ASSOCIAZIONE ITALIANA per l'INGEGNERIA del TRAFFICO e dei TRASPORTI

Giordano Editore

Modeling Driver Injury Severity in Single and Two-vehicle Accidents using Binary Logistic Regression with Interaction

Neero Gumsar Sorum[1*] and Dibyendu Pal[2]

[1] Department of Civil Engineering, North Eastern Regional Institute of Science & Technology, Nirjuli-791109, Arunachal Pradesh, India, E-mail: neerogsorum@gmail.com, https://orcid.org/0000-0001-8894-680X (Corresponding author)*

[2]Department of Civil Engineering, North Eastern Regional Institute of Science & Technology, Nirjuli-791109, Arunachal Pradesh, India, E-mail: pal_here00@yahoo.co.in, https://orcid.org/0000-0002-6419-4639

Abstract

This paper examines the factors influencing driver injury severity (DIS) using the binary logistic regression (BLR) model, analyzing data from 715 and 1629 single and two-vehicle accidents in Shillong and Imphal cities, India, from 2011-2020. The study found that in Shillong, 18 out of 22 categorical variables were significantly associated with DIS, including age (18-24, 25-40, and above 40), gender (female), vehicle type (Light motor vehicle: LMV, heavy motor vehicle: HMV), accident time (6AM-12PM, 12PM-6PM, 6PM-12AM), causes (over-speeding, out-of-control, rush driving, violation of road safety rules, and other) and accident nature (side-collision, rear-collision, overturn, and other). For Imphal, 11 variables were significant, including age (25-40, above 40), vehicle type (LMV), time (6AM-12PM, 12PM-6PM, 6PM-12AM), causes (rush driving, narrow roads), and accident nature (side-collision, rear-collision, overturn). Interaction models revealed 47 two-way combinations for Shillong and 39 for Imphal. These results offer insights for improving driver safety in hilly areas.

Keywords: Road traffic accidents, Driver injury severity, Binary logistic regression, Shillong city, Two-way-interaction.

---

1. Introduction

One of the global burning issues is road traffic accidents (RTAs) because the RTAs cause huge losses to road users (drivers, pedestrians, and passengers), their families, and entire countries. India constituted an 11% share of total worldwide fatalities due to the RTAs (MoRTH, 2021). The RTAs impose an economic burden on Indian society equal to approximately 3% of the gross domestic product. Though India mandated several vehicle safety standards in past decades, traffic accidents, injuries, and deaths are still high in India (Pisharam, Lubbe and Davidsson, 2021). Bhuyan and Ahmed (2013) identified RTAs as an escalating public health concern in Assam, a northeastern state of India. The study found that RTAs predominantly affect young, economically active males, driven by unsafe behaviors, substandard road conditions, and lax enforcement. It underscored the critical need for enhanced surveillance, preventive strategies, road safety initiatives, and improved trauma care infrastructure in the region. The number of fatalities will further increase unless proactive mitigation steps are taken because India's population, number of vehicles, and road construction are increasing day by day. The frequency and severity of RTAs need to be reduced to improve the road user's safety.

Many previous studies have shown that a broad category of factors was statistically associated with accident severity and driver injury severity (DIS). These included driver characteristics (Behnood and Mannering, 2016; Celik and Oktay, 2017), vehicle characteristics (Anarkooli, Hosseinpour and Kardar, 2017), environmental and temporal characteristics (Anarkooli, Hosseinpour and Kardar, 2017; Celik and Oktay, 2017), accident-specific characteristics (Dissanayake and Roy, 2014), and roadway characteristics (Azimi *et al.*, 2020). In Malaysia, Anarkooli, Hosseinpour and Kardar (2017) investigated the impacts of contributing factors to the single-vehicle (SV) rollover accident severity using a generalized ordered probit model. Results revealed that lighting and rainy weather conditions, vehicle type and age, speeding and overtaking operation, and the number of travel lanes increased the severity of SV rollover accidents. Similarly, Dissanayake and Roy (2014) observed that some variables such as driver age, over-speeding, road class, and time of accident, were positively associated with more severe SV run-off-road (ROR) accidents. In another study, Celik and Oktay (2017) examined the various risk factors that influenced accident injury severity in Turkey. It was revealed that accident severity was affected by driver age, vehicle type, road class type, time of accident, and summer and cloudy weather variables. Azimi *et al.* (2020) examined the influencing factors to large truck rollover accidents in the United States using an ordered logit model. They found that sandy roadway surfaces greatly enhanced the severity of rollover accidents. Roque, Jalayer and Hasan (2021) used a mixed logit model to analyze the severity of ROR accidents in the United States. Male drivers had less probability of getting injured compared to females. The ROR accident severity reduced significantly when the shoulder width of the road increased.

In the United States, Zhang, Fu and Cheng (2015) found that driver age and gender, type and age of vehicle, collision type, speeding, distracted driving, drunken driving, and seat belt usage had a significant impact on the DIS. Results of Donmez and Liu (2015) study revealed that distracted driving enhanced the severity of Canadian driver's injury. Behnood and Mannering (2016) found that driver age and gender were the most influential factors to the DIS among unimpaired, alcohol-impaired, and drug-impaired driver groups. The high speed of the vehicle and train, and young-female drivers were identified as the two significant indicators of higher DIS for both heavy motor vehicle (HMV) and light motor vehicle (LMV) (Dabbour, Easa and Haider, 2017). In Pakistan, Waseem, Ahmed and Saeed (2019) found that the probability of being severely injured or killed (IoK) increased for those motorcyclists who got into accidents while driving HMV. Similarly, Islam and Mannering (2020) found that vehicle type, driver age, overall traffic volume, and accident type were statistically significant to the DIS. In Thailand, Se *et al.* (2023) compared the differences in unrestrained and restrained driver injury severities using a mixed logit model. Results revealed that under the influence of alcohol and ROR without roadside guardrail factors were statistically significant to the injury severity of both types of drivers. Yuan *et al.* (2024) employed correlated mixed logit models with heterogeneity to examine the influential factors of accident severity using three-year (2018-2020) data in the United States. The results demonstrated that vehicle-

vehicle collisions, work zones, and older drivers significantly contributed to the increased accident severity.

It is observed from the above literature that many previous studies focused on the individual impacts of contributing driver/temporal/environmental/accident/vehicle variables on accident severity and DIS but failed to account for the potential cross-level interactions between independent variables to capture the unobserved heterogeneity effect. Additionally, many studies fail to address major data gaps, such as the substantial underreporting of accidents, especially in rural and northeastern regions, where nearly half of accidents may remain unrecorded due to limited police coverage and private settlements, resulting in biased estimates of accident rates and contributing factors (Tiwari *et al.*, 2024). Moreover, most studies are from the USA and Southeast Asia but are limited to India. Despite northeastern states such as Arunachal Pradesh, Meghalaya, Mizoram, Assam, and Tripura reporting accident severity rates above the national average (37%), with Assam alone recording over a 20% increase in fatalities in the past five years due to weak accident surveillance and inadequate health infrastructure, including limited emergency response and trauma care, research attention to accident patterns, DIS, and their determinants in these regions remains minimal (Bhuyan and Ahmed, 2013; MoRTH, 2021). Further gaps include the lack of region-specific research that considers the distinct challenges of northeast India, such as mountainous terrain, inadequate road infrastructure, widespread helmet law violations, and socio-demographic factors that intensify unobserved heterogeneity, where most information relies on basic government records instead of comprehensive scientific investigations. Therefore, studies based on RTA data from these places are essential to understand the accident patterns, DIS, and its influencing factors. The lack of proper studies and understanding of identifying and examining the influencing factors associated with DIS, accounting for unobserved heterogeneity, in the northeast states of India motivates the authors to carry out the present study. Hence, the main aim of this study is to examine the impact of various factors and their interactions on DIS in Shillong and Imphal cities using the BLR model. The next section outlines the data and methodology, followed by an analysis and discussion of the model results. The final section presents the study's summary and conclusions.

2. Data and Methods

2.1 Data and study variables description

This study used 10 years (2011-2020) of RTA data from the capital police departments of Meghalaya and Manipur, India, for Shillong and Imphal cities. Data with missing values or involving more than two vehicles were excluded. The final datasets included 715 observations from Shillong and 1629 from Imphal. Six independent variables (driver age, gender, vehicle type, time of accident, cause of accident, and nature of accident) were considered, with 28 categorical variables in each dataset. Table 1 presents the statistical description of these categorical variables (with notation to be used in the interaction model analysis).

Table 1- Statistics description of categorical variables along with notation

Variables	Category (with notation)	Injury Level (%)			
		Shillong		Imphal	
		Non-Fatal (471)	Fatal (244)	Non-Fatal (1222)	Fatal (407)

Driver age	below 18[a]	12(2.6%)	21(8.6%)	65(5.3%)	37(9.1%)
	18-24 (A1)	149(31.6%)	84(34.4%)	239(19.6%)	90(22.1%)
	25-40 (A2)	250(53.1%)	110(45.1%)	734(60.1%)	229(56.3%)
	Above 40 (A3)	60(12.7%)	29(11.9%)	184(15.0%)	51(12.5%)
Driver gender	Male[a]	449(95.3%)	226(92.6%)	1116(91.3%)	365(89.7%)
	Female (G1)	22(4.7%)	18(7.4%)	106(8.7%)	42(10.3%)
Vehicle type	Two-wheeler[a]	120(25.5%)	110(45.1%)	515(42.1%)	221(54.3%)
	LMV (VT1)	231(49.0%)	89(36.5%)	596(48.8%)	179(44.0%)
	HMV (VT2)	120(25.5%)	45(18.4%)	111(9.1%)	7(1.7%)
Cause of accident	Overtake[a]	44(9.3%)	24(9.8%)	109(8.9%)	53(13.0%)
	Over-speeding (C1)	141(30.0%)	133(54.5%)	183(15.0%)	80(19.7%)
	Out of control (C2)	15(3.2%)	32(13.1%)	181(14.8%)	92(22.6%)
	Rush driving (C3)	152(32.3%)	27(11.1%)	295(24.1%)	91(22.4%)
	Drunken driving (C5)	42(8.9%)	13(5.3%)	*	*
	Violation of road safety rules (C6)	42(8.9%)	8(3.3%)	*	*
	Narrow road (C7)	*	*	204(16.7%)	41(10.0%)
	Distracted driving (C8)	*	*	130(10.6%)	46(11.3%)
	Presence of pot holes (C9)	*	*	74(6.1%)	2(0.5%)
	Presence of horizontal curve (C10)	*	*	46(3.8%)	2(0.5%)
	Other* (C4)	35(7.4%)	7(2.9%)	*	*
Time of accident	12AM-6AM[a]	47(10.0%)	32(13.1%)	40(3.3%)	24(5.9%)
	6AM-12PM (T1)	64(13.6%)	36(14.8%)	228(18.7%)	76(18.7%)
	12PM-6PM (T2)	149(31.6%)	68(27.9%)	465(38.0%)	148(36.4%)
	6PM-12AM (T3)	211(44.8%)	108(44.2)	489(40.0%)	159(39.0%)
Nature of accident	Head on collision[a]	139(29.5%)	78(32.0%)	334(27.3%)	123(30.2%)
	Side collision (N1)	75(15.9%)	17(7.0%)	294(24.1%)	85(20.9%)
	Rear end collision (N2)	73(15.5%)	21(8.6%)	251(20.5%)	68(16.7%)
	Overturn (N3)	12(2.5%)	24(9.8%)	21(1.7%)	21(5.2%)
	Fell into gorge (N4)	0	12(4.9%)	*	*
	Hit object (N5)	15(3.2%)	12(4.9%)	158(13.0%)	57(14.0%)
	Hit pedestrian (N7)	143(30.4%)	55(22.5%)	127(10.4%)	43(10.6%)
	Other** (N6)	14(3.0%)	25(10.3%)	37(3.0%)	10(2.4%)

[a]Reference category

**Other cause: For Shillong: Distraction, narrow road, driver tireness*

***Other collision: For Shillong: Intersection accidents, skidding, Hit & run*

For Imphal: Hit strayed animal, Intersection accidents

2.2 Binary logistic regression model

Many statistical models (like ordered probit, ordered logit, binary and multinomial logistic regression, mixed logit model) have been developed to analyze the accident severity and DIS. The selection of a particular model depends on the nature of the dependent variable and the research purpose. In general, it is impossible to propose a particular model as the best because each model has its own limitations and strengths (Mujalli and De Ona, 2013). In the current accident datasets, the dependent variable (DIS) is binary, with outcomes of fatal (death within 30 days) or non-fatal (no death within 30 days). The binary logistic regression (BLR) model was selected due to its suitability for a binary dependent variable (DIS: fatal vs. non-fatal) and its ability to provide interpretable odds ratios for assessing the impact of independent variables on accident severity. Unlike ordered models, which assume ordinal outcomes, BLR accommodates the dichotomous nature of DIS without requiring assumptions about the proportionality of odds across categories. Additionally, BLR's logistic function ensures robust handling of non-linear relationships between predictors and the log-odds of the outcome, making it appropriate for the current datasets (Sze and Wong, 2007; Bonera *et al.*, 2024). For modeling, one category from each independent variable was removed and used as a reference category in the model. The mathematical expression (1) of the BLR model (Joni and Shallal, 2021) is shown as

$$Logit(Y) = \ln\left(\frac{Y}{1-Y}\right) = \beta + b_1x_1 + b_2x_2 + \ldots\ldots\ldots\ldots. + b_nx_n \tag{1}$$

Where, Y is the probability of an occurring fatal accident, β is constant (intercept), b_n is the regression coefficient and x_n is the independent variable.

The presence of significant outliers in the dataset is examined in the data preprocessing phase of the analysis. To remove significant outliers, data with "Zresidual values" greater than 2.56 were identified and excluded. The process of elimination of such data was continuously done till there was no significant difference (1%) in the overall correct prediction value of the model. The existence of a high association between two or more independent variables (i.e., multicollinearity problem) was also examined after the elimination of significant outliers from the datasets. Multicollinearity was checked using the Variance Inflation Factor (VIF), where a value below 5 indicated no multicollinearity (Kyriazos and Poga, 2023). After outlier removal and multicollinearity testing, model goodness-of-fit was assessed using omnibus tests, the Hosmer–Lemeshow test, and Nagelkerke R-Square (Hosmer, Taber and Lemeshow, 1991; Jaber, Juhasz and Csonka, 2021). The p-value for the omnibus test should be less than 0.05 for the model to be statistically significant. It should be greater than 0.05 in the case of Hosmer-Lemeshow test. Nagelkerke R-Square is a measure of how well a BLR model fits the data. A higher value suggests that the model fits the data better. It has a value between 0 and 1. Two models were developed using SPSS: one without interaction and one with two-way interaction. The main-effects model included all independent variables without interactions to establish baseline relationships with DIS. The interaction model incorporated two-way interaction terms to capture synergistic effects between variables, such as driver age × vehicle type and accident time × accident cause, which were hypothesized to influence accident severity based on prior studies (e.g., Chen and Chen, 2011). Notations for the BLR Model-with-interaction are defined in Table 1. The flowchart of the study methodology is presented in Figure 1.

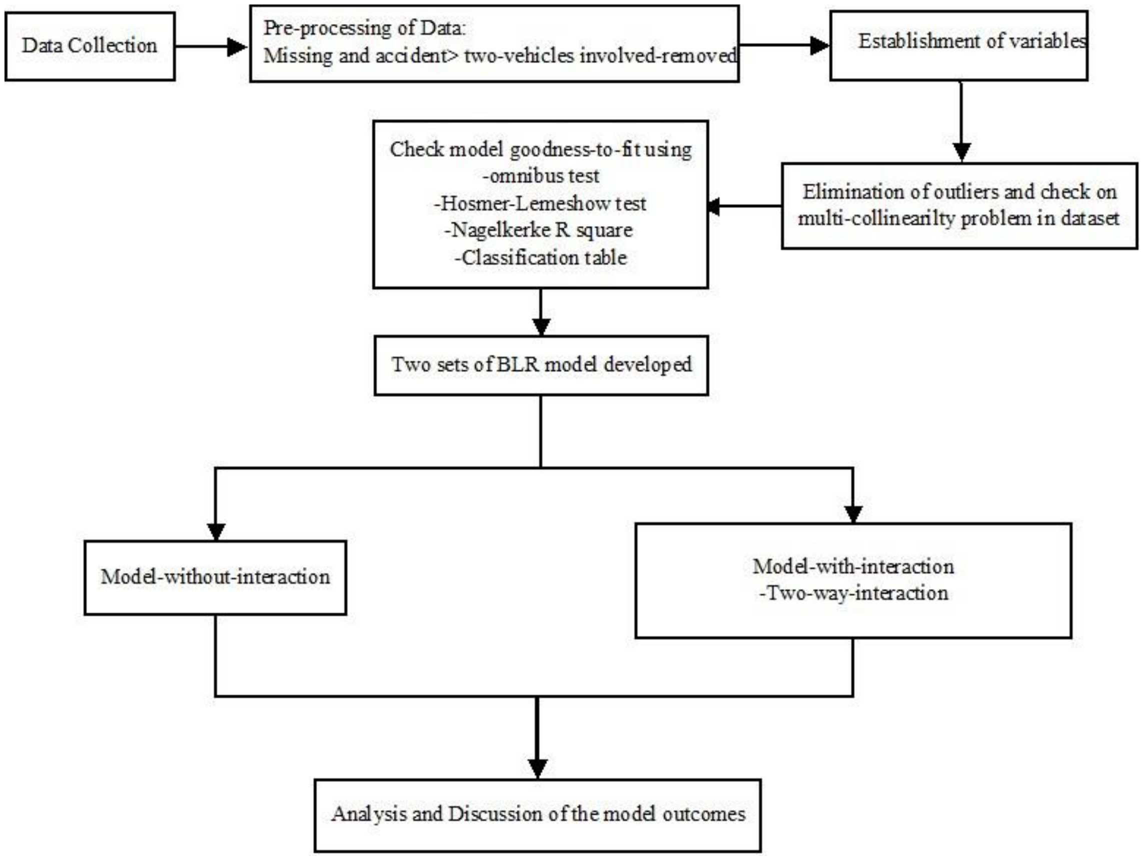

Figure 1: The flowchart of the study methodology

3. Results and discussion

3.1 Results of the BLR model-without-interaction

After removing outliers, 693 observations remained for Shillong city and 1594 for Imphal city. A classification table was used for sensitivity analysis of the results (with and without outliers). The results showed that the overall prediction accuracy increased from 65.9% to 68.0% for Shillong and from 75.0% to 76.7% for Imphal after the successive elimination of 22 observations from the Shillong dataset and 35 observations from the Imphal dataset. The percentage variation in model prediction was less than 1% compared to the earlier iteration when this number of observations was eliminated. The multicollinearity test showed VIF values below 5 for all variables, indicating no multicollinearity. The omnibus tests, Hosmer–Lemeshow test, and Nagelkerke R^2 (Table 2) confirmed that the BLR model fit the datasets well.

Table 2 -Results of the model goodness-to-fit to the data

Study area	Omnibus tests	Hosmer–Lemeshow Test	Nagelkerke R Square
Shillong city	0.000	0.035	0.463
Imphal city	0.000	0.207	0.211

The BLR model-without-interaction estimation results for Shillong and Imphal cities are shown in Tables 3 to 6, presenting regression coefficients (b) and p-values for categorical variables. A positive b indicates higher risk, while a negative b suggests lower risk, with the first line of each variable representing the reference category. Exp(b) represents the odds ratio (OR) of injury severity compared to the reference category, where the OR of the reference category is 1.

3.1.1 Driver age

Table 3 shows that age was a significant factor in DIS. In Imphal city, DIS was a major issue for all age groups except for the 18-24-year group. In Shillong city, drivers under 18 had a higher fatality rate compared to other age groups. In Imphal city, the 18-21-year age group was not significantly associated with DIS. The ORs for the 25-40-year (OR = 0.607) and above 40-year (OR = 0.581) groups were lower than the below 18-year group (OR = 1.000), indicating that drivers below 18 had a higher risk of death compared to those in the other age groups.The results of our study are similar to the findings of some previous studies (Paleti, Eluru and Bhat, 2010; Lee and Li, 2014; Haq, Zlatkovic and Ksaibati, 2021). Haq, Zlatkovic and Ksaibati (2021) observed that young drivers are eager to take unsafe actions and are involved in more severe accidents compared to older drivers.

3.1.2 Driver gender

Gender factor (p-value = 0.632) was statistically insignificant at a 90% confidence level to the DIS for Imphal cities (Table 3). Some previous research (Sagberg, 1999; Kadilar, 2015; Yuan *et al.*, 2017; Eboli, Forciniti and Mazzulla, 2020) had shown similar results. However, the gender factor was significantly associated with the DIS for Shillong city (p-value = 0.035). Table 3 shows that the likelihood of severe IoK to female drivers (OR = 2.453) was two and a half times higher than male drivers in the case of Shillong city. Similar results were observed in some previous studies (Chen and Chen, 2011; Abay, Paleti and Bhat, 2013; Aidoo and Ackaah, 2021). For instance, Aidoo and Ackaah (2021) found that the injury severity of female drivers was higher than that of male drivers.

3.1.3 Vehicle type

All vehicle types, except HMVs in Imphal, were significantly associated with DIS (Table 3). In Shillong city, drivers of LMVs (OR = 0.373) and HMVs (OR = 0.335) had lower fatality rates compared to two-wheeler drivers (OR = 1). This aligns with previous studies (Savolainen and Mannering, 2007; Aidoo and Ackaah, 2021; Karabulut and Ozen, 2023), which found that HMV drivers had a lower probability of severe injury than LMV drivers, and two-wheeler drivers had a higher risk of fatality. A similar trend was observed in Imphal, where LMV drivers (OR = 0.658) had a lower risk of fatality compared to two-wheeler drivers (OR = 1).

Table 3- Results of BLR model-without-interaction for age, gender, and vehicle type

Variable	Study Area	Category	b	S.E.[1]	Wald[2]	p-value	Sig*	Exp(b)
Driver age	Shillong city	below 18[a]	0		9.450	0.024	95%	1
		18-24	-1.423	0.508	7.856	0.005	95%	0.241
		25-40	-1.558	0.509	9.364	0.002	95%	0.210
		Above 40	-1.523	0.580	6.901	0.009	95%	0.218
	Imphal city	below 18[a]	0		7.055	0.070	90%	1
		18-24	-0.211	0.263	0.643	0.423	Not	0.810

		25-40	-0.498	0.238	4.374	0.036	95%	0.607
		Above 40	-0.543	0.289	3.532	0.060	90%	0.581
Driver gender	Shillong city	Male[a]	0.000			0.000	95%	1
		Female	0.897	0.425	4.46	0.035	95%	2.453
	Imphal city	Male[a]	0.000			0.000	95%	1
		Female	0.105	0.219	0.23	0.632	Not	1.110
Vehicle Type	Shillong city	Two-wheeler[a]	0		18.559	0.000	95%	1
		LMV	-0.987	0.250	15.649	0.000	95%	0.373
		HMV	-1.093	0.317	11.888	0.001	95%	0.335
	Imphal city	Two-wheeler[a]	0		10.26	0.006	95%	1
		LMV	-0.419	0.131	10.26	0.001	95%	0.658
		HMV	-20.404	3658.386	0.000	0.996	Not	0.000

[a]Reference category, [1]S.E. = Standard Error, [2]Wald chi-squared test.
Sig = Significant at 90%, 95% Confidence level, or Not Significant.*

3.1.4 Time of accident

Table 4 shows that the time of accident significantly impacted DIS in both cities. All time periods (6AM-12PM, 12PM-6PM, and 6PM-12AM) had lower odds ratios (OR = 0.498, 0.297, 0.305 for Shillong; OR = 0.416, 0.387, 0.441 for Imphal) compared to the 12AM-6AM period (OR = 1). This aligns with findings by Duddu, Madhav and Pulugurtha (2019), suggesting that drivers may drive faster during less congested hours due to time pressure and distractions along the road.

Table 4 -Results of BLR model-without-interaction for time of accident

Variable	Study Area	Category	b	S.E.[1]	Wald[2]	p-value	Sig*	Exp(b)
Time of accident	Shillong city	12AM-6AM[a]	0		14.430	0.002	95%	1
		6AM-12PM	-0.698	0.412	2.871	0.090	90%	0.498
		12PM-6PM	-1.215	0.362	11.284	0.001	95%	0.297
		6PM-12AM	-1.189	0.35	11.563	0.001	95%	0.305
	Imphal city	12AM-6AM[a]	0		9.052	0.029	95%	1
		6AM-12PM	-0.877	0.332	6.980	0.008	95%	0.416
		12PM-6PM	-0.948	0.317	8.935	0.003	95%	0.387
		6PM-12AM	-0.818	0.316	6.692	0.010	95%	0.441

[a]Reference category, [1]S.E. = Standard Error, [2]Wald chi-squared test.
Sig = Significant at 90%, 95% Confidence level, or Not Significant.*

3.1.5 Cause of accident

In Shillong city, all accident causes were statistically significant to DIS, except drunken driving (Table 5). The likelihood of severe injury due to out-of-control accidents (OR = 2.456) was 2.5 times higher than accidents caused by overtaking. Over-speeding (OR = 1.808) also doubled the risk of severe injury. Rush driving, road safety violations, and other causes like distractions (OR = 0.147, 0.037, 0.041) significantly reduced the risk compared to overtaking. These findings suggest that over-speeding and out-of-control causes were major contributors to severe accidents in Shillong, similar to Javid and Al-Roushdi (2019) study in Oman. In Imphal, rush driving (OR = 0.609) and narrow roads (OR = 0.141) were significant, with drivers involved in these causes having a lower risk of severe injury compared to those in overtaking-related accidents.

Table 5 -Results of BLR model-without-interaction for cause of accident

Variable	Study Area	Category	b	S.E.[1]	Wald[2]	p-value	Sig*	Exp(b)
Cause of accident	Shillong city	Overtake[a]	0		88.843	0.000	95%	1
		overspeeding	0.592	0.339	3.059	0.08	90%	1.808
		out of control	0.898	0.523	2.955	0.086	90%	2.456
		rush driving	-1.919	0.43	19.954	0.000	95%	0.147
		drunken driving	-0.785	0.484	2.631	0.105	Not	0.456
		Violation of Road Safety Rules	-3.294	0.848	15.078	0.000	95%	0.037
		other	-3.201	1.134	7.963	0.005	95%	0.041
	Imphal city	Overtake[a]	0		47.074	0.000	95%	1
		over-speeding	-0.247	0.225	1.208	0.272	Not	0.781
		out of control	-0.057	0.223	0.065	0.798	Not	0.945
		rush driving	-0.497	0.216	5.292	0.021	95%	0.609
		narrow road	-1.961	0.319	37.71	0.000	95%	0.141
		Distracted driving	-0.401	0.251	2.558	0.110	Not	0.669
		presence of pot holes	-20.62	4570.802	0.000	0.996	Not	0.000
		presence of horizontal curve	-20.64	5875.108	0.000	0.997	Not	0.000

[a]Reference category, [1]S.E. = Standard Error, [2]Wald chi-squared test.
Sig = Significant at 90%, 95% Confidence level, or Not Significant.*

3.1.6 Nature of accident

Some categorical factors, including fell into gorge, hit object, and hit pedestrian, were statistically insignificant to DIS in Shillong city (Table 6). Overturn (OR = 2.720) and other collision types (OR = 3.073) were significantly more likely to result in DIS compared to head-on collisions. This aligns with Chen *et al.* (2016), who found that overturn collisions had the highest impact on DIS. A similar pattern was observed in Imphal city, where overturn collisions (OR = 2.075) were more likely to result in DIS than head-on collisions. Side and rear-end collisions had lower odds ratios (OR = 0.712, 0.700), while hit pedestrian, hit object, and other collision types were not significantly associated with DIS.

Table 6 -Results of BLR model-without-interaction for nature of accident

Variable	Study Area	Category	b	S.E.[1]	Wald[2]	p-value	Sig*	Exp(b)
Nature of accident	Shillong city	head on collision[a]	0		42.522	0	95%	1
		side collision	-1.362	0.377	13.066	0	95%	0.256
		rear end collision	-1.128	0.37	9.3	0.002	95%	0.324
		overturn	1	0.473	4.477	0.034	95%	2.720
		fell into gorge	23.868	9845.37	0	0.998	Not	2.32E+10
		hit object	0.525	0.624	0.706	0.401	Not	1.690
		Hit pedestrian	-0.419	0.288	2.113	0.146	Not	0.658
		other	1.123	0.485	5.351	0.021	95%	3.073
	Imphal city	head on collision[a]	0		14.684	0.023	95%	1
		side collision	-0.34	0.183	3.449	0.063	90%	0.712
		rear end collision	-0.356	0.192	3.447	0.063	90%	0.700
		overturn	0.73	0.346	4.437	0.035	95%	2.075

hit object	-0.175	0.204	0.737	0.391	Not	0.840
Hit pedestrian	0.141	0.227	0.385	0.535	Not	1.151
other	0.12	0.43	0.077	0.781	Not	1.127

[a]Reference category, [1]S.E. = Standard Error, [2]Wald chi-squared test.
Sig = Significant at 90%, 95% Confidence level, or Not Significant.*

3.2 Results of the two-way interaction model

It is worth mentioning that the gender variable, which was statistically insignificant in Imphal cities, was not included in the interaction analysis. The results of significant categorical-interacted variables for two-way interaction models for two cities are presented in Tables 7-16.

3.2.1 Interaction between driver age and vehicle type

In Shillong city, four significant interactions between driver age and vehicle type were found (Table 7). Drivers aged 18-24, 25-40, and above 40, driving LMVs, had lower injury severity compared to drivers under 18 on two-wheelers. Similarly, 25-40-year-old drivers of HMVs had a lower likelihood of fatality (OR = 0.334) than under-18 two-wheeler drivers. In Imphal city, two significant interactions were observed. Drivers aged 25-40 and above 40, driving LMVs, had lower injury severity (OR = 0.631 and 0.517) compared to under-18 two-wheeler drivers.

Table 7 -Results of significant interaction between driver age and vehicle type

Study area	Interacted Variables	b	S.E.	Wald	p-value	Exp(b)
	Driver Age (A)*Vehicle Type (VT)					
Shillong city	A(1) by VT(1)	-0.962	0.266	13.051	0.000	0.382
	A(2) by VT(1)	-0.915	0.225	16.592	0.000	0.400
	A(2) by VT(2)	-1.097	0.263	17.386	0.000	0.334
	A(3) by VT(1)	-0.811	0.352	5.306	0.021	0.444
Imphal city	A(2) by VT(1)	-0.46	0.145	10.023	0.002	0.631
	A(3) by VT(1)	-0.66	0.223	8.735	0.003	0.517

[a]Drivers aged below 18 years while driving two-wheelers are considered as reference category

3.2.2 Interaction between driver age and cause of accident

In Shillong city, five significant interactions between driver age and accident causes were found (Table 8). Drivers aged 18-24 and 25-40 involved in accidents due to rush driving, road safety violations, drunken driving, and other causes (OR = 0.187, 0.070, 0.126, 0.333, and 0.148) had lower DIS compared to drivers under 18 involved in overtaking accidents.

Table 8- Results of significant interaction between Driver Age and Cause of Accident

Study area	Interacted Variables	b	S.E.	Wald	p-value	Exp(b)
	Driver Age (A)*Cause of accident (C)					
Shillong city	A(1) by C(3)	-1.678	0.452	13.774	0	0.187
	A(1) by C(6)	-2.657	1.046	6.45	0.011	0.07
	A(2) by C(3)	-2.07	0.445	21.647	0	0.126
	A(2) by C(5)	-1.099	0.54	4.138	0.042	0.333

Imphal city	A(2) by C(7)	-1.91	0.773	6.106	0.013	0.148
	A(1) by C(7)	-1.075	0.429	6.268	0.012	0.341
	A(2) by C(3)	-0.565	0.211	7.211	0.007	0.568
	A(2) by C(7)	-2.271	0.439	26.744	0	0.103
	A(3) by C(7)	-2.651	1.026	6.677	0.01	0.071

[a]*Drivers aged below 18 years involved in accidents due to overtaking operation are considered as reference category*

In Imphal city, four significant interactions between driver age and accident causes were found (Table 8), with odds ratios (OR = 0.341, 0.568, 0.103, and 0.071) lower than those for drivers under 18 involved in overtaking accidents. These results suggest that the likelihood of DIS is lower for these combinations compared to the under-18 group. Additionally, narrow road conditions were a common cause of accidents for drivers in the 18-24, 25-40, and above 40 age groups in Imphal

3.2.3 Interaction between driver age and time of accident

In Imphal city, seven significant interactions between driver age and time of accident were found (Table 9). Drivers aged 25-40 and above 40 had lower injury severity in accidents during morning (6AM-12PM), afternoon (12PM-6PM), and night (6PM-12AM) compared to drivers under 18 driving during dawn (12AM-6AM). Additionally, drivers aged 18-24 (OR = 0.546) driving in the afternoon (12PM-6PM) had lower injury severity than those under 18 driving during dawn.

Table 9- Results of significant interaction between driver age and time of accident

Study area	Interacted Variables	b	S.E.	Wald	p-value	Exp(b)
	Driver Age (A)*Time of accident (T)					
Imphal city	A(1) by T(2)	-0.605	0.259	5.437	0.020	0.546
	A(2) by T(1)	-0.817	0.252	10.543	0.001	0.442
	A(2) by T(2)	-0.872	0.215	16.43	0.000	0.418
	A(2) by T(3)	-0.603	0.204	8.700	0.003	0.547
	A(3) by T(1)	-1.23	0.471	6.811	0.009	0.292
	A(3) by T(2)	-0.713	0.308	5.357	0.021	0.490
	A(3) by T(3)	-0.969	0.322	9.074	0.003	0.379

[a]*Drivers aged below 18 years who were involved in dawn-time driving accidents are considered as reference category*

3.2.4 Interaction between driver age and nature of accident

In Shillong city, six significant interactions between driver age and nature of accident were found (Table 10). The 25-40 age group involved in other collisions (OR = 24.581) showed the strongest association with DIS. Drivers aged 18-24 and above 40 involved in overturns had 3.512 and 10.535 times higher chances of severe injury than under-18 drivers in head-on collisions. Drivers aged 18-24 and 25-40 in hit pedestrian, side, or rear-end collisions had lower injury severity (OR = 0.386, 0.251, and 0.263) than under-18 drivers in head-on collisions. In Imphal city, three significant interactions were observed (Table 10). Drivers aged 18-24 in overturns had 5.025 times higher injury severity than under-18 drivers in head-on collisions. Additionally, 25-40-year-old drivers in hit pedestrian accidents (OR = 0.548) and above 40-year-olds in rear-end collisions (OR = 0.334) had lower injury severity compared to under-18 drivers in head-on collisions.

Table 10 -Results of significant interaction between Driver Age and Nature of Accident

Study area	Interacted Variables	b	S.E.	Wald	p-value	Exp(b)
	Driver Age (A)*Nature of accident (N)					
Shillong city	A(1) by N(3)	1.256	0.627	4.012	0.045	3.512
	A(1) by N(7)	-0.951	0.359	7.005	0.008	0.386
	A(2) by N(1)	-1.383	0.457	9.163	0.002	0.251
	A(2) by N(2)	-1.334	0.458	8.48	0.004	0.263
	A(2) by N(8)	3.202	1.044	9.409	0.002	24.581
	A(3) by N(3)	2.355	1.089	4.679	0.031	10.535
Imphal city	A(1) by N(3)	1.614	0.517	9.748	0.002	5.025
	A(2) by N(7)	-0.601	0.291	4.26	0.039	0.548
	A(3) by N(2)	-1.096	0.484	5.127	0.024	0.334

[a]*Drivers aged below 18 years who were involved in head-on collision-type accidents are considered as reference category.*

3.2.5 Interaction between cause of accident and vehicle type

In Shillong city, five significant interactions between cause of accident and vehicle type were found (Table 11). Drivers involved in accidents due to rush driving, drunken driving, or other causes (OR = 0.041, 0.156, 0.148) while driving LMVs had a lower likelihood of fatality compared to those involved in overtaking accidents on two-wheelers. Similarly, drivers involved in rush driving or other causes (OR = 0.088, 0.127) while driving HMVs had lower chances of fatality compared to two-wheeler drivers in overtaking accidents. In Imphal city, two significant interactions were observed. Drivers involved in accidents due to rush driving or narrow roads (OR = 0.604, 0.105) while driving LMVs had a lower likelihood of fatality compared to two-wheeler drivers involved in overtaking accidents.

Table 11- Results of significant interaction between Cause of Accident and Vehicle Type

Study area	Interacted Variables	b	S.E.	Wald	p-value	Exp(b)
	Cause of accident (C)*Vehicle type (VT)					
Shillong city	C(3) by VT(1)	-3.189	0.728	19.183	0.000	0.041
	C(3) by VT(2)	-2.435	0.608	16.046	0.000	0.088
	C(5) by VT(1)	-1.859	0.621	8.965	0.003	0.156
	C(4) by VT(1)	-1.914	0.754	6.447	0.011	0.148
	C(4) by VT(2)	-2.060	1.052	3.837	0.050	0.127
Imphal city	C(3) by VT(1)	-0.504	0.204	6.103	0.013	0.604
	C(8) by VT(1)	-2.253	0.516	19.030	0.000	0.105

[a]*Drivers involved in accidents due to overtaking operation while driving two-wheelers are considered as reference category*

3.2.6 Interaction between time of accident and vehicle type

In Shillong city, four significant interactions between time of accident and vehicle type were found (Table 12). Drivers of LMVs during afternoon and night (OR = 0.195, 0.421, 0.393, 0.217) had lower injury severity compared to two-wheeler drivers during dawn. Similarly, HMV drivers during morning and night had lower chances of fatality than two-wheeler drivers during dawn. In Imphal city, one significant interaction was observed, showing that LMV drivers in the afternoon had a lower likelihood of fatality compared to two-wheeler drivers during dawn.

Table 12- Results of significant interaction between Time of Accident and Vehicle Type

Study area	Interacted Variables	b	S.E.	Wald	p-value	Exp(b)
	Time of accident (T) * Vehicle Type (VT)					
Shillong city	T(1) by VT(2)	-1.634	0.631	6.714	0.010	0.195
	T(2) by VT(1)	-0.864	0.268	10.381	0.001	0.421
	T(3) by VT(1)	-0.935	0.235	15.867	0.000	0.393
	T(3) by VT(2)	-1.529	0.425	12.909	0.000	0.217
Imphal city	T(2) by VT(1)	-0.68	0.172	15.651	0.000	0.507

[a]*Drivers involved in dawn-time accidents while driving two-wheelers are considered as reference category*

3.2.7 Interaction between nature of accident and vehicle type

In Shillong city, six significant interactions between nature of accident and vehicle type were found (Table 13). Drivers involved in overturn accidents while driving HMVs had over seven times higher chances of severe injury (OR = 7.393) than those in head-on collisions while driving two-wheelers. Drivers in side collision, rear-end, and hit pedestrian accidents (OR = 0.242, 0.249, 0.444) while driving LMVs had a lower likelihood of fatality compared to two-wheeler drivers in head-on collisions. Additionally, drivers in side collision and hit pedestrian accidents (OR = 0.193, 0.242) while driving LMVs had lower chances of fatality compared to those in head-on collisions with two-wheelers. In Imphal city, three significant interactions between nature of accident and vehicle type were found (Table 13). Drivers in overturn accidents while driving LMVs had 2.633 times higher likelihood of severe injury than those in head-on collisions while driving two-wheelers. Additionally, drivers in rear-end and hit pedestrian accidents (OR = 0.535, 0.135) while driving LMVs had lower chances of severe injury compared to two-wheeler drivers in head-on collisions.

Table 13- Results of significant interaction between Nature of Accident and Vehicle Type

Study area	Interacted Variables	b	S.E.	Wald	p-value	Exp(b)
	Nature of accident (N)*Vehicle type (VT)					
Shillong city	N(1) by VT(1)	-1.420	0.491	8.376	0.004	0.242
	N(1) by VT(2)	-1.644	0.755	4.737	0.030	0.193
	N(2) by VT(1)	-1.391	0.492	7.998	0.005	0.249
	N(3) by VT(2)	2.001	0.789	6.428	0.011	7.393
	N(7) by VT(1)	-0.812	0.274	8.789	0.003	0.444
	N(7) by VT(2)	-1.420	0.491	8.376	0.004	0.242
Imphal city	N(2) by VT(1)	-0.625	0.231	7.329	0.007	0.535
	N(3) by VT(1)	0.968	0.432	5.009	0.025	2.633
	N(7) by VT(1)	-2.002	0.518	14.959	0.000	0.135

[a]*Drivers involved in head-on collision-type accidents while driving two-wheelers are considered as reference category*

3.2.8 Interaction between cause of accident and time of accident

In Shillong city, seven significant interactions between cause and time of accident were found (Table 14). Injury severity was higher for drivers involved in morning, afternoon, and night accidents due to over-speeding and out-of-control (OR = 2.435, 4.151, 3.321). In contrast, injury severity decreased for drivers involved in accidents due to rush driving and violation of road safety rules (OR = 0.246, 0.119, 0.224, 0.069) compared to those in overtaking accidents during dawn time. In Imphal city, five significant interactions were observed. Drivers involved in afternoon and night accidents due to rush driving (OR = 0.595, 0.480) or narrow road (OR = 0.102, 0.122, 0.124) had lower chances of severe injury compared to those involved in overtaking accidents during dawn time.

Table 14 -Results of significant interaction between Cause of accident and Time of accident

Study area	Interacted Variables	b	S.E.	Wald	p-value	Exp(b)
	Time of accident (T)*Cause of accident (C)					
Shillong city	T(1) by C(1)	0.890	0.377	5.565	0.018	2.435
	T(1) by C(3)	-1.402	0.563	6.200	0.013	0.246
	T(2) by C(2)	1.423	0.513	7.686	0.006	4.151
	T(2) by C(3)	-2.132	0.546	15.249	0.000	0.119
	T(3) by C(2)	1.200	0.575	4.362	0.037	3.321
	T(3) by C(3)	-1.498	0.439	11.673	0.001	0.224
	T(3) by C(6)	-2.671	1.035	6.656	0.010	0.069
Imphal city	C(3) by T(2)	-0.519	0.247	4.416	0.036	0.595
	C(3) by T(3)	-0.735	0.243	9.116	0.003	0.480
	C(7) by T(1)	-2.285	0.739	9.555	0.002	0.102
	C(7) by T(2)	-2.101	0.483	18.950	0.000	0.122
	C(7) by T(3)	-2.088	0.483	18.708	0.000	0.124

[a]*Drivers involved in dawn-time accidents due to overtaking operation are considered as reference category*

3.2.9 Interaction between cause of accident and nature of accident

In Shillong city, three significant interactions between cause and nature of accident were found (Table 15). Drivers involved in hit pedestrian (OR = 1.900) and other (OR = 6.000) accidents due to over-speeding had higher fatality rates compared to those in head-on collisions due to overtaking. Additionally, drivers in overturn accidents caused by out-of-control (OR = 7.5) had significantly higher chances of severe injury compared to those in head-on collisions due to overtaking. In Imphal city, seven significant interactions between cause and nature of accident were found (Table 15). The strongest association with injury severity was observed in rush driving*overturn *(OR = 11.178)*, followed by over-speeding*overturn (OR = 4.192), out-of-control*overturn *(OR = 2.515)*, over-speeding*hit object (OR = 2.159), and over-speeding*hit pedestrian (OR = 2.096). Additionally, drivers in side (OR = 0.104) and rear-end (OR = 0.056) collisions due to narrow road causes had lower chances of severe injury compared to those in head-on collisions due to overtaking.

Table 15 -Results of significant interaction between cause of accident and nature of accident

Study area	Interacted Variables	b	S.E.	Wald	p-value	Exp(b)

	Cause of accident (C)*Nature of accident (N)					
Shillong city	C(1) by N(7)	0.642	0.267	5.798	0.016	1.900
	C(1) by N(8)	1.792	0.535	11.209	0.001	6.000
	C(2) by N(3)	2.015	0.580	12.068	0.001	7.500
Imphal city	C(1) by N(3)	1.433	0.653	4.822	0.028	4.192
	C(1) by N(5)	0.770	0.337	5.218	0.022	2.159
	C(1) by N(7)	0.740	0.394	3.530	0.060	2.096
	C(2) by N(3)	0.922	0.469	3.859	0.049	2.515
	C(3) by N(3)	2.414	1.122	4.627	0.031	11.178
	C(7) by N(1)	-2.268	0.727	9.747	0.002	0.104
	C(7) by N(2)	-2.884	1.015	8.083	0.004	0.056

[a]Drivers involved in head-on collision-type accidents due to overtaking are considered as reference category

3.2.10 Interaction between nature of accident and time of accident

In Shillong city, seven significant interactions between nature of accident and time of accident were found (Table 16). Drivers in overturn-type collisions during the afternoon had 4.870 times higher chances of injury severity than those in head-on collisions during dawn. Similarly, drivers in other-type accidents at night had 2.951 times higher chances of injury severity than those in dawn-time head-on collisions. However, the injury severity was lower in side, rear-end, and hit pedestrian accidents during the afternoon and night compared to dawn-time head-on collisions. In Imphal city, five significant interactions were found. The probability of injury severity was higher in overturn-type accidents during the afternoon and night (OR = 4.853 and 2.621) than in dawn-time head-on accidents, but lower in side, rear-end, and hit object accidents during afternoon and night compared to dawn-time head-on collisions.

Table 16 -Results of significant interaction between nature of accident and time of accident

Study area	Interacted Variables	b	S.E.	Wald	p-value	Exp(b)
	Time of accident (T)*Nature of accident (N)					
Shillong city	T(2) by N(1)	-1.374	0.63	4.756	0.029	0.253
	T(2) by N(2)	-1.133	0.558	4.120	0.042	0.322
	T(2) by N(3)	1.583	0.598	7.016	0.008	4.870
	T(2) by N(7)	-0.943	0.357	6.986	0.008	0.390
	T(3) by N(1)	-1.087	0.406	7.153	0.007	0.337
	T(3) by N(2)	-1.345	0.496	7.368	0.007	0.260
	T(3) by N(7)	1.082	0.441	6.035	0.014	2.951
Imphal city	N(1) by T(2)	-0.618	0.265	5.448	0.020	0.539
	N(2) by T(2)	-0.888	0.314	8.002	0.005	0.411
	N(3) by T(2)	0.963	0.471	4.184	0.041	2.621
	N(3) by T(3)	1.580	0.527	8.995	0.003	4.853
	N(5) by T(3)	-0.738	0.341	4.671	0.031	0.478

[a]Drivers involved in head-on collision-type accidents during dawn-time driving are considered as reference category.

4. Conclusion

This study used binary logistic regression (BLR) to analyze driver injury severity (DIS) in single- and two-vehicle accidents in Shillong and Imphal (2011-2020). DIS was significantly associated with driver age, gender, vehicle type, accident time, cause, and nature, with 18 of 22 variables significant in Shillong and 11 in Imphal. Including two-way interactions revealed 47 significant terms in Shillong and 39 in Imphal, showing complex variable interplays such as age-vehicle type and cause-nature. These results emphasize how combined factors shape DIS and address unobserved heterogeneity often overlooked in prior research.

This study contributes to RTA research in India's underexplored northeast by addressing three key areas. First, it fills the gap in region-specific studies of hilly terrains like Shillong and Imphal, where poor infrastructure and weak accident surveillance prevail. Second, the use of two-way interaction terms captures synergistic effects between variables, offering deeper insights into DIS than factor-based analyses. Third, it draws attention to underreporting, with nearly half of accidents unrecorded due to limited police coverage and private settlements. However, reliance on police data limits coverage of minor accidents, underscoring the need for hospital or insurance data. Future research should integrate continuous variables, advanced models, and broader accident types to build a more comprehensive understanding.

This study offers important implications for reducing DIS in hilly cities like Shillong and Imphal through targeted interventions. High-risk groups include young drivers (under 18 in Shillong; 25-40 and above 40 in Imphal) and two-wheeler riders, calling for stricter enforcement of licensing and helmet laws. Key contributors were over-speeding and loss of control in Shillong, and rush driving with narrow roads in Imphal, highlighting the need for speed bumps, radar monitoring, and safer road designs with wider shoulders and guardrails. Higher DIS during dawn hours (12AM-6AM) points to improved lighting and signage, while overturn accidents in Shillong stress the importance of road safety infrastructure. Public awareness campaigns, particularly addressing rush driving and female driver safety in Shillong, can further reduce risks. Tailored measures for each city could significantly improve safety and lessen the social and economic impact of RTAs.

References

Abay, K.A., Paleti, R. and Bhat, C.R. (2013) 'The joint analysis of injury severity of drivers in two-vehicle crashes accommodating seat belt use endogeneity', Transportation Research Part B: Methodological, 50, pp. 74–89. Available at: https://doi.org/10.1016/j.trb.2013.01.007.

Aidoo, E.N. and Ackaah, W. (2021) 'A generalized ordered logit analysis of risk factors associated with driver injury severity', Journal of Public Health (Germany), 29(2), pp. 471–477. Available at: https://doi.org/10.1007/s10389-019-01135-8.

Anarkooli, A.J., Hosseinpour, M. and Kardar, A. (2017) 'Investigation of factors affecting the injury severity of single-vehicle rollover crashes: A random-effects generalized ordered probit model', Accident Analysis and Prevention, 106(February), pp. 399–410. Available at: https://doi.org/10.1016/j.aap.2017.07.008.

Azimi, G. et al. (2020) 'Severity analysis for large truck rollover crashes using a random parameter ordered logit model', Accident Analysis and Prevention, 135(October 2019), p. 105355. Available at: https://doi.org/10.1016/j.aap.2019.105355.

Behnood, A. and Mannering, F.L. (2016) 'The effects of drug and alcohol consumption on driver-injury severities in single-vehicle crashes', Traffic Injury Prevention, pp. 1–25. Available at: https://doi.org/https://doi.org/10.1080/15389588.2016.1262540.

Bhuyan, P.J. and Ahmed, F. (2013) 'Road Traffic Accident : An Emerging Public Health Problem in Assam', 38(2), pp. 100–104. Available at: https://doi.org/10.4103/0970-0218.112441.

Bonera, M. et al. (2024) 'Network-wide road crash risk screening : A new framework', Accident Analysis and Prevention, 199(February), p. 107502. Available at: https://doi.org/10.1016/j.aap.2024.107502.

Celik, A.K. and Oktay, E. (2017) 'A comparison of ordered and unordered response models for analyzing road traffic injury severities in the North-Eastern Turkey', Periodica Polytechnica Transportation Engineering, 45(3), pp. 119–132. Available at: https://doi.org/10.3311/PPtr.8782.

Chen, C. et al. (2016) 'Driver injury severity outcome analysis in rural interstate highway crashes : a two-level Bayesian logistic regression interpretation', Accident Analysis and Prevention, 97, pp. 69–78. Available at: https://doi.org/10.1016/j.aap.2016.07.031.

Chen, F. and Chen, S. (2011) 'Injury severities of truck drivers in single- and multi-vehicle accidents on rural highways', Accident Analysis and Prevention, 43(5), pp. 1677–1688. Available at: https://doi.org/10.1016/j.aap.2011.03.026.

Dabbour, E., Easa, S. and Haider, M. (2017) 'Using fi xed-parameter and random-parameter ordered regression models to identify signi fi cant factors that a ff ect the severity of drivers ' injuries in vehicle-train collisions', Accident Analysis and Prevention, 107(December 2016), pp. 20–30. Available at: https://doi.org/10.1016/j.aap.2017.07.017.

Dissanayake, S. and Roy, U. (2014) 'Crash Severity Analysis of Single Vehicle Run-off-Road Crashes', Journal of Transportation Technologies, 04(01), pp. 1–10. Available at: https://doi.org/10.4236/jtts.2014.41001.

Donmez, B. and Liu, Z. (2015) 'Associations of distraction involvement and age with driver injury severities', Journal of Safety Research, 52(December 2014), pp. 23–28. Available at: https://doi.org/10.1016/j.jsr.2014.12.001.

Duddu, V.R., Madhav, V. and Pulugurtha, S.S. (2019) 'Crash risk factors associated with injury severity of teen drivers', IATSS Research, 43(1), pp. 37–43. Available at: https://doi.org/10.1016/j.iatssr.2018.08.003.

Eboli, L., Forciniti, C. and Mazzulla, G. (2020) 'Factors influencing accident severity : an analysis by road accident type', Transportation Research Procedia, 47, pp. 449–456. Available at: https://doi.org/10.1016/j.trpro.2020.03.120.

Haq, M.T., Zlatkovic, M. and Ksaibati, K. (2021) 'Assessment of Commercial Truck Driver Injury Severity as a Result of Driving Actions', Transportation Research Board [Preprint]. Available at: https://doi.org/10.1177/03611981211009880.

Hosmer, D.W., Taber, S. and Lemeshow, S. (1991) 'The importance of assessing the fit of logistic regression models: A case study', American Journal of Public Health, 81(12), pp. 1630–1635. Available at: https://doi.org/10.2105/AJPH.81.12.1630.

Islam, M. and Mannering, F. (2020) 'A temporal analysis of driver-injury severities in crashes involving aggressive and non-aggressive driving', Analytic Methods in Accident Research, 27, p. 100128. Available at: https://doi.org/10.1016/j.amar.2020.100128.

Jaber, A., Juhasz, J. and Csonka, B. (2021) 'An Analysis of Factors Affecting the Severity of Cycling Crashes Using Binary Regression Model', Sustainability (Switzerland), 13(6945). Available at: https://doi.org/10.3390/su13126945.

Javid, M.A. and Al-Roushdi, A.F.A. (2019) 'Causal Factors of Driver's Speeding Behaviour, a Case Study in Oman: Role of Norms, Personality, and Exposure Aspects', International Journal of Civil Engineering, 17(9), pp. 1409–1419. Available at: https://doi.org/10.1007/s40999-019-00403-8.

Joni, H.H. and Shallal, M.H. (2021) 'Studying and Analysis of crash severity for different Expressways on Al-Rusafa side for Baghdad city using Binary Logistic Regression Model', IICESAT Conference, College of Material Engineering, University of Babylon, Iraq [Preprint]. Available at: https://doi.org/10.1088/1742-6596/1973/1/012095.

Kadilar, G.O. (2015) 'Effect of driver , roadway , collision , and vehicle characteristics on crash severity : a conditional logistic regression approach', International Journal of Injury Control and Safety Promotion, 7300(September). Available at: https://doi.org/10.1080/17457300.2014.942323.

Karabulut, N.C. and Ozen, M. (2023) 'Exploring Driver Injury Severity Using Latent Class Ordered Probit Model : A Case Study of Turkey', KSCE Journal of Civil Engineering, 27(3), pp. 1312–1322. Available at: https://doi.org/10.1007/s12205-023-0473-6.

Kyriazos, T. and Poga, M. (2023) 'Dealing with Multicollinearity in Factor Analysis: The Problem, Detections, and Solutions', Open Journal of Statistics, 13(03), pp. 404–424. Available at: https://doi.org/10.4236/ojs.2023.133020.

Lee, C. and Li, X. (2014) 'Analysis of injury severity of drivers involved in single- and two-vehicle crashes on highways in Ontario', Accident Analysis and Prevention, 71, pp. 286–295. Available at: https://doi.org/10.1016/j.aap.2014.06.008.

MoRTH (2021) 'Road Accidents in India 2021', Ministry of Road Transport & Highways (MoRTH), pp. 1–237. Available at: https://doi.org/10.1016/s0386-1112(14)60239-9.

Mujalli, R.O. and De Ona, J. (2013) 'Injury severity models for motor vehicle accidents: A review', Proceedings of the Institution of Civil Engineers: Transport, 166(5), pp. 255–270. Available at: https://doi.org/10.1680/tran.11.00026.

Paleti, R., Eluru, N. and Bhat, C.R. (2010) 'Examining the influence of aggressive driving behavior on driver injury severity in traffic crashes', Accident Analysis and Prevention, 42(6), pp. 1839–1854. Available at: https://doi.org/10.1016/j.aap.2010.05.005.

Pisharam, P.P., Lubbe, N. and Davidsson, J. (2021) 'Estimated Lives Saved by Recently Implemented Vehicle Safety Standards in India: Implications and Future Safety Needs', IRCOBI Conference, 395, pp. 13–22.

Roque, C., Jalayer, M. and Hasan, A.S. (2021) 'Investigation of injury severities in single-vehicle crashes in North Carolina using mixed logit models', Journal of Safety Research, 77(xxxx), pp. 161–169. Available at: https://doi.org/10.1016/j.jsr.2021.02.013.

Sagberg, F. (1999) 'Road accidents caused by drivers falling asleep', Accident Analysis & Prevention, 31, pp. 639–649.

Savolainen, P. and Mannering, F. (2007) 'Probabilistic models of motorcyclists ' injury severities in single- and multi-vehicle crashes', Accident Analysis & Prevention, 39, pp. 955–963. Available at: https://doi.org/10.1016/j.aap.2006.12.016.

Se, C. et al. (2023) 'Temporal instability and differences in injury severity between restrained and unrestrained drivers in speeding-related crashes', Scientific Reports, 13(1), pp. 1–20. Available at: https://doi.org/10.1038/s41598-023-36906-7.

Sze, N.N. and Wong, S.C. (2007) 'Diagnostic analysis of the logistic model for pedestrian injury severity in traffic crashes', 39, pp. 1267–1278. Available at: https://doi.org/10.1016/j.aap.2007.03.017.

Tiwari, G. et al. (2024) ‘India Status Report on Road Safety’, Transportation Research and Injury Prevention Centre, Indian Institute of Technology Delhi [Preprint].
Waseem, M., Ahmed, A. and Saeed, T.U. (2019) ‘Factors affecting motorcyclists’ injury severities: An empirical assessment using random parameters logit model with heterogeneity in means and variances’, Accident Analysis and Prevention, 123(March 2018), pp. 12–19. Available at: https://doi.org/10.1016/j.aap.2018.10.022.
Yuan, Q. et al. (2017) ‘What factors impact injury severity of vehicle to electric bike crashes in China ?’, Advances in Mechanical Engineering, 9(8), pp. 1–10. Available at: https://doi.org/10.1177/1687814017700546.
Yuan, R. et al. (2024) ‘Investigating the spatial heterogeneity of factors influencing speeding-related crash severities using correlated random parameter order models with heterogeneity-in-means’, Transportation Letters, 16(9), pp. 989–1001. Available at: https://doi.org/10.1080/19427867.2023.2262201.
Zhang, Y., Fu, C. and Cheng, S. (2015) ‘Exploring driver injury severity at intersection: An ordered probit analysis’, Advances in Mechanical Engineering, 7(2). Available at: https://doi.org/10.1155/2014/567124.