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Modeling Rollover Crash Risks: The Influence of Road Infrastructure and Traffic Stream Characteristics

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Abstract: Rollover crashes are among the most prevalent types of accidents in developing countries. Various factors may contribute to the occurrence of rollover crashes. However, limited studies have simultaneously investigated both traffic stream and road-related variables. For instance, the effects of T-intersection density, U-turns, roadside parking lots, the entry and exit ramps of side roads, as well as traffic stream characteristics (e.g., standard deviation of vehicle speeds, speed violations, presence or absence of speed cameras, and road surface deterioration) have not been thoroughly explored in previous research. Additionally, the simultaneous modeling of crash frequency and intensity remains underexplored. This study examines single-vehicle rollover crashes in Yazd Province, located in central Iran, as a case study and simultaneously evaluates all the variables. A dataset comprising three years of crash data (2015–2017) was collected and analyzed. A crash index was developed based on the weight of crash intensity, road type, road length (as dependent variables), and road infrastructure and traffic stream properties (as independent variables). Initially, the dataset was refined to determine the significance of explanatory variables on the crash index. Correlation analysis was conducted to assess the linear independence between variable pairs using the variance inflation factor (VIF). Subsequently, various models were compared based on goodness of fit (GOF) indicators and odds ratio (OR) calculations. The results indicated that among ten crash modeling techniques, namely, Poisson, negative binomial (NB), zero-truncated Poisson (ZTP), zero-truncated negative binomial (ZTNB), zero-inflated Poisson (ZIP), zero-inflated negative binomial (ZINB), fixed-effect Poisson (FEP), fixed-effect negative binomial (FENB), random-effect Poisson (REP), and random-effect negative binomial (RENB), the FENB model outperformed the others. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) values for the FENB model were 1305.7 and 1393.6, respectively, demonstrating its superior performance. The findings revealed a declining trend in the frequency and severity of rollover crashes.

Keywords: rollover crashes; crash index; crash modeling; traffic stream characteristics

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1. Introduction

Providing safe and sustainable mobility is one of the most important goals of governments. In this regard, transportation experts are constantly trying to investigate the most important factors involved by using different approaches to crash analysis. This issue has become even more important since the number of casualties due to traffic crashes increased in 2020 in some countries. In the United States, for example, despite a decline in travel during the COVID-19 pandemic, the number of fatalities due to traffic crashes has increased by 7.2% compared to the same period in 2019 [1]. A rollover crash is a type of crash in which the driver loses control of the vehicle due to high speed, fatigue, drowsiness, alcohol consumption, etc., and rolls over after leaving the road. Research has shown that one-third of the total number of crashes falls under the rollover type [2]. This percentage varied among different countries, such as the United States, where the share of rollover crashes reported in 2020 was 25%, indicating a 9% increase compared to 2019 [3]. A study of crashes from 2000 to 2007 in three Australian states also found that rollover crashes accounted for 35% of all fatalities [4]. As a result of a rollover crash, the vehicle's roof rotates by 90°. This rollover can be repeated during a crash and might result in serious injuries to the driver and occupants. As reviewed in previous studies [5], risk factors affecting the mitigation or aggravation of injuries or death of the driver and occupants due to rollover may include at least one of the following: occupants being thrown out, not wearing a seat belt, the number of rotations due to rollover, sitting place in the car, damage to the roof, type of vehicle, and demographic characteristics of drivers (e.g., age, gender, and alcohol consumption) [6–10]. The results of a study on a 12.5 cm plate load test showed that the risk of a fatal crash or serious injury is reduced by 24% for every unit of a car roof's strength-to-weight ratio (SWR) [11].

Iran is a developing country with a high number of yearly traffic fatalities. For instance, in 2016, 15,932 people died in traffic accidents [12]. Many factors are involved in Iran's traffic accidents. The two most underlying reasons behind traffic fatalities in Iran are the inability to control the vehicle and the lack of proper attention to the front vehicles. Rollover crashes are among the most common types of road traffic fatalities in Iran. This phenomenon occurs due to the lack of proper control of the vehicle, which is caused by speeding or driver fatigue. The present study aims to investigate single-vehicle rollover crashes by investigating proper variables, including both traffic stream and road-related variables of rollover crashes. In this regard, Yazd province, located in the center of Iran, was selected as the case study, and associated traffic accidents were investigated. Since about 54% of Yazd traffic accidents are rollover crashes, it was possible to gather both road and traffic stream variables. Thus, Yazd traffic accidents and associated variables were selected for further study.

This paper aims, initially, to model rollover crashes and find a superior model among all competing models. Next, it investigates how much each variable might affect rollover crashes. The remainder of this paper is organized as follows: Section 2 examines previous studies and identifies research gaps; Section 3 describes the research method, including data collection, data refinement, and modeling through monitoring Iran's crash data; Section 4 deals with the research findings and presents a discussion of the results; finally, Section 5 summarizes the results.

2. Literature Review

So far, various review studies have been published on variables affecting rollover crashes. For example, a study on rollover crashes on mountain roads showed that adverse weather and topographic conditions could be dangerous. Variables used in this study include speed limit, road median condition, type of road surface (asphalt or not), crash season, working day or holiday at the time of the crash, being day or night, road surface weather conditions, and driver characteristics (e.g., high speed and driver age group). This study compared three types of models, including conventional logit, a non-correlated random parameter logit model, and a correlated random parameter logit model. Previous studies have shown that the correlated random parameter logit model is superior to other models. Therefore, the correlation between the variables was examined by incorporating all variables into the relationship using this model. Also, the above study did not study variables such as roadside slope and other road characteristics [13]. Crashes on mountain arch roads in Wyoming were investigated in a similar study with the same variables. The collected data were modeled using the combined logit model method. Studies showed that weather conditions, road surface conditions, and speed are among the most important variables. In this research, the types of road classifications and other road characteristics were not studied due to the difficulty of data collection [14]. The effect of vehicle type and road geometric design on the occurrence of rollover crashes on mountain roads was investigated. For this purpose, various weight conditions and technical characteristics of heavy vehicles, as well as the road geometric design properties (e.g., the slope of the crash site, being in the superelevation limit, arc angle, and radius in the event of rollover crashes), were investigated using multiple logit models. Studies showed that the speed limit in different road areas should be selected according to the road's geometric design conditions and vehicle type [15]. Exploring the effect of strong winds on rollover crashes on Wyoming roads reveals that wind speed with an angle of 120° relative to the vehicle's direction has the greatest effect on the occurrence of crashes [16].

In a research study, the variables effective in the occurrence of a rollover crash at different intensity levels were investigated. These variables included crash intensity (i.e., property damage only, minor damage, and fatality), light vehicle flow logarithm, heavy vehicle flow logarithm, allowable speed, paved road width, unpaved road width, curvature, number of intersections along the road, type of land use, side road friction, roadside conditions (e.g., a ditch, excavation, and embankment), time of the crash, being day or night, gender, age, education of the driver, use of seat belt while driving, the type of vehicle used, and the defect of the vehicle tire. Data modeling was performed using the random-effects generalized ordered probit model, which was superior to the mixed logit method [17]. Different intensities of crashes of heavy vehicles were investigated using a random parameter ordered logit model. The variables used in this study include the intensity of crashes, driver reaction, driver age group, driver's condition during the crash, driver distraction during the crash, visual impairments in the area of the crash, lack of ability to see road components during the crash properly, number of vehicles involved, road surface conditions, road surface slope, weather conditions, and lighting conditions of the area during the crash [18]. The effects of weather conditions (rainy and snowy), angle of deviation and vehicle rotation, road roughness, longitudinal slope, acceleration, deceleration rate, lateral friction coefficient, and the allowed speed limit were investigated in another study [19].

Various degrees of rollover crash might drastically change crash intensity. Using a support vector machine (SVM) model with explanatory variables including road lighting conditions, weather conditions, slope and curvature of the road, number of vehicles involved in the crash, road surface friction, the intensity of damage to the vehicle, time and location of the crash, driver's driving license, road surface conditions, traffic control method, number of lanes, type of vehicle, type of vehicle maneuver at the time of the crash, gender, driver age, and education showed that the SVM model can adequately predict various crash intensities. Moreover, the polynomial kernel function performed better than the Gaussian RBF [20]. The intensity of crashes was predicted using Logistic regression modeling with independent variables, including driver variables and vehicle and crash conditions. The variables were examined using the odds ratio (OR) measure for each variable. Studies have proved that using safe vehicles can properly reduce rollover crashes. In this respect, for cars where seat belts are annoying to the driver or the design is inappropriate, the probability of the driver's injury intensity due to a rollover crash is 10 times higher [21].

Another study examined the characteristics of the driver and the driving environment in the occurrence of rollover crashes of passenger cars and light trucks. In this study, driver age and gender, road geometric design, road surface conditions, and weather conditions showed that light trucks have twice the risk of rollover crashes [22]. The intensity of crashes in rural thoroughfares was modeled considering the effect of unobserved heterogeneity and the driver's age. In this study, using a mixed logit model, heterogeneity was examined for three age groups, including 16–24 years, 25–65 years, and more than 65 years. In this research, variables including driver age group, driver gender, driving pattern, driving restrictions, number of passengers, vehicle type, road type, number of lanes, type, width of left shoulder, type and width of right shoulder, median type, median width, area topography, posted speed limit, road geometry, road longitudinal profile, section length, AADT, weather conditions, and road lighting conditions were considered in the analyses. The results showed that although the important variables in the occurrence of rollover crashes were different for these three age groups, restraint devices and horizontal curves were important for all age groups [23].

One study investigated the levels of different intensities of rollover crashes in the developing country of Iran. In this study, driver age, education, type of rollover crash, vehicle weight, ABS braking conditions, vehicle technical defect, road type classification, road conditions, road surface geometric design conditions, number of lanes, road posted speed limit, the season of the crash, and road lighting conditions at the time of the crash were examined. To this end, a random threshold random parameter hierarchical ordered probit model was employed to analyze the variables. The results showed that driver education, vehicle braking system (ABS), arches in the traffic lanes, and the allowed speed were the most important variables controlling this phenomenon [24]. Examining factors influencing the incidence of crashes in the United States with variables indeed encompasses vehicle passenger ejection, allowed speed, type of passing traffic, time of the crash, use of seat belts, road geometric design, traffic speed, road slope, towing, road lighting conditions, tire defects, road surface conditions, rollover crash location, vehicle age, being urban or rural crash, driver age, driver crash history, violation of previous driver speed, car airbag conditions, road surface type, day of the week, driver gender, driving history being poisoned, crash area, number of lanes, weather conditions, alcohol and drug use, and driver distraction. The results of generalized ordered logit modeling showed that vehicle passenger ejection, non-use of seat belt, speeding, exceeding the allowed speed, rolling over in the median and roadside, wavy road, the surface being black, and rural location are important variables in this modeling [25].

A study on 3-year rollover crash data in Namibia using mixed logit mode showed that weekends, open roadways, and minibuses were contributing factors that significantly increased rollover crash severity [26]. A study on single-vehicle run-off-road crashes of passenger cars, sports vehicles, and pickups found that seatbelt usage was the most important factor in dealing with these crashes. Also, it was concluded that passenger cars with a higher speed selection approach were in greater danger than other vehicles [27]. Factors affecting injury severity of single-vehicle rollover crashes were investigated to illustrate the heterogeneous impact, temporal stability, and aggregate shift using a random parameter logit model. The results showed an instability in model interpretation in time-space [28].

Many factors might be involved in rollover crash occurrences. As mentioned in previous studies, different variables in the occurrence of rollover crashes have been investigated. However, none of the studies examined the density of intersections by type of intersection, U-turns, roadside parking lots, entry and exit ramps, and traffic stream characteristics in high detail (e.g., standard deviation variables of vehicle speed violations, the presence or absence of speed cameras, and the steps of performing speed control cameras, and road surface deterioration levels). Moreover, the number of crashes at different intensity levels is not considered.

The present study tries to address this research gap and introduces a crash index, which is the composition of both crash intensity and frequencies.

3. Research Method

The research method employed in this paper is presented in Figure 1. As can be seen, the rollover crash hot spots were first identified based on mapping crash coordinates. Then, each of the studied paths was divided into homogeneous parts. Then, the number of crashes at different intensity levels and other independent variables and characteristics, including traffic stream and road characteristics, were collected. Then, the data were refined. After that, correlation analysis between each pair of variables was examined, and finally, rollover crash modeling was performed; important variables were identified, and their corresponding effects were evaluated.

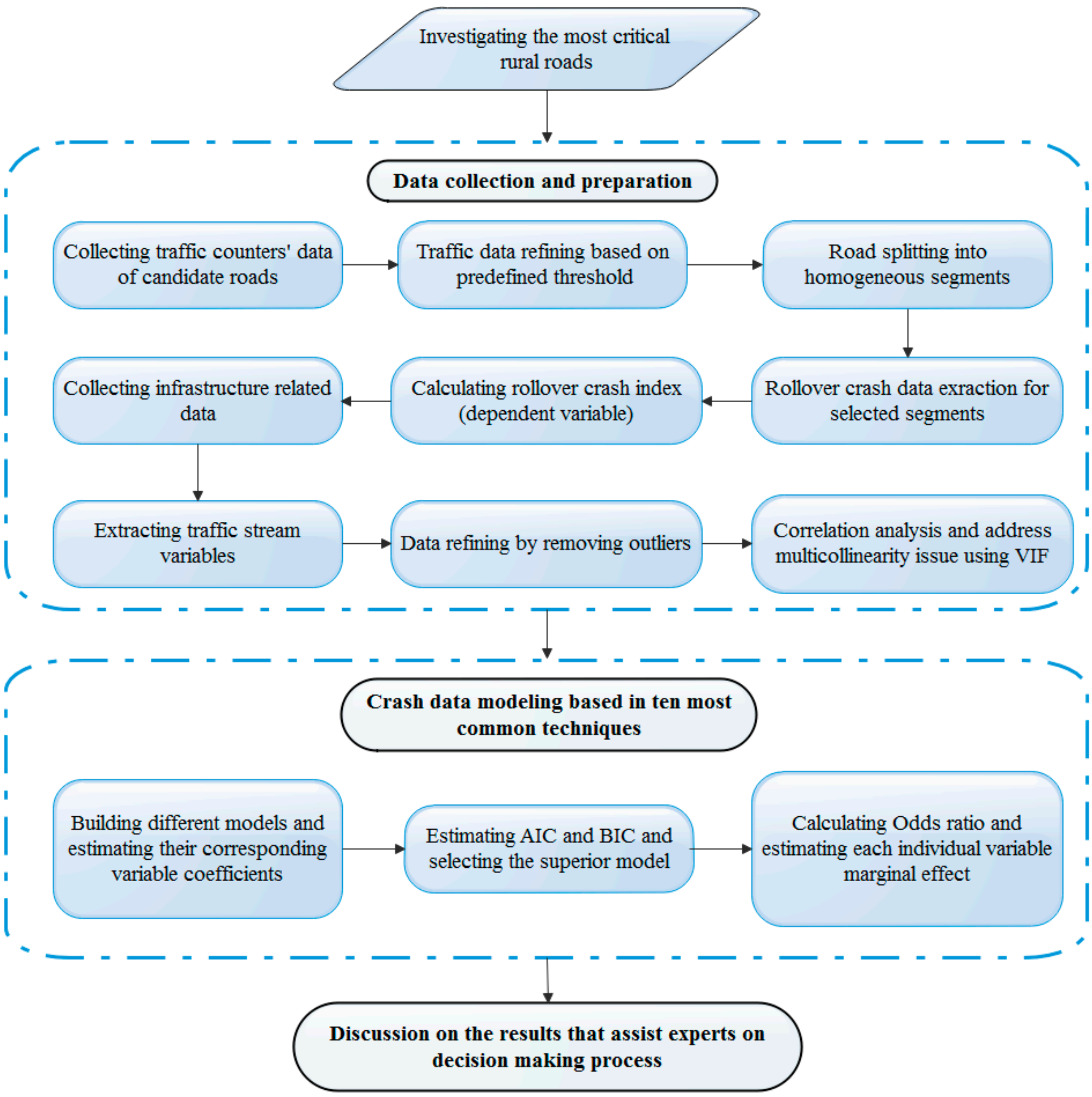

Figure 1. Flowchart of research methods.

3.1. Study Area

In this article, rural rollover crashes in Yazd province were studied. Notably, rollover crashes in Yazd province have a 54% share of total rural crashes. Figure 2 shows a diagram of the distribution of crashes in Yazd province. As can be seen, the crashes are concentrated on arterial roads, which are investigated in the following sections.

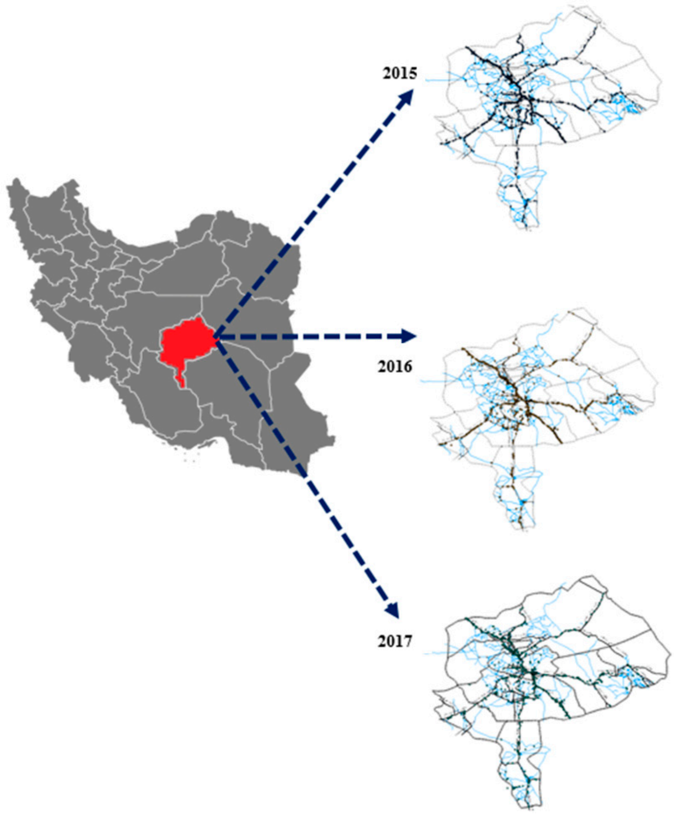

Figure 2. Spatial distribution of rolling over crashes in rural roads of Yazd province.

3.2. Data Collection

Due to the low number of crash frequencies of segments per day, week, and month, this study selected a seasonal data scale to investigate the effect of variables properly. Another important factor to consider when constructing the dependent variable is the intensity of crashes. In this study, the crash index (P) was defined to consider both frequency and intensity. Defined and approved by the Road Safety Commission of the Ministry of Roads and Urban Development of Iran, this index is also used to determine crash hotspots. Equation (1) shows the crash index (P):

$$P = 2.74\left(\frac{I}{A \times T}\right) \quad (1)$$

where P refers to the calculated index rounded to two decimal places; I represents the intensity factor (calculated by Equation (2)) in the period T in terms of years; and coefficient A indicates the performance coefficient of the desired segment. Here, A is 8 for the highway, 6 for the main arterial, 4 for the intra-arterial road, and 2 for the secondary roads.

$$I = x + 3y + 9z \quad (2)$$

where x is the number of property damage-only crashes; y is the number of injury crashes; and z is the number of seriously injured and fatal crashes.

In this study, candidate roads (Figure 2) were initially divided into homogeneous sections, and the corresponding explanatory variables for each section were collected. Notably, almost all sections were highways, with their A parameter in Equation (2) being 8, and some others were rural roads with an A parameter of 6, which is for the main roads. Their P index is calculated to be ready for crash modeling.

Traffic stream variables are extracted using the traffic counters (in the form of conductive loops along the roads). A traffic counter performance greater than 70% was used to find invalid data and remove them from the analysis. Road traffic experts at traffic centers report this threshold. In this paper, seasonal average daily traffic (SADT) stream variables were collected and involved in the study. Variables are 8-fold, namely, the logarithm of average daily traffic equivalent of a seasonal, percentage of heavy vehicles in traffic composition, the average speed of vehicles, the standard deviation of vehicle speed, the average percentage of vehicle violation, the standard deviation of vehicle violation percentage, the average percentage of violation of longitudinal distance, and standard deviation of percentage of longitudinal distance violation. To date, no research has considered the eight variables simultaneously.

Road infrastructure contributing factors are important to consider due to their effect on traffic stream characteristics by influencing vehicle maneuvers and the probability of vehicles colliding. In this regard, road geometry variables (i.e., shoulder width, road pavement width, and road pavement surface conditions) were field surveyed and collected by the Deputy of Highways of the General Directorate of Highways and Road Transportation.

In this paper, road surface quality was also taken into account. The pavement condition index (PCI) and international roughness index (IRI) are two factors explaining show road quality status significantly. Also, some studies employ statistics obtained from the friction of asphalt road surfaces using repetitive tests in the form of British pendulum number (BPN) [29]. However, this research aimed to expand the deterioration rate based on expert opinions in a 5-level structure, which is a well-known and acceptable approach not only in Iran but also in some other road transportation agencies; for instance, the deterioration rate methodology used in Ontario, Canada [30]. Table 1 shows these deterioration levels along with the desired deterioration density based on the road surface quality in terms of damage development. Data were obtained using field surveying yearly by the experts of the Deputy of Highways of the General Directorate of Highways and Road Transport of Yazd Province.

Table 1. Definition of deteriorations at different intensity levels and their corresponding densities.

Road Distress Based on Quality Index	**Distress Intensity (S_i)**				
	Very Low	**Low**	**Mediocre**	**High**	**Very High**
	Distress Density (D_i)				
Road Distress Based on Quantity Index	Low	Mediocre	Significant	Failure	Destructed
Percentage Distress Developed	<10	10–20	20–50	50–80	>80

Another class of the variables were assessed using Google Earth maps. These variables include the density of entry and exit ramps, un-channelized and channelized T-intersections, intersections or squares, interchanges, entry and exit roundabouts, and roadside parking. The above variables are of continuous numerical nature. Also, the modeling structure classified service areas along road segments as a binary variable (zeroes and ones). In this respect, speed cameras play a crucial role in affecting traffic stream characteristics through law enforcement, which affects driver behavior. Thus, speed camera data was collected from Iran's Ministry of Roads and Urban Development. Three different camera statuses were collected and considered as follows: (1) no camera or poles is installed in the desired segment; (2) the pole of the desired camera is installed, but the camera is not installed and is not turned on; and (3) camera pole is installed, and the camera is on. Each of these situations is classified as 1, 2, and 3. Table 2 tabulates the studied variables as well as their statistics.

Table 2. Studied variables involved in the study.

Variable	Abbreviation	Unit
Rollover crash index	RolooverCI	Number
Logarithm of seasonal average daily traffic	LSADT	Logarithm (number)
Heavy vehicle percentage in the traffic	HV	%
Left shoulder width	LeftShoulder	Meter
Pavement width	PavementWidth	Meter
Right shoulder width	RightShoulder	Meter
Pavement quality Very low = 1 Low = 2 Mean = 3 High = 4 Very high = 5	PaveQual	Categorical variable
Speed camera Not installed = 1 Only pole installed = 2 Speed camera installed = 3	SpeedCamera	Categorical variable
Rest area Without rest area = 0 With rest area = 1	RestArea	Categorical variable
Wxit ramp density	ExitRamp	Number per kilometer
Wntry ramp density	EntryRamp	Number per kilometer
Un-channelized T intersection density	UnChanalizedT	Number per kilometer
Channelized T intersection density	ChanalizedT	Number per kilometer
4-leg intersection/roundabout density	IntersectionRandabout	Number per kilometer
Exit U-turn density	ExitUTurn	Number per kilometer
Entry U-turn density	EntryUTurn	Number per kilometer
Interchange	Interchange	Number per kilometer
Roadside parking density	RoadSideParking	Number per kilometer
Mean speed	MeanSpeed	kph
Standard deviation of speed	STDSpeed	kph
Mean speed violation percentage	MeanSpeedVio	%
Standard deviation of speed violation percentage	STDSpeedVio	%
Mean headway violation percentage	MeanDistanceVio	%
Standard deviation of headway violation percentage	STDDistanceVio	%
Section ID	sectionid	-
Time quarter	timequa	-

It is worth mentioning that road infrastructure variables were all constant for the study period but varied among the studied segments. In contrast, traffic stream variables were yearly based and varied both in time and space.

3.3. Investigating the Correlation of Independent Variables

This study conducted a correlation analysis between each variable and other studied variables to deal with the problem of linear dependency. The variance inflation factor (VIF), known as the great index, is estimated for each variable. In statistics, the VIF is the ratio (quotient) of the variance of a parameter estimate when fitting a full model that includes other parameters to the variance of the parameter estimate if the model is fit with only the parameter on its own [31]. The correlation between variables is considered high, and the corresponding model would be unreliable when the estimated VIF is greater than 10 [32]. Table 3 shows the value of the VIF index calculated for the independent variables of the research.

Table 3. VIF index calculated by independent research variables.

Variable	VIF	1/VIF
Lsadt	10.16	0.098424
Hv	3.44	0.290798
Leftshoulder	7.86	0.127251
Pavementwidth	7.97	0.125530
Rightshoulderwidth	2.24	0.445516
Pavequal		
2	4.65	0.215136
3	5.97	0.167565
4	3.49	0.286820
Speedcamera		
2	1.97	0.506331
3	1.71	0.585262
L. RestArea	4.61	0.217083
Exitramp	124.50	0.008032
Entryramp	123.73	0.008082
UnchanalizedT	3.71	0.269448
Chanalizedt	1.61	0.622009
Intersection	4.81	0.208041
Exituturn	8.92	0.112112
Entryuturn	11.49	0.087010
Interchange	3.90	0.256301
Roadsideparking	3.12	0.320127
Meanspeed	4.88	0.204933
Meanspeedvio	5.43	0.184038
Meandistanvio	2.03	0.491606
Stdspeed	2.13	0.468553
Stdspeedvio	2.45	0.408484
Stddistancvio	1.44	0.695103
Mean VIF	13.78	

It can be inferred from Table 4 that average flow logarithm, entry ramp density, exit ramp density, and entry U-turn density have high VIF values. The average VIF value of the independent variables is also above 10.

As mentioned earlier, the entry and exit ramps were very close to each other in terms of descriptive statistics. For this purpose, the first question is whether these two variables have a significant linear mutual independence. Due to the similar conditions of the two variables of entry and exit U-turns, the same process was performed. Tables 4 and 5 show the results of calculated VIF indices between the mentioned variables.

Table 4. VIF index calculations between two variables of entry and exit ramps density.

Variable	VIF	SQRT VIF	Tolerance	R-Squared
Exitramp	44.31	6.66	0.0226	0.9774
Entryramp	44.31	6.66	0.0226	0.9774
Mean VIF	44.31			

Table 5. VIF index calculations between the two variables of entry and exit U-turns density.

Variable	VIF	SQRT VIF	Tolerance	R-Squared
Exituturn	4.81	2.19	0.2080	0.7920
Entryuturn	4.81	2.19	0.2080	0.7920
Mean VIF	4.81			

Based on the significant relationship between the two variables depicted in Tables 4 and 5, two suggestions might be useful to address the correlation issue: (1) to delete variables with a high VIF value; and (2) to make compound variables [33]. In this study, due to having a better description of variable effects, their integration was formed by multiplying them (Table 6). This approach was taken due to similar descriptive statistics of each pair of variables. On the other hand, the variables entryramp and exitramp had the same descriptive statistics. This issue also holds for the variables entryuturn and exituturn. The major feature of this integration is that after the final analysis and measuring odds ratio, their interpretation would be rather simple since they have the same statistical patterns. Furthermore, if the compound variable has a unit amount of effect on a dependent variable, each non-compound variable will have $\sqrt{\text{a}}$ impact.

Table 6. Integrated independent variables (for variables with high VIF value).

Number	Old Variables	New Compound Variables	New Variable Abbreviation
1	exitramp, entryramp	exitramp × entryramp	exitentryramp
2	exituturn, entryuturn	exitutrun × entryuturn	exitentryuturn

Now, the value of the VIF index is calculated based on the newly compounded variables and the previous independent variables. According to the results of Table 7, it is observed that both the VIF of all independent variables and the averaged VIF value are less than 10. Thus, the variables in Table 7 are used to construct and evaluate subsequent models.

After addressing the correlation problem, outliers were removed before analysis. In this regard, data that were in the range of 95% of the values of each variable were included in the calculations. Table 8 shows the descriptive values of the variables after refining and deleting outliers. It is worth mentioning that the dependent variable was found to be the overdispersion phenomenon, indicating that studied sections had varied numbers of rollover crashes from very low frequency to high frequency. This was also true for independent variables based on mean and STD parameters. For example, the variables HV, ExitEntryRamp, UnchanalizedT, and ChanalizedT were greatly different for the studied sections.

Table 7. Estimated VIF values of variables (considering new variables are involved).

Variable	VIF	1/VIF
Lsadt	8.59	0.116391
Hv	3.40	0.294088
Leftshoulder	5.06	0.197522
Pavementwidth	6.30	0.158700
Rightshoulderwidth	2.07	0.483303
Pavequal		
2	4.28	0.233601
3	5.93	0.168572
4	2.92	0.342367
Speedcamera		
2	1.99	0.501978
3	1.63	0.613948
L. RestArea	3.99	0.250553
Exitentryramp	3.65	0.273622
UnchanalizedT	3.55	0.281992
Chanalizedt	1.63	0.614226
Intersection	2.93	0.341746
Exitentryuturn	4.81	0.207853
Interchange	3.52	0.284079
Roadsideparking	2.59	0.386471
Meanspeed	4.11	0.243014
Meanspeedvio	4.49	0.222481
Meandistanvio	1.94	0.514634
Stdspeed	2.11	0.473212
Stdspeedvio	2.46	0.406674
Stddistancvio	1.44	0.696405
Mean VIF	3.56	

Table 8. Descriptive statistics of variables after removing outliers.

Variable	Obs	Mean	Dev. Std	Min	Max
rolooverci	261	10.77333	11.75208	0	59.26
LSADT	261	3.584538	0.3941255	2.8456	4.21075
HV	261	41.44977	14.19489	11.85	67.87
LeftShoulder	261	1.418506	0.5574679	0	2.25
PavementWidth	261	7.049809	1.046004	3.65	8
RightSoulder	261	1.742337	0.227737	1.15	2.15
Pavequal					
2	261	0.1494253	0.3571921	0	1
3	261	0.7049808	0.4569276	0	1
4	261	0.0766284	0.2665119	0	1
Speedcamera					
2	261	0.1494253	0.3571921	0	1
3	261	0.2988506	0.4586337	0	1
L. RestArea	261	0.137931	0.3454901	0	1
ExitEntryRamp	261	0.1037173	0.2139524	0.000356	0.9384766
UnchanalizedT	261	0.249513	0.2178584	0.030303	0.8043478
ChanalizedT	261	0.0157404	0.0217447	0	0.0869565
Inter~Randabout	261	0.024356	0.027621	0	0.09375
ExitEntryUTurn	261	0.0288343	0.032202	0	0.1171875
Interchange	261	0.0324525	0.0543085	0	0.1818182
RoadsideParking	261	0.0703401	0.584383	0	0.2727273

Table 8. *Cont.*

Variable	Obs	Mean	Dev. Std	Min	Max
MeanSpeed	261	85.29318	6.266493	67.71	94.48
MeanSpeedVio	261	15.83398	9.101875	1.71	40.74
MeanDistanceVio	261	6.645249	3.000259	1.9	15.95
STDSpeed	261	3.241954	1.86318	0.92	9.86
STDSpeedVio	261	4.024061	2.389754	0.69	16.58
STDDistanceVio	261	2.425019	1.394873	0.44	6.52

3.4. Modeling Crashes and Calculating Marginal Effects

Safety expert practitioners employ many modeling techniques to create a relationship between dependent and independent variables [34–40]. The present study used the 10 most common types, including Poisson, negative binomial (NB), zero-truncated Poisson (ZTP), zero-truncated negative binomial (ZTNB), zero-inflated Poisson (ZIP), zero-inflated negative binomial (ZINB), fixed-effect Poisson (FEP), fixed-effect negative binomial (FENB), random-effect Poisson (REP), and random-effect negative binomial (RENB). In this paper, STATA release 15 was used to model crash data [41]. Table 9 shows the coefficients of variables extracted by different models. As can be noticed, regardless of constructive models, the negative binomial-based models outperformed Poisson-based ones in terms of AIC and BIC values as a measure of goodness of fit (GOF). Also, there seems that model formulation greatly affect positive or negative impact of independent variables on the dependent variable as there are contrasting effects of explanatory variables on dependent variable in terms of measure of effectiveness (i.e., regression coefficient) and also in terms of positive and variable sign. It can also be found that the FENB model outperformed other competing models. Since the GOF values of the FENB model were significantly lower than other competing models, it was selected for further study.

Table 9. The result of crash modeling based on different methods.

	Regression Coefficients											
	Poisson	NB2	ZTP	ZTNB	ZIP		ZINB		REPoisson	RENB	FEPoisson	FENB
Specific condition for y*	no	no	no	no	If y = 0	If y > 0	If y = 0	If y > 0	no	no	no	no
LSADT	0.4194	0.6944	0.2973	−0.1659	−0.299	−3.7305	−0.16	4.7531	−0.5165	0.8945	1.0349	0.2848
HV	−0.0065	−0.0081	−0.0155	−0.0146	−0.0155	−0.0681	−0.0136	−0.0868	−0.0057	0.0129	−0.00666	0.0151
LeftShoulder	−0.0541	−0.1859	−0.0678	−0.1562	−0.0685	3.2304	−0.1848	4.7193	0.0137	−0.1102	−59.525	0.2289
PavementWidth	0.0112	0.0279	0.1906	0.2333	0.1925	−0.4843	0.2684	−0.487	0.0227	−0.1613	7.14151	−0.1432
RightSoulder	0.1205	−0.3188	−0.0021	−0.195	−0.0025	−3.8444	−0.2088	−5.6225	−0.8394	0.508	−49.7167	1.711
Pavequal												
2	−0.8112	−0.9584	−1.0337	−1.18	−1.034	19.490	−1.1849	18.142	−0.7158	−0.2761	−0.70788	−0.3549
3	−0.7470	−1.1369	−0.7102	−0.8177	−0.711	20.577	−0.861	19.333	−0.9448	−0.6472	−0.96244	−0.8155
4	−0.5144	−0.7655	−0.6808	−0.7332	−0.6795	18.238	−0.7165	16.834	−0.3919	−0.1121	−0.55832	−0.4768
SpeedCamera												
2	0.2960	0.1994	0.1887	0.1028	0.1882	−1.2509	0.0677	−2.6434	0.3238	0.3747	0.329141	0.3687
3	0.0207	0.1465	−0.0269	−0.1082	−0.0273	−0.6809	−0.1098	−0.9602	0.1089	−0.0575	0.119412	−0.0479
RestArea	−0.0617	−0.0226	−0.1626		−0.1629	−0.2881	−0.1362	−0.2245	−0.0997	0.0971	−0.03292	0.1851
ExitEntryRamp	0.4956	0.3124	0.4569	−0.1484	0.459	−8.8442	0.4004	−4.1508	0.0542	0.0162	0.20918	0.1611
UnchanalizedT	−0.5355	−0.562	−0.7726	0.3158	−0.7715	0.5865	−0.7984	2.3934	−0.7419	0.2912	0.000	0.8415
ChanalizedT	0.9486	3.7107	−0.6115	−0.8272	−0.6208	−37.203	0.1653	−47.665	−3.8965	3.3269	0.000	−4.4702
Inter~Randabout	−5.4289	−6.313	−1.5593	0.2699	−1.5467	5.8912	0.7872	2.9129	−2.204	−9.0754	0.000	−16.004
ExitEntryUTurn	8.5641	14.132	−0.7234	0.0911	−0.7377	−33.657	−0.379	−76.876	11.387	19.5266	9.139741	15.505
Interchange	1.1166	−0.3857	0.8952	0.3441	0.8966	−25.04	−0.0809	−25.789	4.9418	2.472	0.000	7.8181
RoadsideParking	−3.5804	−4.4694	−2.7945	−0.2171	−2.7895	30.514	−3.4199	39.103	0.0821	−4.4145	0.000	−8.6664
MeanSpeed	0.0178	0.0314	0.0138	−3.4991	0.0138	−0.085	0.017	−0.152	0.0126	0.0247	0.007048	0.0054
MeanSpeedVio	−0.0212	−0.0323	−0.0172	0.0176	−0.0172	0.0965	−0.0178	0.1528	−0.0076	−0.0298	−0.00309	−0.0218
MeanDistanceVio	−0.0291	−0.0329	−0.0063	−0.0177	−0.0064	0.0689	−0.0032	0.0513	−0.0346	−0.0487	−0.02582	−0.0395
STDSpeed	−0.0191	−0.0052	−0.0661	0.001	−0.0671	−0.322	−0.0719	−0.7212	−0.0324	−0.0005	−0.03567	−0.0179
STDSpeedVio	0.0984	0.1085	0.0789	−0.0512	0.0794	−0.0855	0.0858	0.0778	0.0925	0.089	0.09662	0.0999
STDDistanceVio	−0.0817	−0.0711	−0.014	0.0733	−0.014	0.3175	−0.0272	0.4082	−0.0142	−0.0348	−0.01301	−0.0027
Constant	0.4949	−0.4508	3.275	−0.0277	3.2668	5.8412	2.5794	17.121	5.1996	−4.8917	-	−3.4417
alpha (α)	-	1.4708	-	−0.3956	-		0.3954		0.8260	-	-	-
AIC	3421.0	1752.2	2029.9	1381.4	2252.4		1592.9		2733.4	1661.9	2343.7	1305.7
BIC	3510.1	1844.8	2111.2	1466.0	2430.6		1774.7		2826.1	1758.2	2410.5	1393.6

Note that y* hear is the dependent variable.

This research measured the effect of 23 independent variables on the rollover crash index as a dependent variable using partial derivative calculations. The partial derivative of the dependent variable relative to the desired independent variable is calculated, and the amount of change in output (dependent variable) is obtained per unit change in the desired variable, given that all other variables are set to their mean values. The obtained results are called the marginal effect. For instance, the variable HV shows that one unit increase in heavy vehicle percentage in the traffic stream would change the rollover crash index by 0.015, with all other variables fixed on their average. Table 10 presents the results of partial derivative calculations.

Table 10. Results of partial derivative calculations of the effects of independent variables on the dependent variable (rollover crash index).

	dy/dx	**std. Err**	***p* > |z|**
LSADT	0.285	0.713	0.689
HV	0.015	0.010	0.138
LeftShoulder	0.223	0.466	0.623
PavementWidth	−0.143	0.234	0.540
RightSoulder	1.711	0.785	0.029
Pavequal			
2	−0.355	0.394	0.368
3	−0.815	0.431	−1.058
4	−0.477	0.482	−0.323
Speedcamera			
2	0.369	0.239	0.123
3	−0.048	0.181	0.791
RestArea	0.185	0.320	0.563
ExitEntryRamp	0.161	0.596	0.787
UnchanalizedT	0.841	0.960	0.381
ChanalizedT	−4.470	7.209	0.535
Inter~Randabout	−16.003	8.342	0.055
ExitEntryUTurn	15.505	5.666	0.006
Interchange	7.818	3.604	0.030
RoadsideParking	−8.666	3.265	0.008
MeanSpeed	0.005	0.025	0.833
MeanSpeedVio	−0.022	0.018	0.220
MeanDistanceVio	−0.039	0.032	0.214
STDSpeed	−0.018	0.045	0.690
STDSpeedVio	0.099	0.038	0.008
STDDistanceVio	−0.003	0.054	0.960

4. Discussion

In this section, the results of marginal effects are discussed for some of the important variables from Table 10. The result showed that a 1 unit increase in the LSADT variable increases the percentage of rollover crash risk by 0.285. In other words, if the average seasonal daily traffic increases by 10%, the risk of rollover crashes increases by 0.11%.

Studying the effect of the percentage of heavy vehicles indicates that with each 1% increase in heavy vehicle traffic, the risk of rollover crashes increases by an average of 0.14%. Based on Table 8, one can realize that crossing vehicles were mostly passenger cars since truck share in traffic streams was, on average, 42% of total vehicles. Therefore, if heavy vehicles are encountered, they will be unable to control them, leading to rolling over them.

The study's results on the effect of speed cameras showed the consistent effect of turning on speed cameras in reducing the risk of rollover crashes. Therefore, a portion of the rollover crashes is reduced through vehicle speed management. The standard deviation of vehicle speed was determined, and it was found that increasing it by 1 unit will reduce the risk of rollover crashes by 0.17%. Since speed cameras reduced the risk of rollover crashes and the average traffic stream speeds were close to each other, it is possible to increase the standard speed deviation by 1 unit at low-medium speeds. These conditions lead to lower traffic stream speeds, thereby lowering the risk of vehicle rollover.

Based on the obtained results, a 1% increase in vehicle speed violations reduces the risk of a rollover crash by 0.2%, considering the high traffic flow on rural thoroughfares. The probability of fatigue and drowsiness is lower when the speed of the vehicles increases and, therefore, the probability of rollover decreases. In addition, a 1-unit increase in the standard deviation of the percentage of vehicle speed violations causes an increase of approximately 0.93% in the rollover crash risk index. The underlying reason is that the percentage of vehicle violations indicates the number of vehicles relative to the total number of vehicles at speeds above the speed limit. Hence, an increase in the standard deviation in the percentage of vehicle violations means that a percentage of vehicles are traveling much faster than the posted speed limit, which can be dangerous and cause rollover. With a 1% increase in the percentage of gap violations, the index of the risk of rollover crashes decreases by 0.37%. Increasing the percentage of gap violations means that vehicles are close to each other in traffic, reducing the possibility of vehicle rollover. The standard deviation of gap violence depicts that with a 1 unit increase in the standard deviation, the possibility of rollover crash risk index decreases by 0.03%. In other words, the standard deviation of the percentage of violation of the vehicle gaps seems to have a small effect on the rollover crash index risk.

Research has shown that since installing speed cameras does not have a psychological effect, it does not change the driver's behavior to reduce rollover crashes, although it increased by 3.42% for some reason. In contrast, turning on the speed cameras can reduce the risk of rollover crashes by 0.44%.

Increasing each unit of left shoulder width by average increases the risk of a rollover crash by 2.13%. This increment is because an increase in road shoulder width might increase road level; as a result, drivers try to select a higher speed while driving, which directly increases the chance of studied crashes. Also, every 1 unit increase in the width of the road pavement reduces the risk index of rollover crashes by an average of 1.33%. Increasing the width of the right paved shoulder causes an average of a 15.89% increase in the rollover risk index.

It can also be inferred from the results that reducing the quality level of the road surface from the high-quality level relative to the low deterioration causes an average reduction of 3.3% in the risk of rollover crashes. In addition, more road surface damage reduces the average risk of rollover crashes by an average of 7.57% (average deterioration level compared to low deterioration level). However, since further road breakdowns will be inversely related to the risk of rollover crashes, Level 4 deterioration compared to Level 3 increases the chance of rollover crashes by 3.14%. This result indicates that from one level of deterioration (in this study, Level 3 road surface deterioration), more road surface deterioration increases the risk of rollover crashes compared to the previous level.

According to the studies performed, it is observed that through binary (0 and 1) classification of the road segments without service areas (coded zero) and with a service area (code 1), segments without service areas had, on average, about 1.72% less rollover crash risk index. However, the main causes of rollover crashes are driver fatigue and drowsiness, which are other factors that may play a role in the rollover of vehicles. Secondly, better options, such as the construction of roadside parking lots, can be used and might be a better option in dealing with the problem of taking short-term rest.

Increasing the density of the entry and exit ramps by their average (which is more likely than increasing the density by 1 unit) increases the risk of rollover crashes by 0.16%.

Descriptive studies showed that the mean values of the standard deviation of the entry and exit ramps are close to each other, but their minimum and maximum values are the same. This implies that the density of the entry and exit ramps is the same at the level of the main and highway arterial road network. Therefore, to describe their importance, each of the entry and exit ramps variable can be defined as $D = x/l$, in which x is the number of non-normalized entry and exit ramps (not divided by the length of the axis). According to this definition, 1 unit increase in the density of entry and exit ramps (corresponding to D2) is equivalent to a 1.5% increase in the average rollover risk index. Thus, a 1 unit increase in the density of each variable means a 1.22% increase in the rollover crash risk index. In a more realistic view, the average increase in the density of each entry and exit access ramp corresponds to a 0.32% increase in the risk of rollover crashes.

A 1-unit increase in the density of un-channelized access roads can increase rollover crash risk by 7.81%. In contrast, the results show that channelizing the access roads reduces the risk of rollover crashes. Accordingly, channelizing the flow regulates the flow of traffic and reduces the possibility of a diversion of direct flow and thus reduces its rollover, especially at the entrances of cities.

If the field density increases within the allowable range, the index of rollover crashes will increase by 148.59%. This issue is attributed to the calming of the passageway because of the implementation of these intersections and the prevention of rollover crashes.

Examining U-turns at intersections indicates that the higher their density, the higher the index of rollover crashes. Similarly, for entry and exit ramps, given that the average values and the minimum and maximum densities of entry and exit U-turns are close to each other, they can be considered close to each other. As a result, increasing the density of U-turns in the road network will increase the rollover crash index by 143.96%. Considering that the average values of the entry and exit U-turns are equal to 0.150 and 0.156, respectively, it can be concluded that the entry and exit U-turns have an average effect of 1.80 and 1.87, respectively. Since there will be a percentage increase in the crash risk index, care should be taken when choosing the number of U-turns and their location in the road network.

Increasing the density of interchanges relative to their average value increases the risk of rollover crashes by 2.35%. Further field studies showed that the main reason for this increase is the carelessness of drivers while crossing the above intersections.

Roadside parking lots were important in reducing rollover crashes. Considering the average density of these parking lots (equal to 0.0703), it can be concluded that roadside parking lots have led to a 5.66% reduction in the risk of rolling-over crashes.

Thus, the novelty of this study lies in its simultaneous investigation of traffic stream and road-related variables influencing single-vehicle rollover crashes, including under-explored factors such as T-intersection density, U-turns, roadside parking lots, and road surface deterioration. By introducing a crash index that combines crash frequency and intensity and employing advanced modeling techniques like the fixed-effect negative binomial (FENB) model, this study identifies key predictors and highlights the nuanced impacts of speed variation and road conditions. These findings offer valuable insights and a comprehensive framework for addressing rollover crashes in developing regions.

5. Conclusions

This paper aimed to study rollover crashes on rural roads. To achieve this, the rural roads in the study area were divided into homogeneous segments with similar road and traffic stream characteristics. Data for these segments were collected through field observations and extracted from the database, which included independent variables and three years of statistics on the number and severity of rollover crashes. To simultaneously analyze the frequency and intensity of crashes, a crash index was introduced and used as the dependent variable. To mitigate the correlation effects among independent variables, the variance inflation factor (VIF) technique was applied. Different crash modeling techniques were then evaluated and compared using goodness of fit (GOF) indicators, including the Akaike information criterion (AIC) and Bayesian information criterion (BIC). The findings revealed that the fixed-effect negative binomial (FENB) model outperformed the other models. The analysis identified the most significant variables influencing rollover crashes. These included the density of entry and exit U-turns, the density of channelized T-intersections, the density of roadside parking lots, and the width of the right shoulder of the road, which exhibited the highest rates of change per unit variation of the rollover crash index. Additionally, the standard deviation of mean speed and speed violations were found to have a greater impact than their absolute values. Interestingly, the results suggested that minor road surface deterioration slightly reduces the likelihood of vehicle rollovers compared to normal road conditions, likely due to altered driver behavior. However, as road surface deterioration becomes more severe, the probability of vehicle rollovers increases. Overall, these findings can assist traffic safety practitioners in designing effective strategies to mitigate rollover crashes. The primary limitation of this study was the availability of only one set of traffic counters for each studied segment. Future research should employ more sophisticated models and interpret variables in greater detail to address issues of temporal and spatial instability.

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References

1. NHTSA. *2020 Fatality Data Show Increased Traffic Fatalities During Pandemic*; National Highway Traffic Safety Administration: Washington, DC, USA, 2021.
2. El-Menyar, A.; Al-Thani, H.; Tuma, M.; Parchani, A.; Abdulrahman, H.; Peralta, R.; Asim, M.; Zarour, A.; Latifi, R. Epidemiology, causes and prevention of car rollover crashes with ejection. *Ann. Med. Health Sci. Res.* **2014**, *4*, 495–502. [CrossRef] [PubMed]
3. NHTSA. Early estimates of motor vehicle traffic fatalities and fatality rate by sub-categories in 2020. In *Crash•Stats Brief Statistical Summary*; National Highway Traffic Safety Administration: Washington, DC, USA, 2021.
4. Frechede, B.; Mcintosh, A.S.; Grzebieta, R.; Bambach, M.R. Characteristics of single vehicle rollover fatalities in three Australian states (2000–2007). *Accid. Anal. Prev.* **2011**, *43*, 804–812. [CrossRef] [PubMed]
5. Funk, J.R.; Cormier, J.M.; Manoogian, S.J. Comparison of risk factors for cervical spine, head, serious, and fatal injury in rollover crashes. *Accid. Anal. Prev.* **2012**, *45*, 67–74. [CrossRef]
6. Gloeckner, D.C.; Moore, T.L.; Steffey, D.; Bare, C.; Corrigan, C.F. Implications of vehicle roll direction on occupant ejection and injury risk. Annual proceedings. *Assoc. Adv. Automot. Med.* **2006**, *50*, 155–170.
7. Padmanaban, J.; Moffatt, E.A.; Marth, D.R. Factors Influencing the Likelihood of Fatality and Serious/Fatal Injury in Single-Vehicle Rollover Crashes. In *SAE 2005 World Congress & Exhibition*; Society of Automotive Engineers (SAE): Detroit, MI, USA, 2005.
8. Parenteau, C.S.; Shah, M. *Driver Injuries in US Single-Event Rollovers*; Paper 2000-01-0633; Society of Automotive Engineers: Warrendale, PA, USA, 2000.
9. Parker, D.D.; Ray, R.M.; Moore, T.L.A.; Keefer, R.E. Rollover Severity and Occupant Protection—A Review of NASS/CDS Data. *SAE Trans.* **2007**, *116*, 464–471.
10. Viano, D.C.; Parenteau, C.S.; Edwards, M.L. Edwards, Rollover injury: Effects of near- and far-seating position, belt use, and number of quarter rolls. *Traffic Inj. Prev.* **2007**, *8*, 382–392. [CrossRef] [PubMed]

11. Brumbelow, M.L.; Teoh, E.R.; Zuby, D.S.; McCartt, A.T. Roof Strength and Injury Risk in Rollover Crashes. *Traffic Inj. Prev.* **2009**, *10*, 252–265. [CrossRef] [PubMed]
12. WHO. *Global Status Report on Road Safety*; World Health Organization: Geneva, Switzerland, 2018.
13. Alrejjal, A.; Farid, A.; Ksaibati, K. A correlated random parameters approach to investigate large truck rollover crashes on mountainous interstates. *Accid. Anal. Prev.* **2021**, *159*, 106233. [CrossRef] [PubMed]
14. Alrejjal, A.; Farid, A.; Ksaibati, K. Investigating factors influencing rollover crash risk on mountainous interstates. *J. Saf. Res.* **2022**, *80*, 391–398. [CrossRef]
15. Alrejjal, A.; Ksaibati, K. Impact of mountainous interstate alignments and truck configurations on rollover propensity. *J. Saf. Res.* **2022**, *80*, 160–174. [CrossRef] [PubMed]
16. Alrejjal, A.; Ksaibati, K. Impact of crosswinds and truck weight on rollover propensity when negotiating combined curves. *Int. J. Transp. Sci. Technol.* **2022**, *12*, 86–102. [CrossRef]
17. Anarkooli, A.J.; Hosseinpour, M.; Kardar, A. Investigation of factors affecting the injury severity of single-vehicle rollover crashes: A random-effects generalized ordered probit model. *Accid. Anal. Prev.* **2017**, *106*, 399–410. [CrossRef] [PubMed]
18. Azimi, G.; Rahimi, A.; Asgari, H.; Jin, X. Severity analysis for large truck rollover crashes using a random parameter ordered logit model. *Accid. Anal. Prev.* **2020**, *135*, 105355. [CrossRef] [PubMed]
19. Chen, S.R.; Cai, C.S.; Wolshon, B. From Normal Operation to Evacuation: Single-Vehicle Safety under Adverse Weather, Topographic, and Operational Conditions. *Nat. Hazards Rev.* **2009**, *10*, 68–76. [CrossRef]
20. Chen, C.; Zhang, G.; Qian, Z.; Tarefder, R.A.; Tian, Z. Investigating driver injury severity patterns in rollover crashes using support vector machine models. *Accid. Anal. Prev.* **2016**, *90*, 128–139. [CrossRef] [PubMed]
21. Conroy, C.; Hoyt, D.B.; Eastman, A.B.; Erwin, S.; Pacyna, S.; Holbrook, T.L.; Vaughan, T.; Sise, M.; Kennedy, F.; Velky, T. Rollover crashes: Predicting serious injury based on occupant, vehicle, and crash characteristics. *Accid. Anal. Prev.* **2006**, *38*, 835–842. [CrossRef] [PubMed]
22. Farmer, C.M.; Lund, A.K. Rollover risk of cars and light trucks after accounting for driver and environmental factors. *Accid. Anal. Prev.* **2002**, *34*, 163–173. [CrossRef]
23. Gong, L.; Fan, W. Modeling single-vehicle run-off-road crash severity in rural areas: Accounting for unobserved heterogeneity and age difference. *Accid. Anal. Prev.* **2017**, *101*, 124–134. [CrossRef] [PubMed]
24. Rahimi, E.; Shamshiripour, A.; Samimi, A.; Mohammadian, A. Investigating the injury severity of single-vehicle truck crashes in a developing country. *Accid. Anal. Prev.* **2020**, *137*, 105444. [CrossRef]
25. Khan, I.U.; Vachal, K. Factors affecting injury severity of single-vehicle rollover crashes in the United States. *Traffic Inj. Prev.* **2020**, *21*, 66–71. [CrossRef] [PubMed]
26. Bullard, C.; Jones, S.; Adanu, E.K.; Liu, J. Crash severity analysis of single-vehicle rollover crashes in Namibia: A mixed logit approach. *IATSS Res.* **2023**, *47*, 318–324. [CrossRef]
27. Khan, I.U.; Motuba, D.; Vachal, K. Investigating factors affecting injury severity of single-vehicle run-off-road crashes. *Accid. Anal. Prev.* **2024**, *208*, 107786. [CrossRef]
28. Ren, Q.; Xu, M.; Yan, X. An investigation of heterogeneous impact, temporal stability, and aggregate shift in factors affecting the driver injury severity in single-vehicle rollover crashes. *Accid. Anal. Prev.* **2024**, *200*, 107562. [CrossRef] [PubMed]
29. Baskara, S.N.; Yaacob, H.; Hainin, M.R.; Hassan, S.A. Accident Due to Pavement Condition Â€" A Review. *J. Teknol.* **2016**, *78*, 75–82. [CrossRef]
30. Jannat, G.; Tighe, S. Performance based Evaluation of overall Pavement Condition Indices for Ontario Highway Systems. In Proceedings of the Transportation Association of Canada Conference and Exhibition. 2015. (2 vols) Getting You There Safely, Charlottetown, PE, Canada, 27–30 September 2015.
31. Allison, P.D. *Multiple Regression: A Primer*; Pine Forge Press: Thousand Oaks, CA, USA, 1999.
32. Williams, R. Multicollinearity. 2015. Available online: https://www3.nd.edu/~rwilliam/stats2/l11.pdf (accessed on 4 December 2024).
33. Hosseinlou, M.H.; Mahdavi, A.; Nooghabi, M.J. Validation of the influencing factors associated with traffic violations and crashes on freeways of developing countries: A case study of Iran. *Accid. Anal. Prev.* **2018**, *121*, 358–366. [CrossRef] [PubMed]
34. Hall, T.; Tarko, A.P. Adequacy of negative binomial models for managing safety on rural local roads. *Accid. Anal. Prev.* **2019**, *128*, 148–158. [CrossRef]
35. Jiang, X.; Abdel-Aty, M.; Alamili, S. Application of Poisson random effect models for highway network screening. *Accid. Anal. Prev.* **2014**, *63*, 74–82. [CrossRef]
36. Khattak, M.W.; Pirdavani, A.; De Winne, P.; Brijs, T.; De Backer, H. Estimation of safety performance functions for urban intersections using various functional forms of the negative binomial regression model and a generalized Poisson regression model. *Accid. Anal. Prev.* **2021**, *151*, 105964. [CrossRef] [PubMed]
37. Liu, X.; Saat, M.R.; Qin, X.; Barkan, C.P. Analysis of U.S. freight-train derailment severity using zero-truncated negative binomial regression and quantile regression. *Accid. Anal. Prev.* **2013**, *59*, 87–93. [CrossRef]

38. Mathew, S.; Pulugurtha, S.S.; Duvvuri, S. Exploring the effect of road network, demographic, and land use characteristics on teen crash frequency using geographically weighted negative binomial regression. *Accid. Anal. Prev.* **2022**, *168*, 106615. [CrossRef] [PubMed]
39. Saha, D.; Alluri, P.; Dumbaugh, E.; Gan, A. Application of the Poisson-Tweedie distribution in analyzing crash frequency data. *Accid. Anal. Prev.* **2020**, *137*, 105456. [CrossRef] [PubMed]
40. Rusli, R.; Haque, M.; Afghari, A.P.; King, M. Applying a random parameters Negative Binomial Lindley model to examine multi-vehicle crashes along rural mountainous highways in Malaysia. *Accid. Anal. Prev.* **2018**, *119*, 80–90. [CrossRef] [PubMed]
41. StataCorp. *Stata Statistical Software: Release 15*; Statistical Software; StataCorp LLC: College Station, TX, USA, 2017.