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Analysis Framework to Assess Crash Severity for Large Trucks on Rural Interstate Roads Utilizing the Latent Class and Random Parameter Model

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Abstract

Truck freight has high importance to the national economy as it handles more cargo than other types of freight transportation. To improve the safety of commercial vehicles, several studies have focused on determining factors leading to crashes. Parametric models have been extensively employed to explain crash causal factors for heavy trucks. Unlike studies in the past, a comprehensive framework was proposed in this study to compare crash underlying factors utilizing several statistical approaches. The structural equation modeling approach was used to assess latent factors affecting the crash severity of large trucks. In addition, ordinary (binary) logistic and random parameter models were employed to assess the direct effect of the observed data, and the heterogeneity in parameter means was also estimated. Three crash categories were investigated: single-truck crashes, multi-vehicle truck crashes, and total truck crashes. A total of five years of crash data from 2015 to 2019 were analyzed. The results showed that multiple observed variables were factored to measure crash severity. Direct and indirect effects were identified, in which challenging roadway conditions had an indirect effect on crash severity for single-truck crashes. Random parameter logit models indicated that roadway geometry and adverse weather conditions were among the significant contributing factors increasing crash severity for trucks. This study recommends that improving the situational awareness of truck drivers, providing more frequent rest stops, updating variable speed limit algorithms, and integrating roadway geometry information into connected vehicle applications in Wyoming could be considered to assist stakeholders in promoting safety on rural interstate corridors.

Keywords

freight systems, safety and human factors, safety, freight transportation, trucks

The truck industry is considered essential to freight logistics with a significant impact on the well-being of the U.S. economy. On the other hand, truck crashes have a significant adverse impact on the transportation section, which results in huge losses with respect to productivity, property damage, and most importantly, personal injuries. Commercial truck crashes are increasing at an alarming rate nationwide. According to the Federal Motor Carrier Safety Administration (FMCSA), 5237 large trucks and buses were involved in fatal crashes in 2019, which represents a nearly 47% increase in fatal crashes compared to 2009 (*1*). Injury crashes involving a truck increased by 62% in 2009 compared to 2016. An increase of 13% in injury and property damage only (PDO) crashes was encountered between 2016 and 2019 (*2*). The 2020 large trucks fact sheet of the National

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Highway Traffic Safety Administration (NHTSA) stated that 27% of the fatal crashes involving a heavy truck occur on interstate roads, while 55% occur on rural roadways. The percentage of large trucks involved in fatal crashes, as a proportion of all vehicles across the U.S.A., ranged from 4.0% to 19.0%, with the highest percentage reported in Wyoming (*2*).

The state of Wyoming has three rural interstate roads with a total length of 910 mi: Interstate 25 (I-25) 300 mi, Interstate 80 (I-80) 402 mi, and Interstate 90 (I-90) 209 mi. I-80 includes four weather-based variable speed limit (VSL) sections, while the other two interstate roads include only one VSL section each. In the winter season, during the months from October to April, the interstate roads in Wyoming usually encounter pile-up crashes, especially on I-80. These pile-up crashes could involve more than 60 vehicles, resulting in multiple fatalities, injuries, and PDO crashes. Adverse weather conditions and challenging roadway geometry are usually the main contributing factors behind such catastrophic crashes. According to the U.S. Department of Transportation (U.S. DOT), Wyoming was ranked first in 2019 in fatal crashes involving large trucks per million people, with a rate of 57.02. Truck crashes increased in Wyoming from 2016 to 2019, in which fatal crashes increased by nearly 45%, injury crashes increased by 12%, and PDO crashes increased by 29% (*3*).

The statistics depict serious safety issues that large truck crashes cause, considering the multiple crash severity categories. Accordingly, several studies have investigated the crash severity of truck-involved crashes to provide insights to alleviate the outcome consequences of a crash. This could be done by identifying the factors that might significantly increase the severity of truck-related crashes. Clarifying crash casual factors could help one to select countermeasures and improvements that promote traffic safety for trucks. Multiple factors are known to affect the crash frequency and severity, including roadway geometry, traffic volumes, environmental factors, driver characteristics, vehicle characteristics, and crash characteristics. Traffic volumes, as the main crash exposure, are usually the main significant factor that increases the severity of crashes. In particular, truck traffic is considered a significant factor that might increase the outcome severity of a crash.

Previous studies utilized parametric approaches to investigate crash injury severity for large trucks. Observed variables extracted from historical crash data were mainly utilized to estimate the direct effect of indicator variables on the severity of crashes involving a truck. Despite the selection of the model and its underlying assumptions, the complex interrelationship between crash variables cannot be observed using traditional parametric approaches (*4*, *5*). Unlike other studies, a comprehensive analysis framework was conducted in this study, in which parametric and latent factor analysis approaches were employed. The ordinary logistic model (OLM) and the random parameter logit model (RPLM) were selected as the parametric approaches for the data analysis, while the structural equation model (SEM) was selected to investigate the effect of latent variables on increasing the crash severity of large trucks. The SEM can resolve the complex relationship between the indicator variables, as well as clarifying the direct and indirect impacts for the latent variables on the response variable (*6*). The results of this study will help in providing insights to develop transportation policies, improve carrier operation, and select countermeasures that could help reduce the crash-cost.

Background

Several studies have been conducted with the focus of promoting the operational safety of commercial trucks by determining the causal factors that increase the frequency and severity of truck-related crashes. Usually, truck crashes are investigated by the type of crash, in which they are separated into two main categories, single- and multi-vehicle truck crashes. Investigating the two types of crashes separately would highlight the difference in the crash characteristics for each type, as they are anticipated to be different (*7–12*). In addition, several studies have been conducted to investigate the factors affecting truck crashes on rural interstate roads, accounting for new emerging technologies, such as connected vehicles (CVs) (*13–19*). Zhu and Srinivasan (*20*) included driver behavior factors along with variables extracted from crash reports utilizing an ordered probit model. Among the several significant variables, dummy variables that indicated missing data showed a strong significance toward increasing crash injury severity, which could be because of the gaps in crash reporting or because of the unobserved heterogeneity in the data. However, the study concluded a limitation of the small sample size used in the analysis. Another study provided a comparative analysis for factors affecting the crash severity of large truck crashes using the ordered logit model (*21*). The study showed that variables related to the roadway, crash, vehicle, and driver had a significant effect on the investigated crash severity. Among the significant variables, the season, manner of collision, lighting conditions, driving under the influence (DUI), and percentage of truck traffic were significant.

Data mining approaches have also been adopted to investigate the crash severity of commercial trucks. A recent study used gradient boosting to evaluate the truck crash injury severity (*22*). The analyzed crash data were obtained from two states; North Dakota and Colorado. The study accounted for the scale of the trucking company as a predicting variable. The results showed that small-scale companies had the lowest probability of crash risk. A study conducted by Uddin and Huynh (*23*) used the RPLM to investigate the severity of crashes involving a truck. The study concluded that adverse weather and challenging roadway geometry were significant variables in increasing the severity of crashes involving a truck. The results of the study were in accordance with Naik et al. (*7*). The latter study utilized random parameter ordinal and multinomial regression models. In addition, Bayesian logistic models were adopted to conduct crash severity analysis (*24*). The study included a factor expressing the presence of large trucks in the model and utilized interactions to account for factors affecting the severity of truck crashes. The results of the study showed that adverse weather and steep downgrades would increase the severity of truck-related crashes.

Latent variables, which are unobserved variables, could help in clarifying the complex interrelationship between the crash indicator variables. The SEM could be considered as a promising statistical approach that accounts for these interrelationships. It could quantify latent variables that cannot be directly measured or observed. The SEM was previously used to analyze survey data and to assess driver behavior questionnaires (*16*, *25–29*). Recently, the SEM was adopted to investigate the resultant severity of crashes. It was concluded that injury severity and vehicle damage could be used as indicator variables to measure crash severity (*6*). The results showed that the SEM with the two latent variables provided the best model fit. Another study developed a SEM to estimate truck crash severity (*30*). The developed SEM was factored into five latent variables, as follows: crash, environment, road, driver, and severity. While the study provided reliable results, the development of the measurement model was based on hypothetical assumptions. The results showed that crash severity could be measured using the number of deaths, the number of injured, and the number of cars involved in the crash. Kim et al. (*31*) examined the effect of accessibility on crash severity. It was found that accessibility had a reverse effect on crash severity. Increased accessibility would reduce the crash severity. Khattak and Targa (*32*) utilized an ordinary least squares (OLS) regression to examine the risk factors affecting the large-truck-related crashes. The authors found that dangerous truck-driving behaviors, such as speeding and reckless driving, would increase the probability of truck rollovers. The OLS is a similar statistical technique to the SEM. However, the SEM provides superior model accuracy and precision (*33*).

Methodology

The OLM, RPLM, and SEM were the three statistical approaches used in this study to develop the analysis framework. The ordinary regression model was used in this study to denote the binary logistic model with constant parameters and differentiate it from the random parameter model. The OLM accounts for the binary nature of the crash severity (fatal and injury [F + I] and no injury). The random parameters model was used to account for the variation in the relationships with the response variable within crashes. The SEM was adopted to investigate the latent variables that could influence the severity of truck crashes, while accounting for variance and covariance within and between crashes. It also clarifies the direct and indirect effects for the obtained latent variables on the truck crash severity.

Ordinary Logistic Model

Logistic regression is a common model used in traffic safety and operation studies. Logistic regression is mainly used to analyze categorical data, in which it is applied to a binary, nominal, or ordinal dependent variable. The OLM equation is given in Equation 1:

$$\ln(\boldsymbol{\Pi_j}) = \boldsymbol{\alpha_j} - (\boldsymbol{\beta}_1\boldsymbol{x}_1 + \boldsymbol{\beta}_2\boldsymbol{x}_2 + \boldsymbol{\beta}_3\boldsymbol{x}_3 + \ldots) \quad (1)$$

where $\boldsymbol{x}$ represents the explanatory variables, $\boldsymbol{\alpha}$ represents the response probability when explanatory variables are at the reference level, and $\boldsymbol{\beta}$ represents the regression coefficients. The logit link function takes the form $\log(P/(1-P))$, in which P indicates the probability of success for the response variable y.

Random Parameter Logit Model

The random parameter version of the logit models, also known as the mixed logit model, was adopted in this study to account for the possible observation-specific heterogeneity in the data. In addition to the mean value estimated by the fixed model, the standard deviation of the estimated parameter is also determined. The random parameter model accounts for the individual-level heterogeneity in the data, in which it assumes the random parameter to follow a statistical distribution. Simulated maximum likelihood techniques are used to estimate the parameters associated with random parameter models.

The Wyoming Department of Transportation (WYDOT) records the crash severity according to the KABCO scale: (K) is fatal injury, (A) is incapacitating injury, (B) is non-incapacitating injury, (C) is possible injury, and (O) is no injury/PDO crash. Because of the ordinal nature of crash severity, ordered logistic and ordered probit models emerge as the most commonly used statistical models to conduct crash severity analysis (*17*, *34–37*). Because of limited observations in each crash severity group, the injury severity levels were combined into two levels, no injury and fatal + injury, where $i = 1$ if a crash results in either fatal or any kind of injury and $i = 0$ if a crash results in no injury. Equation 2 provide the linear function to determine the discrete outcome i for observation n (*38*):

$$S_{in} = \boldsymbol{\beta}_i \boldsymbol{X}_{in} + \varepsilon_{in} \tag{2}$$

where $\boldsymbol{X}_{in}$ is the vector of predictors and $\boldsymbol{\beta}_i$ is the associated vector of estimable coefficients.

The mixed logit framework allows the parameter vector $\boldsymbol{\beta}$ to vary across each observation, unlike the ordinary logit model where $\boldsymbol{\beta}$ values are fixed for all observations (*39*, *40*). This accounts for the heterogeneity in crashes by allowing the influence of the predictors to vary with each crash. Similar to ordinary logit model, the mixed logit is estimated by taking the integral of the standard logit probabilities over a density of parameters, as shown in Equation 3 (*38*):

$$P_n(i|\varphi) = \int \frac{EXP(\boldsymbol{\beta}_i \boldsymbol{X}_{in})}{\sum_{i=0}^{1} EXP(\boldsymbol{\beta}_i \boldsymbol{X}_{in})} f(\boldsymbol{\beta}_i|\varphi) d\boldsymbol{\beta}_i \tag{3}$$

where $f(\boldsymbol{\beta}_i|\varphi)$ is the probability density function (PDF) of the random parameter $\boldsymbol{\beta}_i$ and φ is the vector of estimable parameters characterizing the PDF of $\boldsymbol{\beta}_i$. When $\boldsymbol{\beta}$ is allowed to vary, the probability of crash observation n having a particular injury outcome i cannot be calculated by direct computation. Therefore, simulation-based maximum likelihood methods such as Halton draws are usually used to obtain a certain number of random samples of the coefficients. In this study, a simulated maximum likelihood with 500 Halton draws is utilized to obtain reliable estimates (*41*). The available distributions for the random parameters include normal, lognormal, triangular, and uniform, but the best statistical fit was obtained when the random parameters were assumed to be normal, which is in agreement with previous studies (*42*, *43*).

Structural Equation Model

The SEM could be viewed as a variance and covariance analysis in a simultaneous regression modeling approach (*25*, *29*, *44*, *45*). The SEM is a multivariate statistical approach that analyses structural relationships between the measurement model and latent constructs (*46*). Recently, a few studies have utilized the SEM to investigate latent factors that could lead to a crash, as well as to perform real-time risk assessment (*6*, *30*, *31*, *47*, *48*). One main advantage of the SEM is that it can clarify complex relationships (indirect, multiple, and reverse relationships) between exogenous and endogenous latent variables (*49*). In addition, latent variables that are unquantifiable could be estimated using the SEM. Moreover, it simultaneously estimates the path coefficients of the relationships between the latent variables in the context of a full model.

The SEM is developed in two phases: (1) developing the measurement model, which specifies the significant variables that can measure each constructed latent variable with an exogenous model (x-measurement model) and an endogenous model (y-measurement model); and (2) the structural model, which specifies the significant direction of prediction between the exogenous model and the endogenous model.

The measurement model is developed using explanatory factor analysis (EFA), confirmatory factor analysis (CFA), and engineering judgment using previous studies. A minimum of three indicator variables should be used to develop each measurement model to avoid convergence issues (*50*). In addition, it is advised to use a maximum of 30 indicator variables to obtain a converged model and to evade model fitting issues (*51*). The structural model, referred to as path analysis, is formed by linking the exogenous and endogenous latent variables utilizing simultaneous equations (*52*).

The diagonal weighted least squares (DWLS) method was the estimation approach used to develop the SEM in this study, in which no specific distribution is assumed for the investigated variables (*53*, *54*). In addition, this estimation method was used as it was designed to deal specifically with ordinal data, as it led to unbiased results (*55–58*).

The sample size is one of the key factors to develop the SEM, as it is based on the large sample theory (*51*). Various studies have asserted the required minimum sample size to conduct a SEM. One study showed that a minimum of 300 observations is required to develop a SEM (*51*). However, other studies showed that a minimum sample size of 200 would be adequate to meet the assumptions of the large sample theory (*51*). Another study showed that a ratio of 10:1 for the number of observations to the number of investigated indicator variables should be achieved to obtain an adequate sample size (*59*). To measure the adequacy of the sample size used in the analysis, it was suggested to assess the statistical power of the developed SEM (*51*). To determine the statistical power of the model, the confidence intervals surrounding the root mean square error of approximation (RMSEA) should be evaluated as well as the RMSEA value. A RMSEA value less than or equal 0.08 suggests adequate statistical power. Figure 1 shows the structure map and the different elements of the SEM. The measurement models could be expressed as shown in Equation 4 and the structural model is given in Equation 5:

$$\begin{bmatrix} y \\ x \end{bmatrix} = \begin{bmatrix} \lambda_y & 0 \\ 0 & \lambda_x \end{bmatrix} \begin{bmatrix} \eta \\ \xi \end{bmatrix} + \begin{bmatrix} \varepsilon \\ \delta \end{bmatrix} \tag{4}$$

$$\eta = \beta\,\eta + \Gamma\xi + \zeta \tag{5}$$

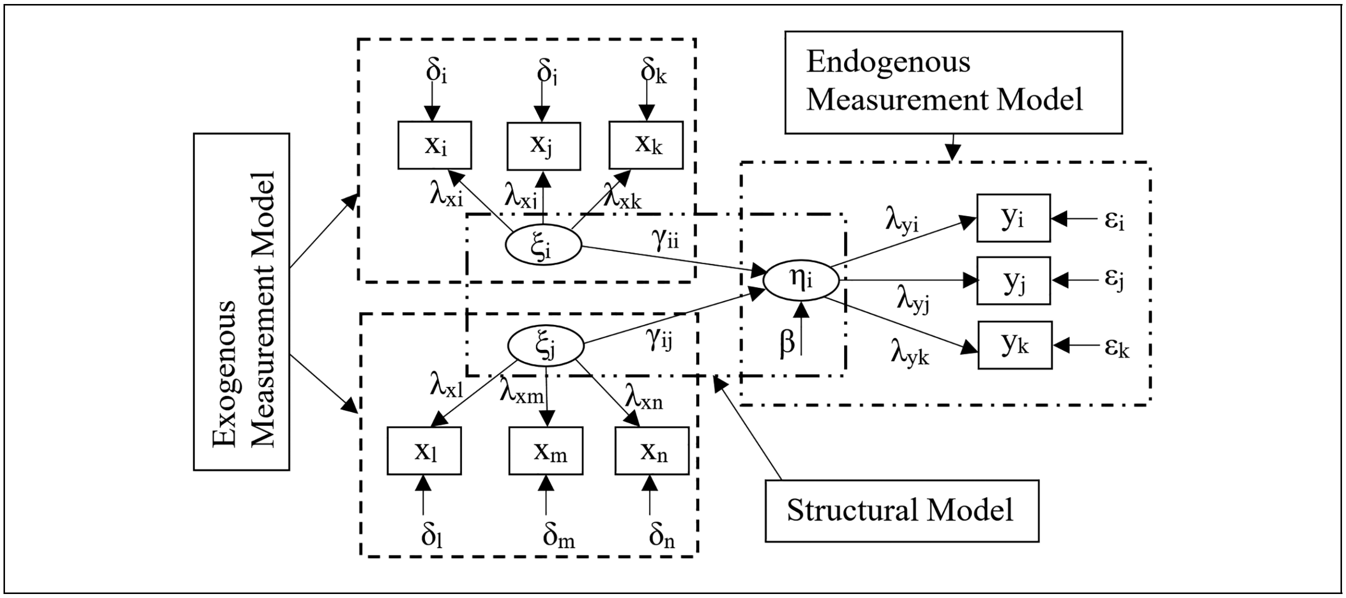

Figure 1. Structural map and the elements of the structural equation model.

where x is the vector of observed exogenous variables, y is the vector of observed exogenous variables, ξ is the vector of latent exogenous variables, η is the vector of latent endogenous variables, δ is the vector of measurement error terms for observed variables x, ε is the vector of measurement error terms for observed variables y, λ_x is the structural coefficients for latent exogenous variables to the observed variables, λ_y is the structural coefficients for latent endogenous variables to the observed variables. The set of exogenous latent variables are collected in η vector, where β is their estimate vector of regression coefficients. The vector for the endogenous latent variables is ξ and γ is their regression coefficients, while ζ is the error term for the structural model.

Data Preparation and Description

Historical crash data, along with other datasets, were extracted for the time period from 2015 to 2019 to perform the analysis for this study. Other datasets were also used in this study, including roadway geometry, pavement width and type, median width and type, shoulder widths and types, and speed limits. The main source of these datasets was WYDOT. WYDOT provides an inclusive online data archiving system, named the Wyoming Roadway Data Portal (WRDP), which documents factors related to the highway system in Wyoming. Three crash datasets formed the historical crash data for Wyoming, namely vehicle data, location data, and individual data. The three datasets provide details for the multiple elements of crashes that occurred in Wyoming. Vehicle data provides details about each vehicle involved in the crash identified with the crash report number; location data provides information about the crash location, the surrounding factors, and environmental conditions; and individual data includes details about the persons involved in the crash. Among the numerous variables used in this study, only the variables that were found to be significant in the analysis models were represented in this study.

Truck-related crashes that occurred on the three interstate roads (i.e., I-25, I-80, and I-90) in Wyoming were the focus of this study. It is worth mentioning that the three interstate roads are categorized as rural mountainous interstate roads, because of their challenging geometric characteristics, surrounding land use, and relatively low traffic volumes. Truck-related crashes refer to crashes that involved at least one truck in the crash. Crash data were processed and subdivided into two datasets to distinguish between the factors affecting the two different crash types. The two subdivisions were (1) single-truck crashes where only one truck was involved in a crash and (2) multi-vehicle truck crashes where more than one vehicle was involved in the crash, including at least one truck. Crashes were almost divided evenly, where 50% of total crashes, which equals 2020 crashes, were single-truck crashes, while a total of 2022 crashes were multi-vehicle truck crashes. Based on the spatial locations of crashes, the roadway geometry, pavement type, number of lanes, median characteristics, and implemented countermeasures were linked to the data. In addition, traffic volume data were extracted from the monthly traffic data reports published by WYDOT.

Table 1 shows the descriptive statistics of the collected datasets used in this study. Data were categorized into several categories to easily explore the indicator variables. The first category was for the crash injury severity

Table 1. Descriptive Statistics of the Investigated Indicator Variables

Category	Name	Description		MV Truck				SV Truck			
				Ave./%	SD	Min.	Max.	Ave./%	SD	Min.	Max.
Response variable	Sev	Crash severity (categorical)	0: PDO	77.19%	na	na	na	85.39%	na	na	na
			1: F + I	22.81%	na	na	na	14.61%	na	na	na
Roadway factors	Grade	Road grade (%) (cont.)		0.08	2.14	−6.53	5.57	−0.07	1.99	−6.53	7.77
	Delta	Deflection angle (degrees) (cont.)		8.76	16.46	0	102.47	8.88	16.95	0	102.47
	MedWid	Median width (feet) (integer)		92.77	80.80	4	956	112.60	112.05	4	956
	MedTyp	Median type (binary)	1: Depressed	67.89%	na	na	na	74.64%	na	na	na
			2: Raised	32.11%	na	na	na	25.36%	na	na	na
	HzAl	Horizontal alignment	0: Straight	15.44%	na	na	na	20.01%	na	na	na
			1: Curve	84.56%	na	na	na	79.99%	na	na	na
	VlAl	Vertical alignment (nominal)	1: Level grade	59.38%	na	na	na	59.38%	na	na	na
			2: Up grade	18.51%	na	na	na	18.51%	na	na	na
			3: Down grade	18.36%	na	na	na	18.36%	na	na	na
			4: Sag	0.49%	na	na	na	0.49%	na	na	na
			5: Crest	3.27%	na	na	na	3.27%	na	na	na
	Nlanes	Number of lanes (integer)		2.095	0.53	1	6	2.20	0.63	1	5
	PavTyp	Pavement type (binary)	1: Asphalt	73.28%	na	na	na	78.76%	na	na	na
			2: Concrete	26.72%	na	na	na	21.24%	na	na	na
Temporal	Season	Season of year (binary)	0: Summer	39.29%	na	na	na	21.84%	na	na	na
			1: Winter	60.71%	na	na	na	78.16%	na	na	na
	Week	Day of week (binary)	0: Weekday	66.95%	na	na	na	63.40%	na	na	na
			1: Weekend	33.05%	na	na	na	36.60%	na	na	na
	Time	Time of day (binary)	0: Daytime	82.93%	na	na	na	80.14%	na	na	na
			1: Nighttime	17.07%	na	na	na	19.86%	na	na	na
	AADT	Annual average daily traffic (cont.)		6402.4	1702.5	1562	11687	6085.5	1568.5	1665	11032
	AADTT	Annual average daily truck traffic (cont.)		2709.5	879.1	241	3996	2608.8	932.1	241	3996
	Tper	Truck percentage (%)		42.10%	11.78%	11.36%	65.80%	41.92%	12.14%	11.99%	65.80%
Environ.	Lcond	Lighting condition	1: Daytime	71.55%	na	na	na	54.93%	na	na	na
			2: Nighttime	24.84%	na	na	na	39.43%	na	na	na
			3: Dusk/dawn	3.61%	na	na	na	5.65%	na	na	na
	Rcond	Road surface condition	1: Dry	50.77%	na	na	na	33.09%	na	na	na
			2: Adverse	49.23%	na	na	na	66.91%	na	na	na
	Rweath	Reported weather	1: Clear	56.41%	na	na	na	37.74%	na	na	na
			2: Adverse	43.59%	na	na	na	62.26%	na	na	na
Crash char.	TrTyp	Type of truck involved in crash (ordinal)	1: Light	0.54%	na	na	na	0.54%	na	na	na
			2: Medium	2.82%	na	na	na	2.82%	na	na	na
			3: Heavy	96.64%	na	na	na	96.64%	na	na	na
	VehN	Number of crashed vehicles (integer)		2.18	1.11	2.00	28.00	1.00	0.00	1.00	1.00
	Speeding	Above speed limit (binary)	0: No	92.68%	na	na	na	93.47%	na	na	na
			1: Yes	7.32%	na	na	na	6.53%	na	na	na
	FxdObj "FHE"	Hitting a fixed object (binary)	0: No	98.52%	na	na	na	95.00%	na	na	na
			1: Yes	1.48%	na	na	na	5.00%	na	na	na
	WrkZn "FHE"	Work zone crash (binary)	0: No	92.13%	na	na	na	95.99%	na	na	na

(continued)

Table 1. (continued)

Category	Name	Description		MV Truck Ave./%	MV Truck SD	MV Truck Min.	MV Truck Max.	SV Truck Ave./%	SV Truck SD	SV Truck Min.	SV Truck Max.
			1: Yes	7.87%	na	na	na	4.01%	na	na	na
	Crshtyp	Crash type	1: Angle	16.97%	na	na	na	0.00%	na	na	na
			2: Opposite	3.56%	na	na	na	0.00%	na	na	na
			3: Rear end	37.26%	na	na	na	0.00%	na	na	na
			4: Rollover	0.74%	na	na	na	25.51%	na	na	na
			5: Other	41.46%	na	na	na	74.49%	na	na	na
Driver	DUI	Driving under influence (binary)	0: No	98.32%	na	na	na	99.60%	na	na	na
			1: Yes	1.68%	na	na	na	0.40%	na	na	na
	Seatbelt	Seatbelt (binary)	0: No	2.18%	na	na	na	2.53%	na	na	na
			1: Yes	97.82%	na	na	na	97.47%	na	na	na
	Gender	Gender (binary)	1: Male	75.46%	na	na	na	94.11%	na	na	na
			2: Female	24.54%	na	na	na	5.89%	na	na	na
	DCond	Condition (binary)	1: Normal	88.77%	na	na	na	92.42%	na	na	na
			2: Other	11.23%	na	na	na	7.58%	na	na	na
	Speeding	Speeding (binary)	0: Yes	92.83%	na	na	na	86.87%	na	na	na
			1: No	7.17%	na	na	na	13.13%	na	na	na
	DL	Driving license (binary)	1: Wyoming	67.49%	na	na	na	93.61%	na	na	na
			2: Other	32.51%	na	na	na	6.39%	na	na	na
	Age	Driver age (ordinal)	1: Less than 25	4.65%	na	na	na	4.65%	na	na	na
			2: 25–60	68.48%	na	na	na	68.48%	na	na	na
			3: Above 60	26.87%	na	na	na	26.87%	na	na	na
Roadway treatments	RS	Rumble strips (nominal)	0: Absent	26.27%	na	na	na	81.62%	na	na	na
			1: Present	73.73%	na	na	na	18.38%	na	na	na
	Grdrail	Guardrail (nominal)	0: Absent	99.11%	na	na	na	95.00%	na	na	na
			1: Present	0.89%	na	na	na	5.00%	na	na	na
	VSL	Variable speed limit (nominal)	0: No	52.61%	na	na	na	51.55%	na	na	na
			1: Yes	47.39%	na	na	na	48.45%	na	na	na
	Barrier	Presence of barrier (nominal)	0: Absent	8.51%	na	na	na	8.51%	na	na	na
			1: Present	91.49%	na	na	na	91.49%	na	na	na

Note: MV = multi-vehicle; SV = single-vehicle; PDO = property damage only; F + I = fatal and injury; Min. = minimum; Max. = maximum; Ave. = average; SD = standard deviation; na = not applicable.

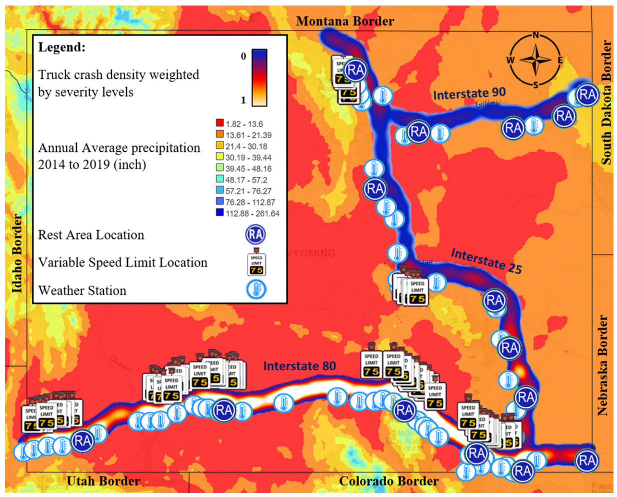

Figure 2. Heat map for truck crashes on rural interstate roads and precipitation in Wyoming.

as the response variable, which included two levels: PDO and F + I crashes. The roadway factors category included several indicator variables that express the roadway geometry, pavement type, and cross-section elements. The temporal category included the traffic volumes and the season in which the crash occurred, as well as truck traffic variables. The season variable was considered in the analysis as it accounts for the seasonal variation for crash frequencies. Crashes that occurred from April 15 to October 15 were considered as summer season crashes, while other crashes were considered as winter crashes. Lighting conditions, roadway surface conditions, and weather reported in the crash reports were the indicator variables for the environment data category. The truck type was included as one of the indicator variables for the crash characteristics category. It was categorized based on the weight of the truck involved in the crash. Driver and roadway treatments were the last two categories in the dataset. The driver category indicates the truck driver characteristics, while the roadway treatments indicate the existing countermeasures implemented at the crash location. Table 1 provides the percentage of each level for the categorical indicator variables: the mean, standard deviation, minimum, and maximum for the continuous and integer indicator variables.

Preliminary Data Analysis and Visualization

To better understand the three investigated rural corridors and provide initial insights into crash factors for truck-related crashes, a preliminary analysis was conducted. Figure 2 provides a visualization for truck-related crashes that occurred on the three interstates in Wyoming, in which crash density weighted by severity is mapped. In addition, weather stations located near the three interstate roads, the weather-based VSL sections, and rest areas are represented. The background of Figure 2 represents the annual average precipitation that occurred in Wyoming from 2014 to 2019. Annual average precipitation rates were extracted from the Wyoming Water and Climate Web Atlas (*13*), which was represented to visually superimpose locations with severe weather conditions and locations with high crash densities. Compared to I-25 and I-90, truck crashes and truck crash severities on I-80 were found to be the highest. The lower part of I-25 encounters higher crash frequencies with relatively high severity. Annual average precipitation levels were utilized as an indicator for adverse weather conditions, as precipitation in Wyoming is associated with snowfall levels. Locations with higher precipitation levels were observed to have higher truck crash rates and crash severities. This might indicate that adverse weather conditions would increase crash frequencies and severities. Accordingly, locations with high precipitation rates on the interstate roads are considered more risky locations.

With higher than the average crash rates per vehicle miles traveled (VMT), I-80 has the majority of road weather information systems (RWISs) as well as VSL sections compared to the other two interstates. When severe weather events occur during winter season, road closures are frequent on Wyoming interstates, and might extend for several days. Usually, trucks stop at the nearest rest area or truck parking as they cannot travel during such events. Each interstate road has five rest areas.

Further investigation was conducted by visualizing the roadway geometry and crash rates for multi-vehicle truck and single-truck crashes, as well as truck crashes in summer and winter. Figure 3 shows the vertical road profiles of I-25, I-80, and I-90 along with the number of horizontal curves per 5 mi of each roadway. Comparing the three interstates, it could be observed that I-80 has steeper vertical grades compared to I-25 and I-90. Horizontal alignment for I-25 shows a higher number of horizontal curves per 5 mi along the alignment.

To provide a more realistic representation for crashes, truck crashes were normalized by annual average daily traffic (AADT). Truck crashes per thousand vehicle miles traveled are represented in Figure 3. Comparing the three rural interstates, it could be noticed that I-80 had the highest truck crash rates. Given that crashes were normalized by traffic volumes, this clearly indicates that I-80 is the most hazardous for trucks in Wyoming.

Several crash severities and types were considered in this study. Two crash severity rates, PDO and F + I, and by season, summer and winter, for multi- and single-

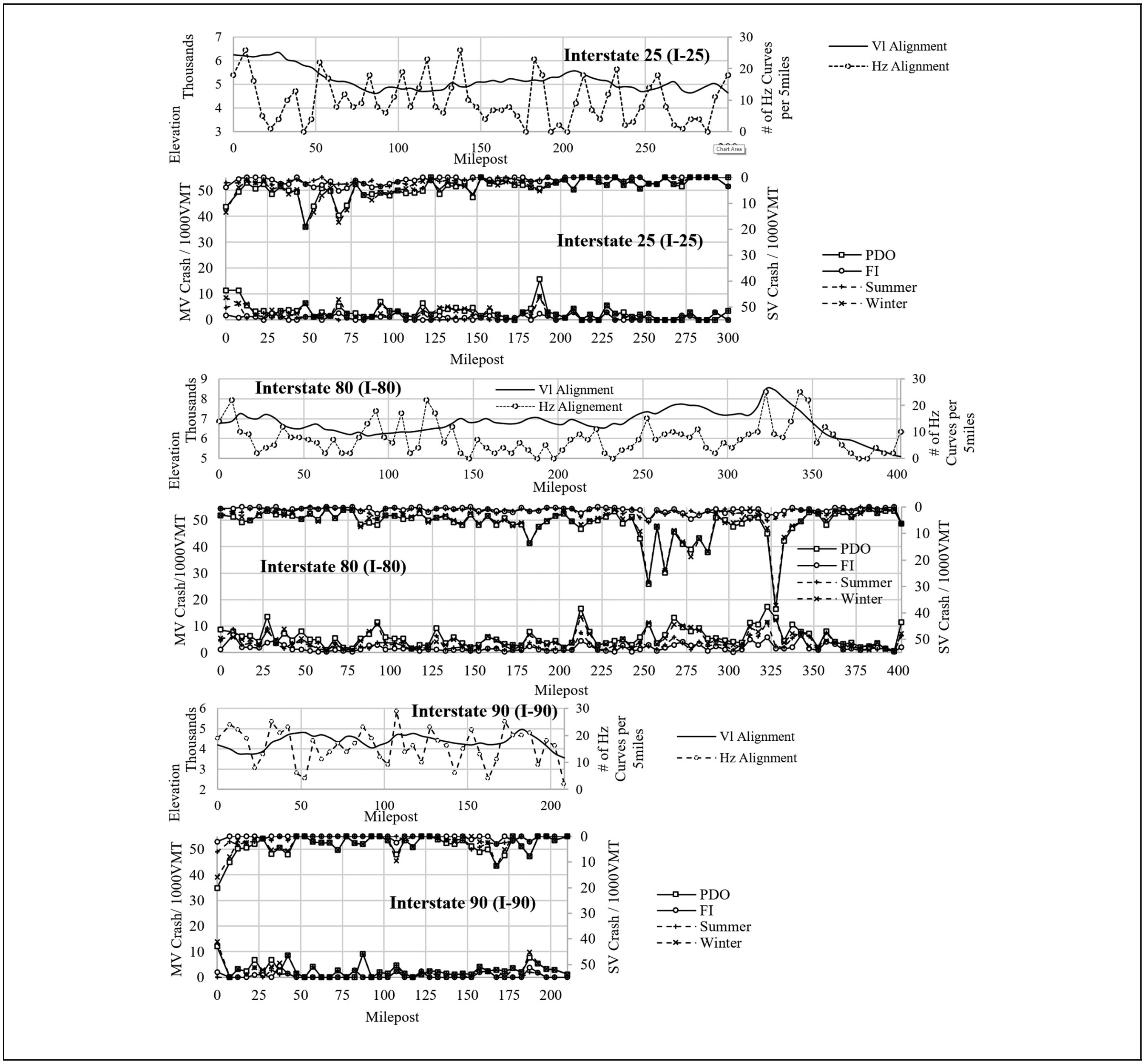

Figure 3. Roadway geometry and crash rates averaged over 5-mi segments.
Note: VMT = vehicle miles traveled; PDO = property damage only; FI = fatal and injury; MV multi-vehicle; SV = single vehicle.

vehicle truck crashes are presented in Figure 3. Single-truck crashes rates are located on the top part of the crash severity subgraphs, while multi-vehicle truck crash rates are presented at the lower part of each subgraph. It could be observed that winter truck crash rates are significantly higher than the rates of summer truck crashes. It could also be noticed that PDO crash rates nearly coincide with the rates of winter crashes. To determine the distribution of PDO and F + I crashes across the winter and summer seasons, percentages were calculated. It was observed that most of F + I crashes with a total of 65.08% as well as 70.43% of PDO crashes occured in winter season.

To initially assess the effect of roadway geometry on crashes, crash rates and roadway geometry were graphed symmetrically. Superimposing crashes and roadway geometry clarifies that more crash rates are located within roadway sections with steep vertical grades and a high number of horizontal curves per 5 mi. This could be observed on I-80 within the section from milepost 250 to milepost 350, I-25 from milepost 0 to 25, and I-90 from milepost 150 to 210.

This preliminary analysis showed that adverse weather conditions as well as challenging roadway geometry could be among the factors that would increase the severity of truck-related crashers. The patterns of the represented truck crash rates justify the several roadway treatments related to intelligent transportation systems (ITSs) that WYDOT implemented on the three rural interstates.

Results

The R® studio statistical software was utilized to develop the OLM and the RPLM. A total of six parametric models were developed, in which three truck crash types were investigated: (1) total truck crashes; (2) multi-vehicle truck crashes; and (3) single-truck crashes. The SEM was applied to the same datasets, in which three latent factor models were developed. SAS software was used to develop the measurement and the structural models for the SEM latent factor analysis.

Parametric Results from the OLM and RPLM

The 95th percentile confidence interval was used to determine significant variables affecting the injury severity of truck crashes. Similarly, the choice of specifying a particular variable as a random parameter was made based on the statistical significance of the standard deviation of the variable's random parameter distribution. Table 2 shows the results obtained for the OLM as well as the RPLM.

Model Fit Statistics. The log-likelihood ratio (LLR) test is employed to compare the performances of the OLM and RPLM. The test statistic, which follows a χ^2 distribution, is computed as twice the difference of the log-likelihoods (LLs) of both models. The degrees of freedom (DFs) are equivalent to the difference in the number of parameters of both models. Therefore, with respect to model fit, the total truck crash and the multi-vehicle truck crash RPLM are the best fit model according to LLR test results comparing the performances of each model pair. The LL ratio test results indicated that the RPLM single-vehicle truck crash model's predictive power was not significantly different from that of the OLM (LLR $\chi^2 = 2.979$, DF = 1, p-value = 0.084) at the 95th percentile confidence level. However, the test statistic was significant at the 90th percentile level. When it comes to the comparison between the total truck crash models (LLR $\chi^2 = 9.887$, DF = 4, p-value = 0.042) and the multi-vehicle truck models (LLR $\chi^2 = 9.817$, DF = 4, p-value = 0.084), it appears that the RPLM outperforms the OLM with respect to the model fit. Other model fit statistics such as the Akaike information criterion (AIC [lower the better]) and the McFadden's R-squared, R^2 (higher the better), point to the same conclusion as the LLR test results.

Crash Characteristics. Crashes between trucks and other vehicles are expected to result in fatality/severe injury (*17*, *24*, *60*). As the number of vehicles in a crash increases, it is expected that the odds of fatal/injury increase by 1.786 times and 1.391 times, found from the total truck crash and multi-vehicle truck crash models, respectively. The increase in the truck percentage variable in the total truck crash model indicates a similar finding.

Speeding for conditions such as adverse weather has been found to be a contributing factor in raising the resulting severity of a crash (*60*) Similar to the previous study, the multi-vehicle truck crash model predicts that speed that is too fast is a significant variable. Among the multi-vehicle crash types, head-on ($\hat{OR} = 8.519$) was found to have the most severe outcome, significantly increasing the odds of fatal/severe injury in the TTC model. Rear-end crashes have similar outcomes in both TTC and MVTC models, with $\hat{OR} = 5.396$ and 5.389, respectively. Multi-vehicle and single-vehicle rollovers appear to result in fatal/injury with estimated odds of 15.951 and 7.989, respectively. These results are synchronous with previous similar studies (*17*, *61*). The angle crash was identified as a random parameter in the total truck crash model with an estimated normal distribution of mean = 0.821 and standard deviation = 1.272. It can be inferred from the result that an estimated 74% of angle crashes are likely to result in fatal/severe injury.

When vehicles collide with a fixed object, such as signs, delineator posts, or fences, as the first harmful event, the resulting severity outcome is likely to be minor injury or no injury (*24*, *60*, *62*). However, the results in this study show that truck crashes are likely to result in a fatal/severe injury when colliding with a fixed object as inferred from the total truck crash and single-truck crash models, $\hat{OR} = 3.285$ and $\hat{OR} = 4.975$, respectively. Among the other crash characteristics, it was found that when crashes occur on roadways or traveled paths, the estimated odds of a higher injury severity decrease by 0.664 and 0.536 times compared to off-roadway or on-shoulder crashes, as inferred from the TTC and MVTC models. A similar result was reported by Ahmed et al. (*17*) and Castro et al. (*63*). Work zone-related crashes were found to result in lower injury severity. However, Khattak and Targa (*32*) showed that truck-involved crashes in work zones are likely to result in higher injury severity. One could argue that the lower speeds in work zones contributed to crashes resulting in lower severity.

Road Characteristics. Limited sight distances on extreme grades often result in fatal/injury crashes (*64*). Similarly, the total truck crash model indicates an estimated odds of 3.559 times a crash resulting in fatal/injury outcome when occurring on a sag grade, while the single-vehicle

Table 2. Ordinary Logistic Model (OLM) and Random Parameter Logit Model (RPLM) for Total, Multi-Vehicle, and Single-Truck Crashes

Variables	OLM					RPLM				
	Est	SE	z-value	p-value	OR	Est	SE	z-value	p-value	OR
Total truck crashes										
constant	−2.677	0.342	−7.836	<0.001	0.069	−2.636	0.428	−6.152	<0.001	0.072
numveh	0.489	0.081	6.042	<0.001	1.631	0.580	0.102	5.718	<0.001	1.786
sag	1.144	0.526	2.177	0.029	3.140	1.270	0.590	2.151	0.032	3.559
HZTYP	0.229	0.114	2.013	0.044	1.258	0.253	0.132	1.922	0.055	1.288
female	0.375	0.118	3.179	0.001	1.455	0.431	0.141	3.060	0.002	1.539
dcond	0.896	0.130	6.903	<0.001	2.449	0.983	0.156	6.288	<0.001	2.672
restraint	−0.641	0.277	−2.310	0.021	0.527	−0.825	0.344	−2.402	0.016	0.438
Opposite	1.887	0.263	7.169	<0.001	6.598	2.142	0.321	6.668	<0.001	8.519
Rearend	1.475	0.127	11.581	<0.001	4.370	1.686	0.171	9.835	<0.001	5.396
Rollover	2.004	0.135	14.838	<0.001	7.416	2.233	0.188	11.903	<0.001	9.332
Fixed	1.076	0.237	4.546	<0.001	2.934	1.189	0.274	4.343	<0.001	3.285
onroad	−0.325	0.118	−2.751	0.006	0.723	−0.409	0.139	−2.954	0.003	0.664
snowy	−0.462	0.098	−4.736	<0.001	0.630	−0.555	0.117	−4.753	<0.001	0.574
wz	−0.587	0.224	−2.623	0.009	0.556	−0.656	0.265	−2.474	0.013	0.519
Tper	0.858	0.375	2.287	0.022	2.359	0.891	0.430	2.071	0.038	2.437
mean.daylight	na	na	na	na	na	−0.410	0.184	−2.230	0.026	0.664
mean.young	−0.503	0.224	−2.245	0.025	0.605	−1.929	1.150	−1.679	0.093	0.145
mean.Angle	0.990	0.165	5.997	<0.001	2.693	0.821	0.444	1.850	0.064	2.273
sd.daylight	na	na	na	na	na	1.091	0.355	3.078	0.002	na
sd.young	na	na	na	na	na	2.584	1.227	2.105	0.035	na
sd.Angle	na	na	na	na	na	1.272	0.689	1.846	0.065	na
AIC			3295.591					3293.656		
LL at convergence			−1631					−1626		
Mcfadden's R^2			0.162					0.165		
Multi-vehicle truck crashes										
constant	−2.849	0.301	−9.461	<0.001	na	−3.749	0.600	−6.246	<0.001	na
numveh	0.557	0.104	5.366	<0.001	1.745	0.892	0.206	4.333	<0.001	2.441
RS	0.247	0.136	1.813	0.070	1.280	0.330	0.189	1.744	0.081	1.391
young	−0.825	0.366	−2.253	0.024	0.438	−1.118	0.524	−2.134	0.033	0.327
female	0.291	0.131	2.220	0.026	1.338	0.422	0.191	2.214	0.027	1.525
dcond	0.972	0.161	6.037	<0.001	2.643	1.400	0.277	5.059	<0.001	4.056
speedtoofast	0.412	0.213	1.936	0.053	1.510	0.639	0.299	2.141	0.032	1.895
Angle	0.811	0.172	4.716	<0.001	2.249	1.060	0.259	4.098	<0.001	2.886
Rearend	1.233	0.135	9.154	<0.001	3.430	1.684	0.251	6.700	<0.001	5.389
Rollover	1.918	0.555	3.454	0.001	6.805	2.770	0.835	3.318	0.001	15.951
onroad	−0.539	0.174	−3.088	0.002	0.584	−0.624	0.246	−2.540	0.011	0.536
snowy	−0.423	0.134	−3.154	0.002	0.655	−0.586	0.193	−3.037	0.002	0.556
wzr	−0.497	0.249	−1.998	0.046	0.608	−0.675	0.363	−1.858	0.063	0.509
mean.medtyp	na	na	na	na	na	−0.368	0.181	−2.038	0.042	0.692
mean.daylight	na	na	na	na	na	−0.833	0.344	−2.424	0.015	0.435
sd.medtyp	na	na	na	na	na	1.652	0.752	2.199	0.028	5.219
sd.daylight	na	na	na	na	na	1.922	0.573	3.353	0.001	na
AIC			1946.2					1944.4		
LL at convergence			−960.1					−955.2		
Mcfadden's R^2			0.115					0.12		
Single-truck crashes										
constant	−1.866	0.364	−5.129	<0.001	0.155	−1.931	0.402	−4.807	<0.001	0.145
Grade	0.070	0.036	1.960	0.050	1.073	0.072	0.037	1.951	0.051	1.075
VSL	−0.426	0.146	−2.927	0.003	0.653	−0.440	0.151	−2.907	0.004	0.644
route90	−0.994	0.446	−2.227	0.026	0.370	−1.039	0.485	−2.143	0.032	0.354
HZTYP	0.364	0.164	2.215	0.027	1.439	0.387	0.172	2.246	0.025	1.472
female	0.903	0.255	3.542	<0.001	2.466	0.943	0.264	3.566	<0.001	2.567
restraint	−1.045	0.348	−3.000	0.003	0.352	−1.044	0.385	−2.709	0.007	0.352
Rollover	1.968	0.152	12.911	<0.001	7.159	2.078	0.167	12.433	<0.001	7.989
Guardrail	1.442	0.268	5.384	<0.001	4.228	1.604	0.289	5.543	<0.001	4.975
dry	0.462	0.150	3.090	0.002	1.588	0.436	0.154	2.833	0.005	1.546
mean.dcond	0.849	0.217	3.908	<0.001	2.337	0.637	0.346	1.844	0.065	1.891

(continued)

Table 2. (continued)

Variables	OLM					RPLM				
	Est	SE	z-value	p-value	OR	Est	SE	z-value	p-value	OR
sd.dcond	na	na	na	na	na	1.705	0.817	2.087	0.037	na
AIC			1381.8					1382.9		
LL at convergence			−680.4					−678.9		
Mcfadden's R^2			0.190					0.191		

Note: AIC = Akaike information criterion; LL = Log-Likelihood; VSL = Variable Speed Limit; Est = Estimate; SE = Standard Error; OR = Odds Ratio; na = Not Applicable.

truck crash model estimates $\hat{OR} = 1.075$ for a crash on a grade (sag or crest) resulting in a fatal/injury outcome. Crashes occurring on a curve often tend to result in higher severity (*24*, *65*). The findings from the total truck crash and single-truck crash models also revealed that the odds of higher injury severity increased for a crash occurring on a curve compared to a straight segment. A notable finding was indicated by the I-90 variable, which shows that single-vehicle truck crashes on I-90 are expected to result in less severe injury outcomes. Previous study has linked this finding to the lower AADT of I-90 and limited mobility on that interstate during adverse weather conditions (*66*). The multi-vehicle truck crash model results show that crashes on segments with rumble strips are expected to result in higher injury severity ($\hat{OR} = 1.391$). It could be argued that drivers overcorrect their driving actions when trying to avoid getting off the roadway due to the presence of rumble strips, which might lead to collide with another vehicle on the roadway or traveled path. Median type (raised) was identified as a random parameter in the MVTC model, with 42% of crashes on segments with a raised median expected to result in fatal/injury outcomes.

As discussed previously, I-80 contains several VSL sections, where they are placed on the most hazardous segments characterized by adverse weather, steep grades, and sharp curves. It appears that the impact of the VSL on single-truck crashes is positive, with crashes occurring on VSL corridors likely to result in less severe injury outcomes.

Driver Characteristics. The predictor driver condition is related to the emotional state of the driver with conditions such as fatigue, sleepiness, angry, emotionally distressed, or agitated. Results indicate that drivers under such non-normal conditions are more likely to experience severe crashes, with estimated $\hat{OR} = 2.672$ (total truck crash), $\hat{OR} = 4.056$ (multi-vehicle truck crash), and $\hat{OR} = 1.891$ (single-truck crash). Furthermore, the single-truck crash model shows the driver condition variable to be a random parameter, indicating an estimated 65% of crashes resulting in fatal/injury outcomes when drivers are in non-normal conditions.

Female occupants (driver/passenger) are estimated to experience severe injuries compared to their male counterparts. Similar results have been reported in previous studies (*17*, *61*). As expected, use of proper safety restraints (e.g., seatbelt) in the vehicle reduces the estimated odds of a higher injury severity by 0.438 times (total truck crash) and 0.352 times (single-truck crash), which is in accordance with other studies (*61*, *67*).

With respect to driver age, previous studies have found that senior drivers were likely to sustain higher levels of injury in a crash compared to young or mid-aged drivers (*68*, *69*). The multi-vehicle truck crash model suggests that young drivers have estimated higher odds of experiencing no injury. As the "young" variable was established as a random variable from the total truck crash model, it can be inferred that only 23% of young-aged drivers are likely to experience a fatal/injury outcome from a truck-involved crash.

Environmental Characteristics. Results from the single-truck crash model show that a dry road increased the estimated odds of fatality/injury by 1.546 times. Furthermore, crashes during snowy road conditions appear to result in lower injury severity as found from the total truck crash model ($\hat{OR} = 0.574$). Researchers argued that wet/snowy road surface conditions made drivers more cautious of the surroundings and drive at lower speeds. Thus, when crashes occur in a wet/snowy surface condition, the resulting injury outcomes were less severe (*68*, *70*). The daylight variable has been found to be a random parameter, with an estimated 35% (total truck crash) and 33% (multi-vehicle truck crash) of the crashes resulting in fatality/injury.

SEM Development and Results for Single and Multi-Vehicle Truck Crashes

EFA and CFA were used to pre-specify and develop the exogenous and endogenous latent factors that were used as the measurement models for the SEM. Crash data were randomly divided into two portions with a ratio of 20:80, in which EFA was applied on 20% of the data, while the remaining 80% was used to conduct the CFA. The application of EFA and CFA on the same dataset should be avoided, as it might hinder the external validity of the obtained factors (*44*). The CFA is distinguished from the EFA as it provides a more parsimonious solution (*45*).

To avoid convergence issues, a minimum of three indicator variables were selected to measure each latent variable. The generalized least squares (GLS) method with a varimax orthogonal rotation was the adopted extraction method. A cutoff value of 0.4 was used for the factor loading values (*51*). The obtained Kaiser–Meyer–Olkin (KMO) values were found to be 0.791, 0.774, and 0.714 for the total, multi-vehicle, and single-truck crashes, respectively. The latent variables are considered well factored if the KMO value is above 0.5 (*16*, *29*). The same variables were loaded for the EFA and the CFA, which resulted in a total of six factors being obtained for each truck crash type. Table 3 shows the obtained latent variables and their factor loading.

Table 3 shows that the observed variables were similarly loaded for the total and the multi-vehicle truck crashes. However, different variables were loaded to form the latent variables for the single-truck crash model. This could be because of the distinct nature and crash characteristics for single-truck crashes.

Figures 4–6 show the developed SEM to estimate the crash severity of truck-related crashes. The latent variables are presented with oval shapes, indicator variables are represented with rectangular shapes, and the arrows represent the direction of the path model. Model estimates, known as path coefficients, are provided on the top of the path arrows. The obtained standard error and the significance level presented in the form of the *t*-value are provided below the path arrow. For the three developed models, the latent variable representing the crash severity of trucks was considered as the endogenous variable. Direct and indirect relationships could be observed from the developed models. A direct relationship occurs when the exogenous variable is directly connected to the endogenous latent variable (i.e., a challenging driving environment is directly connected to the crash severity). An indirect relationship occurs when the endogenous latent variable is connected to the endogenous latent variable through an intermediate endogenous latent variable. The provided path coefficients demonstrate the standardized estimates for the linear equations, in which all the provided coefficients were significant at the 95% confidence level.

The measurement models obtained for the total truck crashes and the multi-vehicle truck crashes are generally similar to each other. The observed crash severity, number of vehicles involved in the crash, and the crash type were factored to express the crash severity of truck crashes as a latent variable. The results showed that the increase in injury severity and the number of vehicles involved in the crash would increase the crash severity of truck crashes, given the positive estimates of 0.143 and 11.772 for total and multi-vehicle truck crashes, respectively. The negative sign of the estimate for the crash type indicates that compared to angle crashes, other crash types will reduce the severity of truck crashes. Truck type was found to be significant in explaining the crash severity of total truck crashes. The obtained estimate of 0.903 shows that having a heavy truck involved in the crash would increase the severity of total truck crashes, compared to medium and small trucks. The presence of rumble strips was found to reduce the latent factor of a challenging driving environment. This could be because of the known benefits of rumble strips, as they alert the driver to encroaching the edge of the travel path. The single-truck SEM had a unique latent factor, namely the presence of a bridge. This latent factor could be explained by the three observed variables: (1) number of lanes, (2) pavement type, and (3) the presence of guardrails.

The path coefficients and directions are used to interpret the effect of the developed measurement models on the truck crash severity. For the single-truck crash model, the presence of a bridge had an indirect effect on the severity of a single-truck crash through the intermediate factor interaction with traffic. The results showed that for each one unit increase in bridge presence, the interaction with traffic reduced by 0.841 units, while each unit decrease in the interaction between traffic would increase the crash severity of a single-truck crash. This could be because of the higher probability of drowsy or distracted driving behavior when having less surrounding traffic, which could lead to a single-truck crash with higher injury severity.

Interestingly, a challenging driving environment had a dissimilar effect on the crash severity of single and multi-vehicle truck crashes. Having a challenging driving environment would increase the severity of single-truck crashes, while decreasing the severity of multi-vehicle truck crashes. This contradictory impact could be explained by accounting for the observed variables that are factored into this latent variable. The presence of a work zone is one of the variables factored in the latent variable of challenging driving environment. Usually, lane reduction or lane closures are associated with work zones, which increases the probability of having a single-truck crash over being involved in a multi-vehicle truck crash.

As anticipated, adverse weather conditions as well as challenging roadway geometry would increase the severity of total truck crashes. However, the adverse weather conditions had an indirect effect on increasing the crash severity through the presence of challenging roadway

Table 3. Obtained Factor Loading and Latent Variables from the Confirmatory Factor Analysis

Variable	Total						MV						SV					
	F1	F2	F3	F4	F5	F6	F1	F2	F3	F4	F5	F6	F1	F2	F3	F5	F6	F7
sev	0.42	na	na	na	na	na	0.75	na	na	na	na	na	0.65	na	na	na	na	na
numveh	0.75	na	na	na	na	na	0.55	na	na	na	na	na	na	na	na	na	na	na
Crshtyp	−0.68	na	na	na	na	na	−0.55	na	na	na	na	na	−0.51	na	na	na	na	na
TrTyp	0.81	na	na	na	na	na	na	na	na	na	na	na	na	0.71	na	na	na	na
Age	na	na	na	na	na	na	na	na	na	na	na	na	na	−0.47	na	na	na	na
Season	na	0.57	na	na	na	na	na	0.56	na	na	na	na	na	na	na	na	−0.51	na
Wcond	na	0.67	na	na	na	na	na	0.68	na	na	na	na	na	na	na	0.48	na	na
RCond	na	0.76	na	na	na	na	na	0.82	na	na	na	na	−0.52	na	na	na	na	na
IntRe	na	na	−0.47	na	na	na	na	na	na	na	na	na	na	na	na	na	0.54	na
Route	na	na	0.87	na	na	na	na	na	0.83	na	na	na	na	na	0.85	na	na	na
Tper	na	na	0.90	na	na	na	na	na	0.87	na	na	na	na	na	0.87	na	na	na
DL	na	na	na	na	na	na	na	na	−0.53	na	na	na	na	0.59		na	na	na
AAADT	na	na	na	na	na	na	na	na	na	na	na	na	na	na	0.51	na	na	na
nighttime	na	na	na	0.77	na	na	na	na	na	0.80	na	na	na	na	na	na	na	na
DUI	na	na	na	0.46	na	na	na	na	na	0.43	na	na	0.51	na	na	na	na	na
Lighting	na	na	na	0.77	na	na	na	na	na	0.80	na	na	na	na	na	na	na	na
Vlcond	na	na	na	na	0.48	na	na	na	na	na	0.67	na	na	na	na	0.48	na	na
HZTYP	na	na	na	na	0.43	na	na	na	na	na	0.65	na	na	na	na	0.56	na	na
PavTyp	na	na	na	na	0.72	na	na	na	na	na	0.49	na	na	na	na	na	na	0.70
Guardrail	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	0.47
nlanes	na	na	na	na	na	−0.52	na	na	na	na	na	−0.60	na	na	na	na	na	0.52
RS	na	na	na	na	na	−0.45	na	na	na	na	na	−0.53	na	na	na	na	−0.46	na
wzr	na	na	na	na	na	0.66	na	na	na	na	na	0.63	na	na	na	na	0.65	na
restraint	na	na	na	na	na	na	na	na	na	na	na	na	−0.44	na	na	na	na	na

Latent variable and factor names

F1 : Crash severity
F2 : Adverse weather
F3 : Interaction with traffic
F4 : Lack of perception
F5 : Challenging roadway geometry
F6 : Challenging driving environment
F7 : Presence of a bridge

Note: MV = multi-vehicle; SV = single vehicle; DUI = driving under the influence; AAADT = annual average daily truck traffic; na = not applicable.

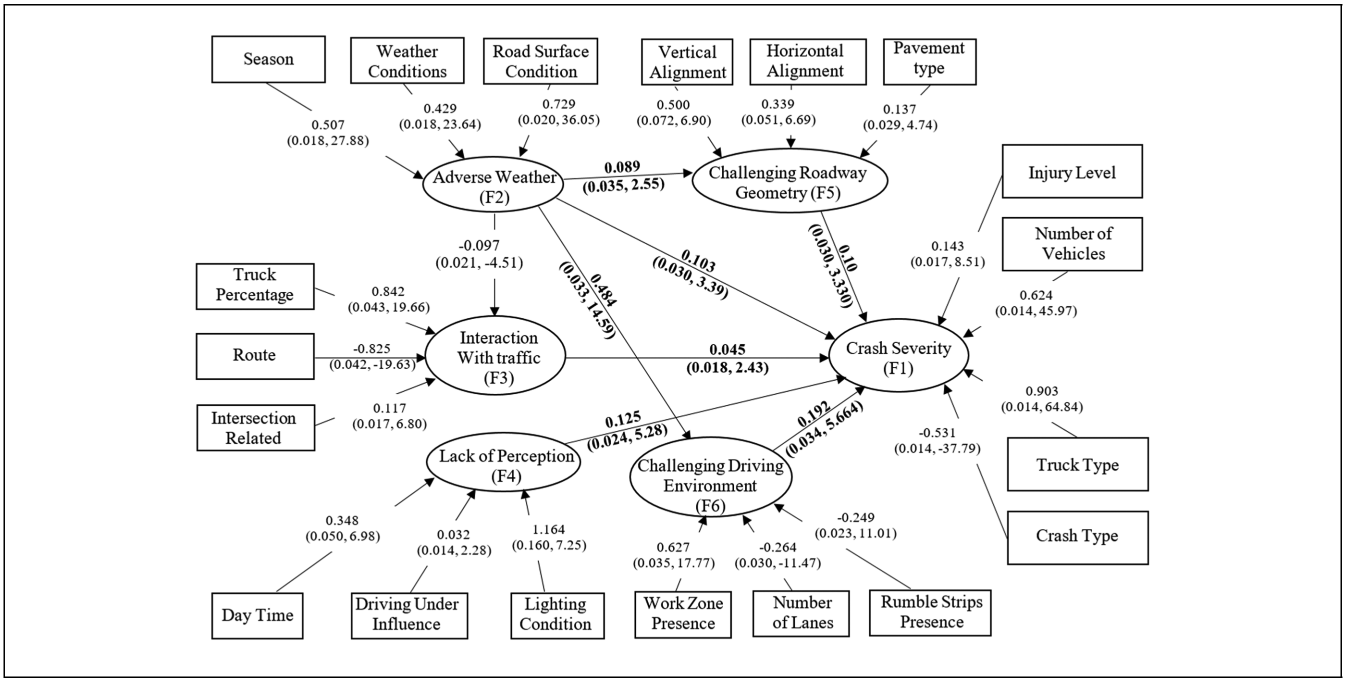

Figure 4. Structural equation model (path model) of total truck crashes.

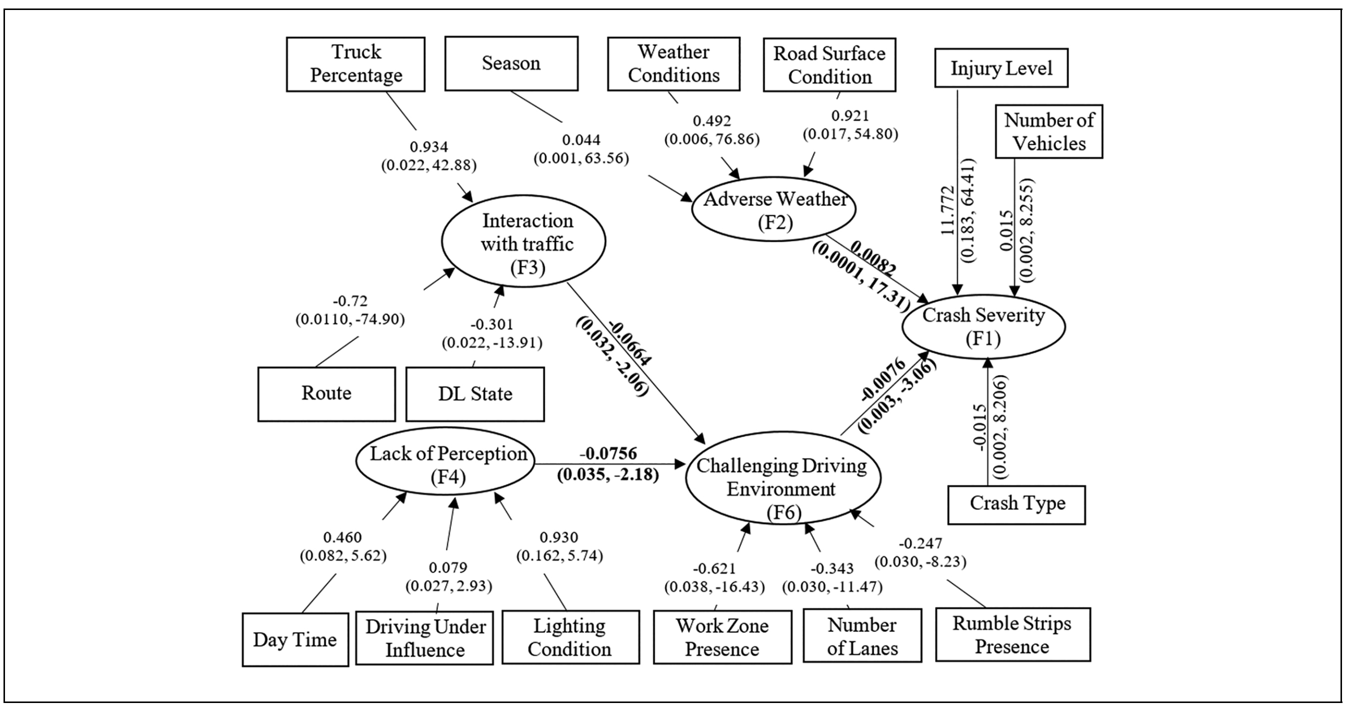

Figure 5. Structural equation model (path model) of multi-vehicle truck crashes.
Note: DL State = Driving License State.

geometry. This could be explained as adverse weather conditions did not have a direct impact on increasing the crash severity of total truck crashes. However, they would deteriorate the ability of truck drivers to correctly navigate through sharp curves and steep grades. It was found that a one unit increase in adverse weather would worsen drivability on challenging roadway geometry by 0.089 units, while a one unit increase in challenging

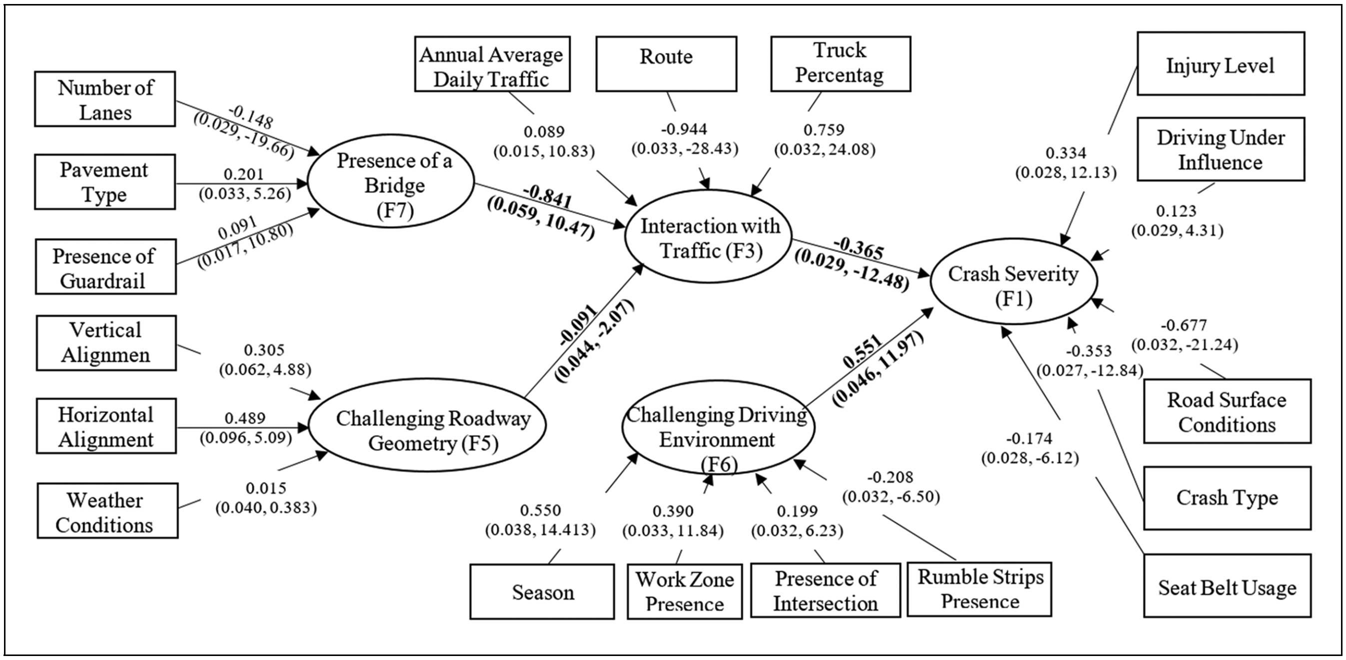

Figure 6. Structural equation model (path model) of single-truck crashes.

Table 4. Model Fit Indices and Statistical Power Summary for the Developed Structural Equation Models

Model fit index	Obtained values of indices			Threshold values
	Total truck crashes	Multi-vehicle truck crash	Single-truck crash	
Standardized root mean square residual	0.0518	0.0536	0.0584	<0.050
Goodness of fit index (GFI)	0.9210	0.9104	0.900	>0.900
Parsimony index—adjusted GFI	0.8950	0.8909	0.8894	>0.900
RMSEA estimate	0.0549	0.0603	0.0668	<0.055
Bentler comparative fit index	0.901	0.898	0.893	>0.900
Akaike information criterion	1347	1579	1768	Lower is better

Note: RMSEA = root mean square error of approximation.

roadway geometry would increase the severity of total truck crashes by 0.1 units.

Goodness of Fit and Statistical Power

Table 4 shows the model fit indices to assess the performance of the developed SEMs, in which several thresholds should be met. The several provided model fit indices reflect a different aspect of model fit (*71*). The developed models show an acceptable model fit for the three developed models, although there is a slight variation from the thresholds. The obtained standardized root mean square residuals (SRMRs) were above the threshold limit; however, values below 0.08 would provide a good model fit (*72*). In addition, the parsimony index was slightly below the limits of the acceptable threshold. The statistical power of the model could be measured using the RMSEA value. Even though the RMSEA were slightly above the threshold, it is still considered to have adequate statistical power as the obtained value is below 0.08. In addition, the RMSEA is considered a less preferable index to assess the goodness of fit when having relatively large sample sizes (*72*). Several path models were developed for the three truck crash types; however, the models with the lowest AIC and better performance indices were selected.

Limitations

Several driver behavior factors might influence the outcome severity of truck-related crashes. Driver behavior factors could include age, driving experience, speeding, distracted driving, drowsy driving, and so forth. However, crash data generally suffer from absence of driver behavior factors as they are difficult to collect. Accordingly, most of the utilized factors here in this study are related to the crash characteristics. Available driver behavior factors, such as age, DUI, speeding, safety belt usage, and gender, were included in the analysis. Furthermore, some of the presented driver behavioral factors might be subjective, as they are based on narratives for drivers, which might be biased toward higher adoption rates. This might be a cause of the absence of such factors in the significant variables in the developed models. Traffic volumes, as the main crash exposure factor, are aggregated over a year per roadway section. This might be an indication of the level of traffic at a specific roadway section, but it does not reflect the actual traffic encountered at the crash event. The findings from this study support the need for future investigation into heavy truck casual effects that include driver behavior factors that clarify other factors that might influence truck crashes. Furthermore, future work could be aimed toward investigating the correlation among the random parameters. Sophisticated modeling approaches such as the correlated RPLM with heterogeneity in means and variances could provide more insights into driver performance and other factors.

Conclusions and Discussions

The results of this study could provide guidance to transportation agencies and policy makers to select effective interventions that may help in reducing truck-related crash severity. This study showed that factors affecting the severity of truck-related crashes are caused by multiple contributing factors, not a single erroneous decision or action, which was in line with previous studies (*73–75*). The SEM could potentially allow understanding the systematic approach to truck safety. While the SEMs showed the direct and indirect effects of crash contributing factors, logistic models only showed the direct effects of variables on crash severity.

Preliminary data analyses showed that locations that encounter harsh weather conditions and challenging roadway geometry also receive higher crash frequencies/severities. The results of the preliminary analysis were also supported by the developed model results. The results from the SEMs showed that adverse weather conditions and challenging roadway geometry have direct and indirect impacts on increasing the severity of truck crashes. Combinations of multiple challenging driving conditions could significantly increase the probability of having more severe crash injuries because of the direct and indirect impacts found in the SEM results.

This study showed the importance of assessing the crash severity of trucks using multiple analysis approaches. The OLM showed the direct effects of variables on the response variables while providing easy interpretation for the results. However, it does not allow the parameters to vary across observations. The random parameter model was utilized in this study to account for the individual-level heterogeneity in the crash data. On the other hand, parametric approaches do not clarify the indirect impact of observations on crashes. On the other hand, SEMs do not provide a clear quantified impact in the form of parameter estimates. Therefore, this study highlights the importance of investigating truck crash data using multiple approaches that will complement one another. This would help practitioners extract deeper and more useful insights into crash contributing factors for developing mitigation strategies.

The random parameters model indicated that truck percentage was among the significant variables that contribute to an increased crash severity. This study also clarified the adverse impact of severe weather conditions on increasing crash severity for trucks. Utilizing the SEM approach, the direct and indirect effects of factors on truck crash severity were clarified. In addition, the crash mitigation strategies in the form of countermeasures implemented on the investigated rural corridors were found to be effective in enhancing the safety of commercial vehicles. These countermeasures included VSLs, guardrails, and rumble strips. Speeding was among the variables found to increase the crash severity of trucks. There is a major issue with respect to truck drivers' compliance with posted VSLs, especially in adverse weather conditions. Usually, truck drivers speed in reduced visibility, which might lead to increased crash frequencies, crash severities, or both. It would be recommended to increase traffic enforcement to provide homogeneous operating speeds. Comparing the I-80 corridor to the other two interstate corridors (I-90 and I-25), I-80 can be considered more crucial to freight operations in Wyoming, given the longer length, higher traffic volumes, and harsher driving conditions. In addition, the preliminary analysis showed that I-80 receives higher crash frequencies and severities. It could be recommended to either increase the frequency or capacity of truck rest areas for emergency situations.

To increase drivers' trust in the VSL system, an appropriate operating speed that matches the environmental and the road surface conditions should be provided. Thus, it would be recommended to update the algorithms of the VSL corridors to account for real-time conditions to reduce subjectivity. Real-time weather detection systems based on machine vision that collect weather data from cameras and sensors could provide a consistent quantification for the encountered weather conditions. This quantification could assist Traffic Management Centers (TMCs) in determining appropriate operating speeds.

The presence of rumble strips was found to be effective in reducing crash severity in the developed models. Since this study also showed that adverse weather negatively affects crash injury severity, the positive effect of rumble strips could be undermined. A previous study showed that during severe snowstorms, compacted snow located on the roadway could negatively influence the performance of rumble strips (*76*). The study also concluded that the effectiveness of rumble strips in adverse weather could be enhanced by a higher level of winter maintenance operations. Therefore, it could be recommended to update maintenance policies with respect to the snow removal processes. Furthermore, upgrading the equipment by adding tow plows would allow the plowing of wider road widths.

The results of this study highlighted the importance of increasing situational awareness for commercial truck drivers with upcoming hazardous events. This could be performed by communicating real-time information with respect to upcoming hazardous events. These hazardous events could include adverse weather conditions, bad road surface conditions, challenging roadway geometry, road closures, work zone locations, and upcoming crashes. Real-time information could be communicated via several platforms. Recently, a CV pilot on I-80 was deployed to enhance the operational safety of commercial trucks. In addition, real-time information could be communicated using 511 applications, and via the Commercial Vehicle Operator Portal (CVOP). By communicating such information, the situation awareness of truck drivers would be enhanced, as well as their preparedness for encountered dangerous events.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: S.M. Gaweesh; data collection: S.M. Gaweesh, I.U. Ahmed; analysis and interpretation of results: S.M. Gaweesh, I.U. Ahmed; draft manuscript preparation: S.M. Gaweesh, I.U. Ahmed, M.M. Ahmed. All authors reviewed the results and approved the final version of the manuscript.

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