM – 12:00 PM)	12:00 AM – 03:00 AM	0.22		1.25	
	03:00 AM – 06:00 AM	0.39*		1.48*	
	06:00 AM – 09:00 AM	-0.18*		0.84*	
	12:00 PM – 03:00 PM	-0.03		0.97	
	03:00 PM – 06:00 PM	-0.12		0.88	
	06:00 PM – 09:00 PM	-0.09		0.92	
	09:00 PM – 12:00 PM	0.10		1.11	
Day of the week (Wednesday)	Sunday	0.68	0.21	1.97	1.24
	Monday	-0.78	0.01	0.46	1.01
	Tuesday	-1.00*	0.05	0.37*	1.06
	Thursday	-1.71**	0.03	0.18**	1.03
	Friday	-1.48**	0.01	0.23**	1.01
	Saturday	-0.82	0.34**	0.44	1.41**
Light condition (Daylight)	Dusk, dawn, or dark unlighted road	-0.40	0.11	0.67	1.12
	Lighted road (dark)	1.84**	0.18	6.29**	1.2
Weather condition (Apparently normal)	Cloudy	0.03		1.03	
	Rain	0.00		1.00	
	Snow, fog, smoke, smog, sleet, or hail raining	0.50*		1.66*	
Road class (Interstates)	US route	-13.64	0.48*	<0.001	1.61*
	NC route or state secondary route	-1.00	0.73**	0.37	2.07**
	Local street, driveway, public/private area	-2.07	0.57**	0.13	1.77**
Functional class of road (Principal arterial – interstate)	Principal arterial – other	4.38*	-0.04	79.99*	0.96
	Minor arterial	3.71	-0.24	40.83	0.79
	Major collector	5.02**	0.38	>100.00 **	1.46
	Local	3.24	0.02	25.48	1.03
Road characteristic (Straight-leveled road)	Straight-hillcrest/bottom	1.06	-0.16	2.89	0.86
	Straight-grade	-0.01	-0.17	0.99	0.84
	Curve-leveled/grade/hillcrest	0.72	0.41**	2.06	1.51**
Traffic control at the crash location (No control)	Presence of stop/yield sign	-15.81	-0.01	<0.001	0.99
	Presence of stop and go signal	-0.64	-0.16*	0.53	0.86*
	Flashing signs (with/without stop)	-6.19	-0.24	0.00	0.79
	Railroad crossing related signs/signals	-2.92	0.62	0.05	1.85
	Double yellow or no passing	2.65**	-0.58	14.09**	0.56
	Presence of human control or warning signs	-4.04	-0.53	0.02	0.59
Speed limit (≤ 35 mph)	40–45 mph	1.79**	0.09	5.98**	1.09
	50–55 mph	2.54**	0.32	12.66**	1.37
	≥ 60 mph	3.43**	0.37	30.84**	1.45
Crash type (Ran off road)	Jackknife, overturn/rollover	11.61	-0.32	>100.00	0.72
	Animal or movable object	-9.16	-1.99**	<0.001	0.14**
	Parked vehicle or fixed object	11.20	-0.46	>100.00	0.63
	Rear-end collision	10.98	0.13	>100.00	1.14
	Left/right turn crashes	10.56	-0.36	>100.00	0.70
	Head-on collision	15.35	1.55**	>100.00	4.72**
	Sideswipe, angle, or backing up	9.95	-0.71**	>100.00	0.49**
	Other	-8.12	-0.87**	<0.001	0.42**
Physical condition of the driver	Fatigue / impairment / medical condition	3.23**	0.48	25.32**	1.62

Variable (Reference category)	Category	Estimate		Odds Ratio	
		Severe injury	Moderate injury	Severe injury	Moderate injury
Contributing factor (No contributing factor)	Disregarding signs or signals	1.19**		3.30**	
	Exceeded safe speed / speed limit or fail to reduce speed	0.18*		1.19*	
	Improper turn or right turn on red	-0.49*		0.61*	
	Crossed centerline, improper lane change, or use of an improper lane	0.03		1.03	
	Overcorrected, oversteered, or improper passing	-0.29		0.75	
	Improper backing, failing to yield to the right of way, or driver inattention	0.04		1.04	
	Improper backing or parking	-0.68**		0.51**	
	Operating too closely, aggressive driving, or alcohol use	0.14		1.15	
	Visibility constraints, weather constraints, or defective equipment	0.33		1.39	
Trailer type (No trailer)	Boat, camper, horse, utility, house trailer, or towed vehicle	1.12	-0.51**	3.06	0.60**
	Tanker or other non-semi trailer	0.49	-0.23	1.64	0.79
	Enclosed van, flatbed, or other semi trailer	0.28	-0.06	1.32	0.94
	Flatbed, platform, or double trailer	-1.06	-0.10	0.35	0.9
Government land use (0% area)	≤ 25%	0.03		1.03	
	>25%	1.02**		2.77**	
Light commercial land use (0% area)	≤ 25%	1.78**	-0.02	5.95**	0.98
	>25% and ≤ 50%	-0.49	-0.01	0.62	0.99
	>50% and ≤ 75%	0.2	-0.17	1.22	0.85
	>75%	5.06**	0.21	>100.00 **	1.23
Light industrial land use (0% area)	≤ 25%	0.13		1.14	
	>25% and ≤ 50%	0.20*		1.22*	
	>50% and ≤ 75%	0.19		1.21	
	>75%	0.36**		1.43**	
Office land use (0% area)	≤ 25%	-1.20**	-0.15**	0.30**	0.86**
	>25% and ≤ 50%	-0.54	-0.11	0.59	0.90
	>50%	-10.36	-0.11	<0.001	0.90
Resource land use (0% area)	≤ 25%	0.22**		1.25**	
	>25% and ≤ 50%	0.39		1.48	
	>50%	-0.88		0.41	
Number of households (≤ 500)	>500 and ≤ 1000	-0.43**		0.65**	
	>1000	-0.10		0.90	
Employment estimate (≤ 500)	>500 and ≤ 1000	-1.15*	0.00	0.32*	1.01
	>1000 and ≤ 1500	1.31**	0.04	3.70**	1.04
	>1500	0.71	0.00	2.04	1.00

Note: The values represented in parenthesis in the variable column (left-most) show the reference category
** Significant at a 95% confidence level
* Significant at a 90% confidence level

A negative value of the estimate indicates a lower likelihood of the outcome. For example, an estimate of -1.00 results in an odds ratio equal to 0.36 and indicates that the outcome is 64% less likely to occur than the reference category. Similarly, in the case of a positive coefficient of 1.00, the odds ratio is equal to 2.71, which indicates that the outcome is 171% times more likely to occur compared to the reference category. The results obtained are grouped and discussed based on crash and crash location characteristics, road characteristics, driver characteristics, and the influence of surrounding off-network characteristics.

5.1 Crash and Crash Location Characteristics

Past research on truck crash analysis indicates that time of the day, lighting condition, and weather condition have a significant influence on the crash patterns (Pahukula, Hernandez, and Unnikrishnan 2015; Naik et al. 2016; Uddin and Huynh 2017; Shao et al. 2020). The results from this research also show that time of the day, day of the week, lighting condition, and weather condition are significantly associated with the injury severity of crashes involving trucks.

Truck crashes occurring in the dawn time period (03:00 AM – 06:00 AM) are positively associated with severe and moderate injury truck crashes, while those occurring during the morning period (06:00 AM – 09:00 AM) are negatively associated with severe or moderate injury truck crashes compared to the morning peak period (9:00 AM – 12:00 PM). The results from this research further indicate that the crashes occurring during weekdays (Monday to Friday) are negatively associated with injury severity, while those occurring on the weekends (Saturday and Sunday) are positively associated with injury severity compared to a typical Wednesday. The dark lighted road condition is positively associated with the severe injury truck crashes. The occurrence/presence of snow, smoke, fog, and so on is positively associated with the truck crash injury severity compared to the normal weather conditions. This can be attributed to the poor visibility while driving under those conditions.

The results from this research indicate the significance of crash characteristics such as crash type and contributing factors associated with the truck crash injury severity. Head-on collision is positively associated with the truck crash injury severity, whereas crashes involving animals or movable objects and sideswipe crashes are negatively associated with the severity of the truck crash. The results from the model can be explained by trucks' difficulty in maneuverability, operating characteristics, and the presence of blind spots which was also explained in study by Chang and Mannering (1999).

5.2 Driver Characteristics

Driver distraction and driver inattention influence the occurrence of crashes (Zhu and Srinivasan 2011b). The results from this research indicate that most of the contributing factors such as disregarding speed limits, signs, or signals significantly influence the frequency of severe and moderate injury truck crashes. Disregarding signs or signals and not being compliant with the safe speed has a positive association with severe and moderate injury truck crashes. Further, past research indicates that driver impairment has a significant influence on the occurrence of crashes involving trucks (Lemp, Kockelman, and Unnikrishnan 2011; Shao et al. 2020). The results from this research also indicate that driver fatigue or impairment is positively associated with severe injury truck crashes. Shao et al. (2020) found that the presence of truck trailers can have a positive influence on the injury severity of a crash. However, the results from this research indicate that trucks with a boat, camper, horse, utility, or house trailer or a towed vehicle truck trailer have a negative association with a moderate injury severity.

5.3 Road Characteristics

Road facility properties have a significant influence on severe and moderate injury truck crashes. The findings from past literature show that crashes occurring on non-interstate highways tend to be more severe (Zhu and Srinivasan 2011a; Zhu and Srinivasan 2011b). Therefore, the interstate is considered as the reference category in the road class variable. The results from this research indicate that truck crashes on the US route, NC (state) route, secondary state route, and local roads are positively associated with moderate injury truck crashes. Similarly, principal arterial roads and major collector roads are positively associated with severe injury truck crashes compared to an interstate. The presence of curvature on a road (level, hillcrest, or bottom grade) is positively associated with severe and moderate injury truck crashes compared to the straight-leveled road conditions. This can be attributed to the difficulty of maneuvering trucks, especially on roads with the presence of horizontal or vertical curves.

Other parameters such as the speed limit and the type of control present at the crash location also contribute to the crash rates. The presence of double yellow or no-passing zones is positively associated with the severe injury truck crashes, and the presence of a stop and go signal is negatively associated with moderate injury truck crashes. The results from this research also indicate that roads with a speed limit of >40 mph are positively associated with severe injury truck crashes.

5.4 Land Use and Demographic Characteristics

Various land use categories have a statistically significant influence on varying levels of truck crash injury severity. The land use variables are quantified based on the percentage of an area within the buffer created with the reference category indicating the absence of the corresponding land use type. The variables are classified into five categories: 0% area, ≤ 25% (low proportion of area within buffer), >25% and ≤ 50% (low to moderate proportion of area within buffer), >50% and ≤ 75% (moderate to high proportion of area within buffer), and >75% (high proportion of area within buffer).

The presence of areas with government, light commercial, light industrial, and resource land uses in the vicinity are positively associated with severe and moderate injury truck crashes. Particularly, areas with a significant amount of commercial and industrial land uses have a positive association with severe injury truck crashes, attributing to the substantial trucking activity (both in-house and external trips). The presence of office land use is negatively associated with moderate and severe injury truck crashes, accrediting to the lower trucking activity rates in the areas like business parks.

Demographic characteristics such as household estimates and employment estimates have a significant effect on severe and moderate injury truck crashes. Areas with household estimates (≤ 1000) are negatively associated with severe and moderate injury truck crashes compared to the areas with household estimates of 500 or less. As the employee estimates in an area increase, the likelihood of severe injury truck crashes also increases. The presence of areas with employee estimates of >1000 and ≤ 1500 are associated with severe injury truck crashes compared to the areas with employee estimates of 500 or less.

6. Summary and Conclusions

Motor vehicle crashes involving trucks are of great concern due to their impact on fatalities and crash costs. Crash, driver, surrounding weather/lighting conditions, land use, and demographic characteristics influence truck crash injury severity patterns. This research focuses on capturing potential risk factors of varying truck crash injury severity levels using a discrete choice modeling approach (the partial proportional odds model). Motor vehicle crash data from 2013 to 2017 for Mecklenburg County in North Carolina was used in this research, and the land use and demographic/socioeconomic variables within a 0.50-mile radius of each crash were captured and used for modeling.

The findings from this research indicate that lighting condition, type of location, driver characteristics, and other road characteristics have a significant effect on the injury severity of crashes involving trucks. The presence of dark lighting conditions and the presence of fog, snow, and so on increase the likelihood of a severe or moderate injury crash involving a truck. Roads with a double yellow or no-passing zone also have a higher likelihood of a severe or moderate injury crash involving a truck. Factors such as driver fatigue, driver impairment, and driver inattention increase the likelihood of a severe or moderate injury crash involving a truck. Similarly, the presence of a speed limit over 40 mph and road curvature also increase the likelihood of a severe or moderate injury crash involving a truck.

The presence of government, light commercial, light industrial, and resource land uses within 0.50 miles also increases the likelihood of a severe or moderate injury crash involving a truck. Similarly, the likelihood of a severe or moderate injury crash involving a truck is higher if the number of people employed within the buffer zone is >1000 and <1500.

The findings indicate the need for effective geometric design and improved visibility to reduce the risk of getting involved in a crash with a truck. Some of the potential countermeasures to reduce risk and enhance safety include the use of intelligent transportation systems (ITS) technologies such as variable speed limit signs or dynamic message signs to harmonize the speed of the stream in a corridor thereby, resulting in relatively safe vehicle maneuvering. Additionally, advanced driver warning and crash avoidance systems (Bao et al. 2012) and truck traffic signal priority could be explored in high-risk areas.

From the findings, it can also be concluded that land use and demographic characteristics significantly influence the injury severity of crashes involving trucks. In addition to the proactive approach and incorporating truck crash trends (frequency by injury severity) into the planning process, adopting truck traffic management strategies (such as off-peak delivery incentives) at the regional level, education, and enforcement could reduce associated risks. The methodological framework adopted (data capturing, processing, and modeling) in this research is transferable and cross-disciplinary which makes it implementable for other areas of analysis.

6.1 Study Limitations and Scope of Future Research

This research provided comprehensive insights on the influence of surrounding land use and demographic characteristics on the truck crash injury severity patterns using a discrete choice modeling approach. While this research study considers a wide range of variables and factors by incorporating multiple datasets to identify crash risk factors of the motor vehicle crashes involving trucks, some of the limitations and gaps need to be accounted for in future work.

The data used in this research were obtained from the HSIS, which includes crashes on state-maintained roads. The inclusion of crashes from other sources could help researchers to identify trends in land use and other on-network characteristics on state-maintained as well as non-state-maintained roads.

Traffic volume and percentage of trucks on the road at the time of the crash were not available in the datasets. It is recommended to capture these data elements and use them in the analysis. Further, the study area was limited to a county due to the lack of available data at the state level. In addition, developing and using statewide land use and demographic datasets would also help identify factors influencing crashes involving trucks by area type (e.g., urban vs. rural).

The TAZ-level estimates are typically provided for the base year, which does not indicate any variation over the future years. Considering other sources or granular data on demographic characteristics (census block-level or parcel-level data) for modeling and analysis would be worthwhile.

The scope of this research is limited to crashes involving trucks. Truck drivers may or may not be at fault in these crashes. Researching and identifying risk factors when the truck driver is or is not at fault will add to the body of knowledge. Likewise, a comparison of crash risk factors associated with passenger cars and trucks along with at-fault and not-at-fault drivers merits further research.

Bibliography

American Trucking Association (ATA). ATA Freight Forecast Projects Continued Long-term Growth in Volumes. 2020. https://www.trucking.org/news-insights/ata-freight-forecast-projects-continued-long-term-growth-volumes. Accessed February 23, 2021.

Alrejjal, A., A. Farid, and K. Ksaibati. "A Correlated Random Parameters Approach to Investigate Large Truck Rollover Crashes on Mountainous Interstates." *Accident Analysis and Prevention* 159 (2021): 106233.

Anderson, J., and S. Hernandez. "Heavy-Vehicle Crash Rate Analysis: Comparison of Heterogeneity Methods using Idaho Crash Data." *Transportation Research Record* 2637, no. 1 (2017): 56-66.

Bao, S., D. J. LeBlanc, J. R. Sayer, and C. Flannagan. "Heavy-Truck Drivers' Following Behavior with Intervention of an Integrated, In-Vehicle Crash Warning System: A Field Evaluation." *Human Factors* 54, no. 5 (2012): 687-697.

Behnood, A., and N. S. S. Al-Bdairi. "Determinant of Injury Severities in Large Truck Crashes: A weekly Instability Analysis." *Safety Science* 131 (2020): 104911.

Behnood, A., and F. Mannering. "Time-of-Day Variations and Temporal Instability of Factors Affecting Injury Severities in Large-Truck Crashes." *Analytic Methods in Accident Research* 23 (2019): 100102.

Chang, L. Y., and F. Mannering. "Analysis of Injury Severity and Vehicle Occupancy in Truck- and Non-Truck-Involved Accidents." *Accident Analysis and Prevention* 31, no. 5 (1999): 579-592.

Chen, C., G. Zhang, Z. Tian, S. M. Bogus, and Y. Yang. "Hierarchical Bayesian Random Intercept Model-Based Cross-Level Interaction Decomposition for Truck Driver Injury Severity Investigations." *Accident Analysis and Prevention* 85 (2015): 186-198.

Dorf, P. *Freight Forecast: More Boom Less Gloom*, DAT Super Database. 2019. https://www.dat.com/blog/post/freight-forecast-more-boom-less-gloom. Accessed October 17, 2019.

Eluru, N., and S. Yasmin. "A Note on Generalized Ordered Outcome Models." *Analytic Methods in Accident Research*, 2015, 8:1-6.

Evans, L., and M. C. Frick. "Mass Ratio and Relative Driver Fatality Risk in Two-Vehicle Crashes." *Accident Analysis and Prevention* 25, no. 2 (1993): 213-224.

Federal Motor Carrier Safety Administration (FMCSA), United States Department of Transportation (USDOT). Large Truck and Bus Crash Facts – 2018. September 2020. https://www.fmcsa.dot.gov/sites/fmcsa.dot.gov/files/2020-09/LTBCF%202018-v5_FINAL-09-15-2020.pdf. Accessed January 24, 2021.

Golob, T. F., W. W. Recker, and J. D. Leonard. "An Analysis of the Severity and Incident Duration of Truck-Involved Freeway Accidents." *Accident Analysis and Prevention* 19, no. 5 (1987): 375-395.

Harkey, D. L. "Evaluation of Truck Crashes using a GIS-Based Crash Referencing and Analysis System." *Transportation Research Record* 1686, no. 1 (1999): 13-21.

Hosseinzadeh, A., A. Moeinaddini, and A. Ghasemzadeh. "Investigating Factors Affecting Severity of Large Truck-Involved Crashes: Comparison of the SVM and Random Parameter Logit Model." *Journal of Safety Research* 77 (2021): 151-160.

Insurance Institute for Highway Safety (IIHS). Fatality Facts 2018 - Large Trucks. December 2019. https://www.iihs.org/topics/fatality-statistics/detail/large-trucks. Accessed January 24, 2021.

Islam, M. B., and S. Hernandez. "Modeling Injury Outcomes of Crashes Involving Heavy Vehicles on Texas Highways." *Transportation Research Record* 2388, no. 1 (2013): 28-36.

Kim, K., I. M. Brunner, and E. Y. Yamashita. "Influence of Land Use, Population, Employment, and Economic Activity on Accidents." *Transportation Research Record* 1953, no. 1 (2006): 56-64.

Lemp, J. D., K. M. Kockelman, and A. Unnikrishnan. "Analysis of Large Truck Crash Severity Using Heteroskedastic Ordered Probit Models." *Accident Analysis and Prevention* 43, no. 1 (2011) :370-380.

Moridpour, S., E. Mazloumi, and M. Mesbah. "Impact of Heavy Vehicles on Surrounding Traffic Characteristics." *Journal of Advanced Transportation* 49, no. 4 (2015): 535-552.

Naik, B., L. W. Tung, S. Zhao, and A. J. Khattak. "Weather Impacts on Single-Vehicle Truck Crash Injury Severity." *Journal of Safety Research* 58 (2016): 57-65.

National Highway Traffic Safety Administration (NHTSA). Traffic Safety Facts – 2018 Fatal Motor Vehicle Crashes: Overview. October 2019. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812826. Accessed July 18, 2020.

Pahukula, J., S. Hernandez, and A. Unnikrishnan. "A Time of Day Analysis of Crashes Involving Large Trucks in Urban Areas." *Accident Analysis and Prevention* 75 (2015): 155-163.

Pasupuleti, N., and S. S. Pulugurtha. "Spatial Extent and Modeling Intracity Truck Crashes." *Procedia-Social and Behavioral Sciences* 104 (2013): 1188-1197.

Pulugurtha, S. S., and N. Pasupuleti. Geo-Spatial and Statistical Methods to Model Intracity Truck Crashes. In Green Streets, Highways, and Development 2013: Advancing the Practice, 2013 (pp. 251-261).

Pulugurtha, S. S., V. R. Duddu, and Y. Kotagiri. "Traffic Analysis Zone Level Crash Estimation Models Based on Land Use Characteristics." *Accident Analysis & Prevention* 50 (2013): 678-687.

Savolainen, P. T., F. L. Mannering, D. Lord, and M. A. Quddus. "The Statistical Analysis of Highway Crash-Injury Severities: A Review and Assessment of Methodological Alternatives." *Accident Analysis and Prevention* 43, no. 5 (2011): 1666-1676.

Shao, X., X. Ma, F. Chen, M. Song, X. Pan, and K. You. "A Random Parameters Ordered Probit Analysis of Injury Severity in Truck Involved Rear-End Collisions." *International Journal of Environmental Research and Public Health* 17, no. 2 (2020): 395.

Song, L., and W. Fan. "Combined Latent Class and Partial Proportional Odds Model Approach to Exploring the Heterogeneities in Truck-Involved Severities at Cross and T-Intersections." *Accident Analysis & Prevention* 144 (2020): 105638.

Uddin, M., and N. Huynh. Factors Influencing Injury Severity of Crashes Involving HAZMAT Trucks. *International Journal of Transportation Science and Technology* 7, no. 1 (2018): 1-9.

Uddin, M., and N. Huynh. "Truck-Involved Crashes Injury Severity Analysis for Different Lighting Conditions on Rural and Urban Roadways." *Accident Analysis and Prevention* 108 (2017): 44-55.

U.S. Transport. *The Importance of the Trucking Industry*. 2019. https://www.us-transport.com/the-importance-of-the-trucking-industry/. Last accessed February 21, 2021.

Wang, Y., and C. G. Prato. "Determinants of Injury Severity for Truck Crashes on Mountain Expressways in China: A Case-Study with a Partial Proportional Odds Model." *Safety Science* 117 (2019): 100-107.

Washington, S. P., M. G. Karlaftis, and F. L. Mannering. Statistical and Econometric Methods for Transportation Data Analysis. 2nd Edition. Boca Raton: Taylor and Francis Group, Chapman & Hall / CRC, 2011.

Williams, R. "Generalized Ordered Logit/Partial Proportional Odds Models for Ordinal Dependent Variables." *The Stata Journal* 6, no. 1 (2006): 58-82.

Zaloshnja, E., and T. R. Miller. "Costs of Large Truck-Involved Crashes in the United States." A*ccident Analysis and Prevention* 36, no. 5 (2004): 801-808.

Zheng, Z., P. Lu, and B. Lantz. "Commercial Truck Crash Injury Severity Analysis using Gradient Boosting Data Mining Model." *Journal of Safety Research* 65 (2018): 115-124.

Zhu, X., and S. Srinivasan (2011a). "A Comprehensive Analysis of Factors Influencing the Injury Severity of Large-Truck Crashes." *Accident Analysis and Prevention* 43, no. 1 (2011): 49-57.

Zhu, X., and S. Srinivasan (2011b). "Modeling Occupant-Level Injury Severity: An Application to Large-Truck Crashes." *Accident Analysis and Prevention* 43, no. 4 (2011): 1427-1437.

Zou, W., X. Wang, and D. Zhang. "Truck Crash Severity in New York City: An Investigation of the Spatial and the Time of Day Effects." *Accident Analysis and Prevention* 99 (2017): 249-261.

About the Authors

Dr. Sarvani Duvvuri received her Ph.D. in Infrastructure and Environmental Systems (INES) from the University of North Carolina at Charlotte, NC, where she is currently a Postdoctoral Researcher with the Infrastructure, Design, Environment, and Sustainability (IDEAS) Center. Her current research interests include traffic operations and safety, traffic simulation, and connected and automated vehicles.

Dr. Srinivas S. Pulugurtha, P.E., F.ASCE is currently working as a Professor and Research Director of the Department of Civil and Environmental Engineering at the University of North Carolina at Charlotte. He is also the Director of the IDEAS Center.

Dr. Sonu Mathew received his Ph.D. in Infrastructure and Environmental Systems (INES) from the University of North Carolina at Charlotte, NC. He is a Postdoctoral Researcher with the IDEAS Center. His current research interests include traffic safety, traffic flow modeling and simulation, ITS, connected and automated vehicles, and spatial modeling.