Examining Driver Injury Severity in Motor Vehicle Crashes: A Copula-Based Approach Considering Temporal Heterogeneity in a Developing Country Context

Shahrior Pervaz*
Graduate Research Assistant
Department of Civil, Environmental and Construction Engineering
University of Central Florida, and
Assistant Professor
Accident Research Institute
Bangladesh University of Engineering and Technology, Dhaka
Tel: 1-407-561-0298
Email: shahrior.pervaz@ucf.edu
ORCiD number: 0000-0001-7966-7083

Tanmoy Bhowmik
Assistant Professor
Department of Civil and Environmental Engineering
Portland State University
Tel: 1-407-927-6574
Email: tbhowmik@pdx.edu
ORCiD number: 0000-0002-0258-1692

Naveen Eluru
Professor
Department of Civil, Environmental and Construction Engineering
University of Central Florida
Tel: 407-823-4815, Fax: 407-823-3315
Email: naveen.eluru@ucf.edu
ORCiD number: 0000-0003-1221-4113

*Corresponding author

ABSTRACT

Using data from a developing country, the current study develops a copula-based joint modeling framework to study crash type and driver injury severity as two dimensions of the severity process. To be specific, a copula-based multinomial logit model (for crash type) and generalized ordered logit model (for driver severity) is estimated in the study. The data for our analysis is drawn from Bangladesh for the years of 2000 to 2015. Given the presence of multiple years of data, we develop a novel spline variable generation approach that facilitates easy testing of variation in parameters across time in crash type and severity components. A comprehensive set of independent variables including driver and vehicle characteristics, roadway attributes, environmental and weather information, and temporal factors are considered for the analysis. The model results identify several important variables (such as driving under the influence of drug and alcohol, speeding, vehicle type, maneuvering, vehicle fitness, location type, road class, road geometry, facility type, surface quality, time of the day, season, and light conditions) affecting crash type and severity while also highlighting the presence of temporal instability for a subset of parameters. The superior model performance was further highlighted by testing its performance using a holdout sample. Further, an elasticity exercise illustrates the influence of the exogenous variables on crash type and injury severity dimensions. The study findings can assist policy makers in adopting appropriate strategies to make roads safer in developing countries.

Keywords: Developing country, Driver injury severity, Crash type, Copula model, Temporal heterogeneity.

1 BACKGROUND

Road traffic crashes disproportionately affect low and middle-income countries of the world. It is estimated that with only 60% of the world's registered vehicles, these countries account for 93% of the crash fatalities in the world (WHO, 2019). It is not surprising that per-capita death rates in these countries is more than three times higher than per-capita death rates in high-income countries (WHO, 2019). While high-income countries have shown some success in reducing the number of road deaths, low and middle-income countries are still in the initial stages of developing remedial solutions. The current study contributes to literature on driver injury severity analysis using data from Bangladesh.

In Bangladesh, a developing country in south-east Asia, 3-5% of national's gross domestic products (GDP) are lost due to road traffic crashes (Pervaz et al., 2022; WHO, 2019). The unique driver behavior, roadway characteristics, traffic composition, traffic flow, and roadway environment contribute to a fundamentally different system compared to the systems in developed countries. It is common for roadways designed as limited access facilities to be operated with severe encroachments due to markets or roadside settlements. Further, heterogenous, and mixed traffic flow results in complex interactions (compared to developed countries). Compounding the challenges, the recent economic growth and rising per capita income have induced rapid motorization in the country while road safety management and interventions have not been progressed at the same pace.

1.1 Earlier Research

Road safety research, similar to other developing countries, is hindered in Bangladesh due to financial constraints and underreporting of crash data. In Bangladesh, police record the crash information once a crash occurs and store the data in the Micro-Computer Accident Analysis Package (MAAP5) database. This database is later shared with different road safety organizations of the country. As the police reported database provides detailed crash information, several road safety research have been conducted relying on this database. Most of earlier research efforts using these data described the crash and casualty characteristics of pedestrians (Hoque and Mahmud, 2010; Pervaz et al., 2016), motorcyclists (Akter and Pervaz, 2019; Pervaz et al., 2020a), bicyclists (Hoque et al., 2008), children (Hoque et al., 2009), car involved crashes (Ahsan et al., 2011), urban crashes (Pervaz et al., 2020b; Uddin et al., 2021), highway crashes (Hoque et al., 2020, 2014) and overall safety situation of the country (Pervaz et al., 2022) employing descriptive analytics. Many studies also focused on the hazardous road location identification (Hoque and Mahmud, 2009; Mahmud et al., 2011) and safety ratings of roadways (Hoque et al., 2016). While these studies identify important crash characteristics and trends, the impacts of different attributes on crashes cannot be obtained from these studies.

A small set of studies applied statistical and econometric models. In modeling crash frequency analysis, studies applied Poisson regression (Hadiuzzaman et al., 2016; Sadeek and Rifaat, 2020) and negative binomial regression models (Hadiuzzaman et al., 2016; Islam et al., 2022) to estimate the impact of roadway, traffic and sociodemographic characteristics on crash counts. In the realm of injury severity studies, several research efforts were conducted. Researchers examined crash injury severity (Anowar et al., 2014; Hossain et al., 2022; Kamruzzaman et al., 2014), pedestrian injury severity (Hasanat-E-Rabbi et al., 2022; Saha et al., 2021; Sarkar et al., 2011; Zafri et al., 2020), motorcyclist injury severity (Rahman et al., 2021), unconventional and transit vehicle occupant severity (Saha et al., 2023, 2022). These efforts considered severity outcome as a dichotomous variable (usually fatal and non-fatal injury), or a polytomous variable (with categorical outcomes including fatal, major injury, minor injury, and no-injury). For dichotomous variables, as expected, researchers predominantly applied binary probit/logit models (Hossain et al., 2022; Rahman et al., 2021; Sarkar et al., 2011; Zafri et al., 2020). For polytomous variable, research efforts mostly applied ordered probit model (Barua and Tay, 2010; Hasanat-E-Rabbi et al., 2022; Kamruzzaman et al., 2014), partial proportional odds model (Anowar et al., 2014; Hasanat-E-Rabbi et al., 2022), and multinomial logit model (Hasanat-E-Rabbi et al., 2022). Advanced models including latent segmentation-based logit models were also employed for injury severity analysis (Saha et al., 2023, 2022, 2021). In these advanced studies, the authors captured the unobserved heterogeneity by estimating differential impacts of a variable in higher-risk and lower-risk segments while also estimating the heterogeneity in means of a variable within a segment in the model system.

The significant contributing factors to injury severity outcome reported in these studies are road user characteristics (such as gender, age, activities, restraint use, alcohol and drug suspicion), vehicle characteristics (such as single-vehicle, trucks, buses, cars, baby taxies, auto rickshaws, tractors, non-motorized vehicles, motorcycles and vehicle defects), roadway attributes (such as rural area, regional roads, city roads, undivided roads, two-way streets, non-intersection, flat roads, police control, stop control, and dry pavement), environmental and weather factors (such as weekend, off-peak periods, nighttime, dawn and dusk, night-lighted, night-unlighted, rainy season and winter season), built environment and land-use characteristics (such as bus stop, distance from airport, distance from ferry station and mixed-land use), and crash specific characteristics (such as head-on, rear-end, right-angle, hit-pedestrian, hit-objects, hit-parked-vehicles, and sideswipe crash types).

1.2 Study Context

The review has highlighted the breadth of research examining injury severity in Bangladesh. Yet, there are several important issues that need to be addressed in the modeling efforts. The research on severity analysis assumes the entire parameter space to remain the same across the entire population of crash records. While literature has developed latent class models that address this limitation to some extent, it is possible that some variables (such as crash type) can mediate the influence of several independent variables (Yasmin et al., 2014a, 2014b).

The current study proposes a framework that explicitly allows for a crash type specific injury severity profile. Specifically, we recognize that crash type and severity represent joint decisions and are modeled as a joint econometric model system with two dimensions (Rana et al., 2010; Yasmin et al., 2014b). The approach allows to accommodate for the influence of observed and unobserved factors affecting crash type and severity. We employ a joint copula framework with a multinomial logit model for crash type and generalized ordered logit model for crash severity. The copula-based approach offers several advantages. First, copula-based approaches offer the flexibility to link error terms that are not from the same distribution. Second, copula-based approaches allow for an analytical formulation i.e., the probability expressions for the joint models are closed form expression and can be evaluated analytically (without simulation). Thus, the model estimation procedures are based on maximum likelihood and are likely to be more accurate compared to linking approaches that require us to adopt simulation based maximum likelihood estimation (see Bhat, 2011 for more details). Finally, copula-based approach via the different copulas offers various dependency structures that span the potential spectrum of dependencies (see Bhat and Eluru, 2009 and Yasmin and Eluru, 2014b for more details). In our analysis, we consider six copula structures including Gaussian copula, the Farlie-Gumbel-Morgenstern (FGM) copula, and set of Archimedean copulas (Frank, Clayton, Joe and Gumbel).

Further, earlier research using data from multiple years has implicitly assumed temporal stability of parameters. As noted by Mannering (2018), temporal stability needs to be assessed carefully for multi-year data (Mannering, 2018). The proposed econometric model system incorporates various spline functional forms that allow for temporal variations in parameter effects over time (see Eluru and Gayah, 2022). The spline functional form is an improvement on the year specific dummy effects and allows for easy examination of change in parameter values across years (Shabab et al., 2024 for a detailed discussion on the spline approach). In the spline approach, instead of creating year specific dummy variables, we create time variables using the following approach:

$$nYear_1 = Max(Year_{record} - Year_{base} + 1, 0) \tag{1}$$

$$nYear_2 = Max((Year_{record} - Year_{base} + 1) - 1, 0) \tag{2}$$

…

$$nYear_N = Max((Year_{record} - Year_{base} + 1) - (N - 1), 0) \tag{3}$$

where $Year_{record}$ corresponds to year of the observation, $Year_{base}$ corresponds to the first year of data (in this study, $Year_{base} = 2000$), and $N(1, 2, \dots, N)$ represents the years starting from 2000. The approach will yield the same number of variables as the year dummy approach. These variables can be interacted with any independent variable to test the temporal stability of that variable[1]. The approach effectively serves as a piecewise linear formulation for each parameter

[1]Our equation system begins with the possibility that all parameters are temporally unstable. We consider the interaction of the variable and year splines for the base year to the last year of the data to test this variability based on the t-statistics of the parameter values. If the interaction becomes significant for the base year only, then the slope of

over the years. For illustration, let's consider a small dataset with driving under the influence of drug and alcohol (DUI) variable where DUI is equal to 1 if the driver is found driving under the influence of drug and alcohol and 0 otherwise. Table 1 presents the dataset for the six-year period (2000 to 2005) of DUI variable.

Table 1: Example Dataset for Spline Formulation

Year	DUI	nYear1	nYear2	nYear3	nYear4	nYear5	nYear6	DUI*nYear1	DUI*nYear2	DUI*nYear3	DUI*nYear4	DUI*nYear5	DUI*nYear6
2000	1	1	0	0	0	0	0	1	0	0	0	0	0
2001	0	2	1	0	0	0	0	0	0	0	0	0	0
2002	1	3	2	1	0	0	0	3	2	1	0	0	0
2003	0	4	3	2	1	0	0	0	0	0	0	0	0
2004	0	5	4	3	2	1	0	0	0	0	0	0	0
2005	1	6	5	4	3	2	1	6	5	4	3	2	1

In the spline formulation approach, we will use a total of six variables (DUI*nYear1 to DUI*nYear6) to capture the change of the slope of the DUI variable effect over time in the model. For example, if the estimates for DUI variable are found to be 0.30 (for DUI*nYear$_1$), -0.45 (for

the effect of the variable will not change for the rest of the years which implies that the variable is truly linear over time. If the variable shows significant effect for base year and another year, let's say for the fourth year, then the variable slope remains the same up to the third year and from the fourth year, the slope of the effect will change. If the analyst wants to consider a temporally invariable effect, the analyst can simply introduce the variable of interest directly in the model.

DUI*nYear$_3$), and 0.25 (for DUI*nYear$_6$) for the year 2000, 2002 and 2005 respectively, the net estimate of DUI variable by year is as follows:

- For the year 2000, the estimate is 0.30,
- For the year 2001, the estimate is 0.60 (0.30*2),
- For the year 2002, the estimate is 0.45 (0.30*3-0.45),
- For the year 2003, the estimate is 0.30 (0.30*4-0.45*2),
- For the year 2004, the estimate is 0.15 (0.30*5-0.45*3),
- For the year 2005, the estimate is 0.25 (0.30*6-0.45*4+0.25),

The illustration described above shows how the spline variables allow for flexible evaluation of changes in parameter effects over time.

In summary, the current research effort contributes to safety literature both methodologically and empirically. In terms of methodology, we formulate a copula-based temporal multinomial (MNL)-generalized ordered logit (GOL) model to jointly estimate crash type and severity sustained by drivers in motor vehicle crashes. The study examines six copula structures - Gaussian, Farlie-Gumbel-Morgenstern (FGM), Frank, Clayton, Joe, and Gumbel to consider a wide range of dependency structures. We also accommodate for the potential heterogeneity across drivers in the dependency effect of crash type and injury severity within the proposed model system. In terms of empirical analysis, using police reported crash data from Bangladesh for the years 2000 to 2015, the study focuses on injury severity sustained by drivers in motor vehicle crashes. We use six crash types (head-on, rear-end, right-angle, sideswipe, single-vehicle and hit-parked-vehicle crashes) and four severity levels (fatal, grievous, simple and no injury) as our dependent variable categories. A comprehensive set of exogenous variables including driver and vehicle characteristics, roadway attributes, environmental and weather information, and temporal factors is considered for the analysis of the models.

2 METHODOLOGY

The focus of our study is to jointly model the crash type and injury severity outcome of drivers in motor vehicle crashes using a copula-based joint multinomial logit (MNL)-generalized ordered logit (GOL) modeling framework. For the current study, we followed the methodology presented by Yasmin et al. (2014b). The econometric frameworks for both components are described in the following sections.

2.1 The Crash Type Model Component

Let q $(q = 1,2, \dots \dots, Q)$ be the indices to represent drivers and k $(k = 1,2, \dots \dots, K)$ represents crash types (here, k = 1 for head-on, k = 2 for rear-end, k = 3 for right-angle, k = 4 for sideswipe, k = 5 for single-vehicle, and k = 6 for hit-parked-vehicle crashes). Let j be the index for the discrete outcome that corresponds to the injury severity level j $(j = 1,2, \dots \dots, J)$ of driver q. In this study, j takes four severity levels: $j = 1$ for no injury, $j = 2$ for simple injury, $j = 3$ for grievous injury, and $j = 4$ for fatal injury. In the joint framework, the modeling of crash type is undertaken using the multinomial logit structure. Thus, the propensity of a driver q involving in a specific crash type k takes the form of:

$$u_{qk}^{*} = \beta_k x_{qk} + \xi_{qk} \tag{4}$$

where, x_{qk} is a column vector of exogenous variable, β_k is a row vector of unknown parameters specific to crash type k and ξ_{qk} is an idiosyncratic error term (assumed to be standard type-I extreme value distributed) capturing the effects of unobserved factors on the propensity associated with crash type k. A driver q is assumed to be involved in a crash type k if and only if q is associated with the maximum propensity among all k crash types, that is if the following condition holds:

$$u_{qk}^{*} > \max_{l=1,2,\ldots,k,\ \ and\ l\neq k} u_{ql}^{*} \tag{5}$$

The condition demonstrated in equation 5 can be expressed as a series of binary outcome models for each crash type k (Lee, 1983). Let η_{qk} be a dichotomous variable with $\eta_{qk} = 1$ if a driver q ends up in a crash type k and $\eta_{qk} = 0$ otherwise. Thus, we can define a stochastic term v_{qk} as follows:

$$v_{qk} = \xi_{qk} - \left\{\max_{l=1,2,\ldots,k,\ \ l\neq k} u_{ql}^{*}\right\} \tag{6}$$

The reader would note that in this study the v_{qk} term is specified following Portoghese et al. (2011) which is different than Lee's transformation (please see Yasmin et al., 2014b for detailed description).

By substituting the right side for u_{qk}^{*} from equation 4 in equation 5, we can write:

$$\eta_{qk} = 1\ \ if\ \ \beta_k x_{qk} + v_{qk} > 0 \tag{7}$$

In equation 7, the probability expression of crash type is dependent on the distributional assumption of v_{qk}, which in turn depends on the distributional assumption of ξ_{qk}. Thus, an assumption of independent and identical Type 1 Gumbel distribution for ξ_{qk} results in a logistic distributed v_{qk}. Consequently, the probability expression for the corresponding crash type can be expressed as follows:

$$\Lambda_k(\beta_k x_{qk}) = Pr(v_{qk} > -\beta_k x_{qk}) = \frac{\sum_{l \neq k} exp\ (\beta_k x_{ql})}{exp\ (\beta_k x_{qk}) + \sum_{l \neq k} exp\ (\beta_k x_{ql})} \tag{8}$$

2.2 The Injury Severity Model Component

In the joint model framework, the modeling of driver injury severity is undertaken using generalized ordered logit (GOL) specification. In the traditional ordered logit (OL) model, the discrete injury severity levels (y_{qk}) are assumed to be associated with an underlying continuous latent variable (y_{qk}^*). This latent variable is typically specified as the following linear function:

$$y_{qk}^* = \alpha_k z_{qk} + \varepsilon_{qk}\ ,\ \ y_{qk} = j_k, if\ \tau_{k,j-1} < y_{qk}^* < \tau_{k,j} \tag{9}$$

where, y_{qk}^* is the latent injury risk propensity for driver q if he/she was involved in a crash type k, z_{qk} is a vector of exogenous variables, α_k is a row vector of unknown parameters and ε_{qk} is a random disturbance term assumed to be standard logistic. $\tau_{k,j}$ $(\tau_{k,0} = -\infty\ , \tau_{k,J} = \infty)$ represents the threshold associated with severity level j for crash type k, with the following ordering conditions: $(-\infty < \tau_{k,1} < \tau_{k,2} < \ \dots\dots\dots < \tau_{k,J-1} < +\infty)$.

GOL is a flexible form of the traditional OL model that relaxes the restriction of constant threshold across population. The GOL model represents the threshold parameters as a linear function of exogenous variables (Eluru et al., 2008; Srinivasan, 2002). In order to ensure the ordering of observed discrete injury severity levels, we employ the following parametric form followed by Eluru et al. (2008):

$$\tau_{k,j} = \tau_{k,j-1} + exp(\phi_{kj} + \delta_{kj}'\ \mathrm{G}_{kj}) \tag{10}$$

where, G_{kj} is a set of explanatory variables associated with the j^{th} threshold (excluding a constant), δ'_{kj} is a vector of parameters to be estimated and ϕ_{kj} is a parameter associated with injury severity level j. The remaining structure and probability expressions are similar to the OL model. For identification reasons, we need to restrict one of the δ'_j vectors to zero.

Given these relationships across the different parameters, the resulting probability expressions for driver q sustaining an injury severity level j in a crash type k take the following form:

$$Pr(y_{qk} = j_k) = \Lambda_k\big(\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\, G_{kj}) - \alpha_k z_{qk}\big) - \Lambda_k\big(\tau_{k,j-2} + exp(\phi_{k,j-1} + \delta'_{k,j-1}\, G_{k,j-1}) - \alpha_k z_{qk}\big) \tag{11}$$

where, $\Lambda_k(.)$ is the standard logistic cumulative distribution function. The probability expression of equation 11 represents the independent injury severity model for a crash type k.

2.3 The Joint Model: A Copula-based Approach

The crash type and the injury severity component discussed in previous two subsections can be brought together in the following equation system:

$$\begin{gathered} \eta_{qk} = 1 \;\; if \;\; \beta_k x_{qk} > -v_{qk} \\ y^*_{qk} = \alpha_k z_{qk} + \varepsilon_{qk}\,, \;\; y_{qk} = 1[\eta_{qk} = 1]\, y^*_{qk} \end{gathered} \tag{12}$$

The notation $1[\eta_{qk} = 1]$ represents an indicator function taking the value 1 if $\eta_{qk} = 1$ and 0 otherwise.

However, the level of dependency between the underlying crash type outcome and the injury severity level of driver depends on the type and extent of dependency between the stochastic terms v_{qk} and ε_{qk}. These dependencies (or correlations) are explored in the current study by using a copula-based approach. A copula is a mathematical device that identifies dependency among random variables with pre-specified marginal distribution (please see Bhat and Eluru, 2009; Trivedi and Zimmer, 2007 for a detailed description of the copula approach). In other words, it is a multivariate distribution function defined over the unit cube that links uniformly distributed marginals (Eluru et al., 2010). In constructing the copula dependency, the random variables (v_{qk} and ε_{qk}) are transformed into uniform distributions by using their inverse cumulative distribution functions, which are then coupled or linked as a multivariate joint distribution function by applying the copula structure. Let us assume that $\Lambda_{vk}(.)$ and $\Lambda_{\varepsilon k}(.)$ are the marginal distribution of v_{qk} and ε_{qk}, respectively and $\Lambda_{vk,\varepsilon k}(.,.)$ is the joint distribution of v_{qk} and ε_{qk}. Subsequently, a bivariate distribution $\Lambda_{vk,\varepsilon k}(v,\varepsilon)$ can be generated as a joint cumulative probability distribution of uniform [0, 1] marginal variables U_1 and U_2 as below:

$$\Lambda_{vk,\varepsilon k}(v,\varepsilon) = Pr(v_{qk} < v, \varepsilon_{qk} < \varepsilon)$$

$$= [\Lambda_{vk}^{-1}(U_1) < v, \Lambda_{\varepsilon k}^{-1}(U_2) < \varepsilon\,] \qquad (13)$$

$$= [U_1 < \Lambda_{vk}(v), U_2 < \Lambda_{\varepsilon k}(\varepsilon)\,]$$

The joint distribution (of uniform marginal variable) in equation 13 can be generated by a function $C_{\theta q}(.,.)$ (Sklar, 1973), such that:

$$\Lambda_{vk,\varepsilon k}(v,\varepsilon) = C_{\theta q}(U_1 = \Lambda_{vk}(v), U_2 = \Lambda_{\varepsilon k}(\varepsilon)) \qquad (14)$$

where $C_{\theta q}(.,.)$ is a copula function and θ_q the dependence parameter defining the link between v_{qk} and ε_{qk}. It is important to note here that the level of dependence between crash type and injury severity level can vary across drivers. Therefore, in the current study, the dependence parameter θ_q is parameterized as a function of observed crash attributes as follows:

$$\theta_q = fn(\gamma_k s_{qk}) \tag{15}$$

where, s_{qk} is a column vector of exogenous variable, γ_k is a row vector of unknown parameters (including a constant) specific to crash type k and fn represents the functional form of parameterization. Based on the dependency parameter permissible ranges, alternate parameterization forms for the six copulas are considered in our analysis. For Gaussian, Farlie-Gumbel-Morgenstern (FGM) and Frank Copulas we use $\theta_q = \gamma_k s_{qk}$, for the Clayton copula we employ $\theta_q = exp\,(\gamma_k s_{qk})$, and for Joe and Gumbel copulas we employ $\theta_q = 1 + exp\,(\gamma_k s_{qk})$.

2.4 Estimation Procedure

The joint probability that the driver q gets involved in a crash type k and sustaining injury severity level j, from equation 8 and 11, can be written as:

$$
\begin{aligned}
&Pr(\eta_{qk} = 1, y_{qk} = j_k) \\
&= Pr\left\{(\beta_k x_{qk} > -v_{qk}), \begin{pmatrix} (\tau_{k,j-2} + \exp(\phi_{k,j-1} + \delta'_{k,j-1}\,\mathrm{G}_{k,j-1}) - \alpha_k z_{qk}) \\ < \varepsilon_{qk} < (\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\,\mathrm{G}_{kj}) - \alpha_k z_{qk}) \end{pmatrix}\right\} \\
&= Pr\Big((\beta_k x_{qk} > -v_{qk}), (\varepsilon_{qk} < \tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\,\mathrm{G}_{kj}) - \alpha_k z_{qk})\Big) \\
&\qquad - Pr\Big((\beta_k x_{qk} > -v_{qk}), (\varepsilon_{qk} \\
&\qquad < \tau_{k,j-2} + exp(\phi_{k,j-1} + \delta'_{k,j-1}\,\mathrm{G}_{k,j-1}) - \alpha_k z_{qk})\Big)
\end{aligned} \tag{16}
$$

$$= \Lambda_{\varepsilon k}\big(\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\,\mathrm{G}_{kj}) - \alpha_k z_{qk}\big) - \Lambda_{\varepsilon k}\big(\tau_{k,j-2} + exp(\phi_{k,j-1} + \delta'_{k,j-1}\,\mathrm{G}_{k,j-1}) - \alpha_k z_{qk}\big) - \big(Pr\big[v_{qk} < -\beta_k x_{qk}\,, \varepsilon_{qk} < \big(\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\,\mathrm{G}_{kj}) - \alpha_k z_{qk}\big)\big] - Pr\big[v_{qk} < -\beta_k x_{qk}\,, \varepsilon_{qk} < \big(\tau_{k,j-2} + exp(\phi_{k,j-1} + \delta'_{k,j-1}\,\mathrm{G}_{k,j-1}) - \alpha_k z_{qk}\big)\big]\big)$$

The joint probability of equation 16 can be expressed by using the copula function in equation 14 as:

$$\begin{aligned} Pr(\eta_{qk} = 1, y_{qk} = j_k) &\\ &= \Lambda_{\varepsilon k}\big(\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\,\mathrm{G}_{kj}) - \alpha_k z_{qk}\big) \\ &- \Lambda_{\varepsilon k}\big(\tau_{k,j-2} + exp(\phi_{k,j-1} + \delta'_{k,j-1}\,\mathrm{G}_{k,j-1}) - \alpha_k z_{qk}\big) \\ &- \big[C_{\theta q}\big(U^k_{q,j}, U^k_q\big) - C_{\theta q}\big(U^k_{q,j-1}, U^k_q\big)\big] \end{aligned} \tag{17}$$

where $U^k_{q,j} = \Lambda_{\varepsilon k}\big(\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\,\mathrm{G}_{kj}) - \alpha_k z_{qk}\big)$, $U^k_q = \Lambda_{vk}\big(-\beta_k x_{qk}\big)$

Thus, the likelihood function with the joint probability expression in equation 17 for crash type and driver injury severity outcomes can be expressed as:

$$L = \prod_{q=1}^{Q}\left[\prod_{k=1}^{K}\prod_{j=1}^{J}\{Pr(\eta_{qk} = 1, y_{qk} = j_k)\}^{\omega_{qkj}}\right] \tag{18}$$

where, ω_{qkj} is dummy with $\omega_{qkj} = 1$ if the driver q sustains crash type k and an injury severity level of j and 0 otherwise. All the parameters in the model are then consistently estimated by maximizing the logarithmic function of L. The parameters to be estimated in the model are: β_k in the MNL component, α_k and $\tau_{k,j}$, ϕ_{kj}, δ'_{kj} in GOL component, and finally γ_k in the dependency component. In our analysis we employ six different copulas structure - the Gaussian copula, the

Farlie-Gumbel-Morgenstern (FGM) copula, and set of Archimedean copulas including Frank, Clayton, Joe and Gumbel copulas (a detailed discussion of these copulas is available in Bhat and Eluru, 2009). We use the GAUSS matrix programming software to run the models (Aptech, 2015).

3 DATA DESCRIPTION

The data for our analysis are compiled from the Micro-Computer Accident Analysis Package (MAAP5) database preserved in the Accident Research Institute (ARI) of Bangladesh University of Engineering and Technology (BUET). We focus on the injury severity outcome sustained by drivers involved in a road crash. A total of 60,465 driver level records were obtained for the years 2000 to 2015. Crashes involving hit-pedestrian and other non-motorized vehicles are excluded during the analysis as driver injury severity distribution is greatly influenced by these crash types. For instance, preliminary analysis found that nearly 98% of drivers do not sustain any injury during hit-pedestrian crashes. We also disregard crashes that involve more than two motor vehicles. After cleaning and processing the data, a total of 35,261 driver injury records were retained for the analysis. This study considers 10,000 records randomly for model estimation while setting aside the remaining 25,261 records for validation purposes. This study considers six crash types including head-on (HO), rear-end (RE), right-angle (RA), sideswipe (SS), single-vehicle (SV) and hit-parked-vehicle (HPV) as the dependent variable for crash type analysis and four severity levels including fatal injury (FI), grievous injury (GI), simple injury (SI) and no injury (NI) for severity analysis. Regarding the crash types, it is worthwhile to mention that the hit-parked-vehicle crash type includes crashes that occur due to the collisions between a moving vehicle and a vehicle that is parked predominantly on the street/roadside or stopped for passenger boarding/alighting or goods loading/unloading activities. The single-vehicle crashes include run-off-road, overturned, and hit-object crashes. For independent variables, a comprehensive set of exogenous variables including driver and vehicle characteristics (such as restraint use, driving under influence of drug and alcohol, speeding, vehicle type, maneuvering, vehicle fitness, and defect), roadway attributes (such as location, road class, presence of divider, road geometry, surface condition, and traffic control system), environmental and weather factors (such as time of the day, season, light and weather conditions), and temporal factors (such as year-spline variables) is considered for model estimation. The sample share of the variables considered for the final model estimation is presented in Table A.1 in the Appendix section.

4 EMPIRICAL ANALYSIS

4.1 Model Specification and Overall Measures of Fit

The empirical analysis of the current study involves a series of model estimation. *First,* we developed a multinomial logit (MNL) to model six crash types and ordered logit (OL) to model driver injury severity for each crash type. *Second,* we estimated the temporal instability of the variables by using year splines and the interaction of year splines with other exogenous variables in both MNL and OL model systems. Next, we parametrized the thresholds to relax the monotonic effect of the OL models and developed generalized ordered logit (GOL) models. *Third,* with these independent model results, we build a joint model with six different copula structures: 1) Gaussian, 2) FGM, 3) Frank, 4) Clayton, 5) Joe, and 6) Gumbel. *Fourth*, based on the significance of copula dependence parameter for each crash type, copula models that allow for different dependency structures for different crash types and injury severity combinations were estimated. Further, we parametrized dependence parameter in our model system.

The alternative copula models estimated are non-nested and hence, cannot be tested using the traditional log-likelihood ratio test (Yasmin et al., 2014b). We employ the Bayesian Information Criterion (BIC) to determine the best model among all copula models. The BIC for a given empirical model is equal to:

$$BIC = -2LL + N_p \, ln(Q) \quad (19)$$

where LL is the log-likelihood value at convergence, N_p is the number of parameters, and Q is the number of observations. The model with the *lower* BIC value is the preferred model. The BIC values of the estimated models are shown in Table 2.

Table 2: Comparison of the Estimated Models

Model	Log-likelihood	No. of Parameters	BIC
MNL and OL models	-21,756.61	115	44,572.41
MNL and OL models with temporal heterogeneity	-21,280.59	152	43,961.14
MNL and GOL models with temporal heterogeneity (Independent copula)	-21,262.90	155	43,953.40
Gaussian copula	-21,260.90	155	43,949.40
FGM copula	-21,261.10	155	43,949.80
Frank copula	-21,260.20	155	43,948.00
Clayton copula	-21,262.90	155	43,953.40
Joe copula	-21,264.40	154	43,947.19
Gumbel copula	-21,264.90	154	43,948.19

Model	Log-likelihood	No. of Parameters	BIC
Joe-Frank copula	-21,259.80	155	43,947.20
Joe-Frank-FGM copula	-21,259.80	155	43,947.20
Gumbel-Frank copula	-21,262.10	154	43,942.59
Gumbel-Frank copula with parameterized dependency	-21,256.30	155	43,940.20

Table 2 demonstrates that the MNL-OL models (separate model system) considering temporal heterogeneity outperform the models without considering temporal heterogeneity. This finding underscores that the effects of the several exogenous variables are not stable over time both on crash type and injury severity analysis. Further, MNL-GOL models outperform the MNL-OL models in terms of BIC value. The comparison exercise among copula models shows that with exclusively a single copula dependency structure, all the copula structures except Clayton offer better performance than independent model as shown in Table 2. The copula parameters for head-on and hit-parked-vehicle crash types were found statistically insignificant in all copula structures. The copula parameters for rear-end and right-angle crash types were observed to be significant in Joe and Gumbel structures while for sideswipe crash type, all the copula structures except Clayton showed significant copula parameters. For single-vehicle crash type, the FGM structure offered significant copula parameters for our dataset. We also tested the performance of combinations such as Joe-Frank, Joe-Frank-FGM and Gumbel-Frank copula structures and found that Gumbel-Frank combination offered improved BIC (lower) compared to other copula structures. Further, we parametrized the dependency parameter in the Gumbel-Frank copula structure and found that parameterization provides improved BIC (lower) compared to the unparameterized Gumbel-Frank structure. Therefore, the Gumbel-Frank copula with parameterized dependence was selected in our study.

4.2 Estimation Results

In this section, we present the results of the Gumbel-Frank copula model with parametrized dependency. Table 3 and Table 4 show the crash type component and injury severity component respectively. The copula parameters are presented in the last row panel of Table 4. For ease of presentation, the crash type component and injury severity component are discussed separately. The results of the independent models are shown in Table A.2 and Table A.3 in the Appendix section.

Crash Type Component

The coefficients in the crash type component (Table 3) represent the effects of exogenous variables on each crash type relative to the base category head-on crash type. A positive (negative) sign of a coefficient for a crash type in Table 3 signifies that an increase in the variable is likely to result in a higher (lower) likelihood of that crash type relative to the head-on crash type. The impacts of the variables are discussed by variable characteristics separately in the following sections.

Table 3: MNL (Crash Type) Model Component in the Gumbel-Frank Copula Model with Parameterized Dependence (Base: Head-on)

Variables	Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Constant	-0.623	-15.609	-4.074	-27.233	-1.425	-31.575	-1.067	-19.371	-1.991	-26.618
Driver Characteristics										
DUI suspicion (Base: Not DUI suspect)										
DUI suspect*	--	--	--	--	--	--	0.239	5.320	--	--
DUI suspect* nYear4	--	--	--	--	--	--	-0.308	-4.903	--	--
Vehicle Characteristics										
Vehicle type (Base: 4-wheeler light vehicles)										
Bus	--	--	--	--	--	--	0.023	2.930	--	--
Truck	--	--	--	--	--	--	-0.050	-5.519	0.133	2.068
Truck*nYear4	--	--	--	--	--	--	--	--	-0.282	-1.889
Truck*nYear7	--	--	--	--	--	--	--	--	0.345	1.956
Truck*nYear10	--	--	--	--	--	--	--	--	-0.281	-2.182
Motorcycle	--	--	--	--	--	--	-0.672	-5.737	-0.086	-3.816
Motorcycle*nYear4	--	--	--	--	--	--	0.688	4.442	--	--

Variables	Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Motorized 3-wheelers	-0.058	-5.209	-0.108	-2.154	-0.052	-3.517	-0.068	-4.849	-0.072	-3.219
Informal vehicles	0.017	1.740	--	--	0.025	2.120	--	--	--	--
Vehicle maneuvering (Base: Straight and others)										
Overtaking	--	--	--	--	0.301	4.325	--	--	--	--
Overtaking*nYear4	--	--	--	--	-0.333	-3.545	--	--	--	--
Crossing	--	--	0.129	4.198	--	--	--	--	--	--
Turning	--	--	--	--	--	--	0.028	2.352	--	--
Fitness certificate (Base: Not present)										
Present	-0.012	-2.423	-0.043	-2.584	--	--	--	--	-0.028	-2.893
Roadway Characteristics										
Location type (Base: Rural area)										
Urban area	0.169	5.215	--	--	--	--	-0.082	-2.869	--	--
Urban area*nYear4	-0.186	-4.231	--	--	--	--	--	--	--	--
Urban area*nYear7	--	--	--	--	--	--	0.290	3.003	--	--
Urban area*nYear10	--	--	--	--	--	--	-0.549	-3.693	--	--
Urban area*nYear13	--	--	--	--	--	--	0.397	2.129	--	--

Variables	Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**
Road class (Base: National highways)										
Feeder roads	0.029	3.156	--	--	--	--	0.296	7.109	--	--
Feeder roads*nYear4	--	--	--	--	--	--	-0.380	-6.202	--	--
Village roads	--	--	--	--	--	--	0.047	4.020	-0.076	-2.559
City roads	0.027	3.037	0.569	6.089	--	--	0.048	3.175	--	--
City roads*nYear4	--	--	-0.611	-4.825	--	--	--	--	--	--
Presence of divider (Base: Not divided)										
Divided	0.533	13.080	0.430	4.543	0.179	3.286	--	--	0.071	5.301
Divided*nYear4	-0.579	-10.266	-0.453	-3.508	-0.170	-2.288	--	--	--	--
Road geometry (Base: Straight and slope)										
Curve section	-0.073	-6.106	--	--	--	--	--	--	-0.116	-3.886
Facility type (Base: Not at intersection)										
Intersection	--	--	0.542	7.274	0.263	6.991	--	--	0.027	2.657
Intersection*nYear4	--	--	-0.597	-5.903	-0.301	-5.961	--	--	--	--
Surface quality (Base: Good)										
Rough	--	--	--	--	--	--	0.057	3.862	--	--

Variables	Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**
Road features (Base: None/narrowing/restricted)										
Bridge and culvert	--	--	--	--	--	--	0.041	2.471	--	--
Environmental and Weather Characteristics										
Time of the day (Base: Other than late night))										
Late night	--	--	--	--	--	--	0.338	9.063	0.052	4.966
Late night*nYear4	--	--	--	--	--	--	-0.423	-7.952	--	--
Light condition (Base: Daylight, dawn and dusk)										
Night lighted	0.026	2.425	--	--	--	--	--	--	0.040	2.252
Night not lighted	--	--	--	--	--	--	0.033	3.077	0.188	2.807
Night not lighted*nYear4	--	--	--	--	--	--	--	--	-0.201	-2.114

Note: "*" Represents the effect of the variable for the base year 2000 (nYear1*DUI suspect). If the interaction of a variable becomes significant for the base year only, then the slope of the effect of that variable will not change for the rest of the years which implies that the variable impact is linear. For this variable, the coefficient (estimate for "nYear1*variable") is the mean effect for the base year, for the second year the mean effect will be 2*coefficient, for the third year the mean effect will be 3*coefficient, and so on; "--" Represents the variables are not significant at 90% confidence level.

Driver characteristics

Among driver characteristics considered, only driving under influence (drug and alcohol) variable offers a significant impact in the crash type model. Specifically, we observe that a driver under influence of drug and alcohol is likely to be involved in a single-vehicle crash. The finding might appear counter-intuitive on first glance. Given that we are considering crash type conditional on a crash, the finding implies that driving under the influence is likely to increase the probability of single vehicle crashes relative to other crash types. This could be because drivers under the influence of drugs and alcohol are less alert, likely to react slower and have a lower ability to control the vehicles. Similar findings are also reported in many studies from developed countries (Bham et al., 2012; Hyun et al., 2021). The results also show that the effect of this variable is not stable over the years and the negative sign of the variable "DUI suspect*nYear4" implies that the slope of the impact reduces in the 4^{th} year (in the year 2003). The net impact of the variable for the year 2000 is 0.239 while the impact for 2003 is 0.648 (0.239*4-0.308). As we discussed earlier, we tested for varying impact in a piece-wise linear manner and for this variable, we found only one change in the slope.

Vehicle characteristics

Several vehicle characteristics were tested in the model. With regards to vehicle type, buses show a positive impact on single-vehicle crashes compared to 4-wheeler light vehicles. The results can be explained by driver's fatigue and lax regulation around late-night driving and break requirements for bus drivers in developing countries. Trucks are found to be associated with reduced propensity for single-vehicle crashes and higher propensity for hit-parked-vehicle crashes. On-street and roadside truck parking/loading/unloading activities, truck parking along the medians and dividers, particularly on national and regional highways are common in Bangladesh and are likely to be responsible for higher involvement of trucks in hit-parked-vehicle crashes. For hit-parked-vehicle crashes, the impact of the truck variable is found to be unstable over the years. For this crash type, we found changes in the slope of the truck impact in the years 2003, 2006 and 2009. Motorcycles are found to be less likely to be involved in single-vehicle and hit-parked-vehicle crashes compared to 4-wheeler light vehicles. For single-vehicle crashes, this variable positively changes the slope of the impact in the year 2003. Motorized 3-wheelers have negative effects on all crash types compared to 4-wheeler light vehicles. The results also show that informal vehicles increase the likelihood of rear-end and sideswipe crash types. These informal vehicles are mostly locally built vehicles that are likely to offer substandard safety features and are operated at lower speed. The differential speeds of these vehicles and other high-speed vehicles might trigger the rear-end and sideswipe crash types.

As expected, with respect to the vehicle maneuvering, the findings indicate that overtaking increases the sideswipe crash type and crossing increases the right-angle crash type while turning increases the single-vehicle crashes compared to the straight and other maneuvers. However, the slope of the effect of overtaking maneuvering is found to be reduced in the year 2003 for sideswipe crashes. The change cannot be attributed to something definitively. The change can possibly be attributed to several road safety interventions in Bangladesh including but not limited to, dissemination of driver education, road geometric and operational improvement of the roads in this time frame and possible advocacy efforts of Accident Research Center. In addition, the variable representing fitness certificate (associated with vehicle fitness for roadway usage) presents a negative impact on the likelihood of rear-end, right-angle and hit-parked-vehicle crashes.

Roadway characteristics

The impact of the location type indicates that with respect to rural area, crashes in urban areas are more likely to be rear-end crashes and less likely to be single-vehicle crashes. These findings are intuitive as divided roadways, higher intersection density, and stop-and-go situations in congested flows are some common features of urban areas of Bangladesh. The results also indicate that the effect of the urban area variable exhibits temporal instability for both crash types. For rear-end crashes, the impact decreases in the year 2003 while for single-vehicle crashes, the impact changes in the years 2006, 2009 and 2012.

With respect to road class, the results show that feeder roads have a higher likelihood of being rear-end and single-vehicle crash types compared to the national and regional highways. However, the effect on the single-vehicle crash type is not stable over time and the effect changes in the year 2003. The village roads also increase the likelihood of single-vehicle crashes while decrease the likelihood of hit-parked-vehicle crashes. City roads increase the likelihood of rear-end, right-angle and single-vehicle crashes compared to national highways while showing temporal instability for right-angle crashes. These results can be attributed to design deficiencies, narrower roads, and roadside linear settlements along the roadways across the country.

The results also suggest that divided roads have a higher likelihood of all crash types, except for single-vehicle crashes. Further, the slope of the impact is found to be lower in the year 2003 for rear-end, right-angle and sideswipe crashes. Crashes that occur on curve sections are less likely to be rear-end and hit-parked-vehicle crash types compared to straight and slope/grade sections. This is expected as drivers are more likely to stop and park the vehicles on straight section compared to curve section, thus, likelihood of being rear-end and hit-parked-vehicle crash types is lower. All these findings are in general consistent with many studies (Bham et al., 2012; Intini et al., 2020; Ye et al., 2008).

With respect to road facility type, crashes that occur at intersections are more likely to be right-angle, sideswipe and hit-parked-vehicle types compared to non-intersection locations (as found in Pervaz et al., 2024; Rana et al., 2010). This is quite expected as intersections have more crossing, passenger boarding/alighting, parking, and vendor activities compared to non-intersections across the country. The results also indicate that the effect of this variable is not stable over time on the right-angle and sideswipe crashes and the effect decreases starting from the year 2003.

With regards to surface quality, crashes that occur on the rough surface are more likely to be single-vehicle crashes. Similarly, crashes on bridge-culverts are more likely to be single-vehicle crashes.

Environmental and weather characteristics

With respect to the time of the day, late nighttime shows a positive impact on single-vehicle and hit-parked-vehicle crashes compared to other times of the day (see Intini et al., 2020 for similar finding). This might be attributable to lower visibility and driver impairment due to fatigue at late night. For single-vehicle crashes, the slope of the effect is found to be reduced in the year 2003.

The results indicate that nighttime even in the presence of light has a positive impact on rear-end and hit-parked-vehicle crashes while nighttime without lighting has a positive impact on single-vehicle and hit-parked-vehicle crashes compared to the daylight condition. The results are intuitive and might be attributed to the reduced visibility during these conditions (Bham et al., 2012). For hit-parked-vehicle crashes, the variable shows temporal change in the year 2003.

Injury Severity Component

The results of the severity component of the joint model are presented in Table 4. A positive (negative) sign for a coefficient in Table 4 signifies that an increase in the variable is likely to result in higher (lower) severity in the crash type. The impacts of the variables are discussed in the following sections.

<u>Driver characteristics</u>

With respect to driver characteristics, speeding increases the severity of drivers in head-on and hit-parked-vehicle crashes. This finding is very much expected and has been established in safety literature for both developed and developing country contexts (Abdel-Aty, 2003; Abegaz et al., 2014; Paleti et al., 2010). For head-on crashes, the variable changes the slope of the effect in the year 2006.

<u>Vehicle characteristics</u>

Vehicle type variables significantly impact driver severity. The results indicate that bus drivers are likely to sustain a less severe injury in all crash types except right-angle compared to the drivers of 4-wheeler light vehicles. However, the slope of the effect is found to be higher from the year 2003 for rear-end and sideswipe crashes. Trucks have a negative effect on the driver injury severity for all crash types except right-angle (as found in Rana et al., 2010). The reduced severity propensity can be attributed to the vehicle size, capacity against structural deformation and stability. Further, the variable shows temporally unstable effect for the years 2003 and 2006 for head-on crashes while for the year 2003 for rear-end crashes.

Table 4: GOL (Injury Severity) Model Component in the Gumbel-Frank Copula Model with Parameterized Dependence

Variables	Head-on		Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Threshold between NI-SI	0.491	7.016	2.292	19.939	1.697	4.630	-0.935	-2.761	1.619	16.838	1.514	8.367
Threshold between SI-GI	0.896	15.193	2.705	9.639	1.936	2.993	-0.578	-5.609	2.338	3.679	1.966	4.663
Threshold between GI-FI	1.779	2.581	3.875	2.230	3.886	2.734	0.007	2.707	3.001	3.313	2.758	1.527
Driver Characteristics												
Speeding related (Base: Not speeding)												
Speeding*	0.075	4.010	--	--	--	--	--	--	--	--	0.045	1.752
Speeding *nYear7	-0.130	-3.539	--	--	--	--	--	--	--	--	--	--
Vehicle Characteristics												
Vehicle type (Base: 4-wheeler light vehicles)												
Bus	-0.100	-7.565	-0.976	-5.881	--	--	-0.290	-2.877	-0.055	-2.752	-0.136	-2.687
Bus*nYear4	--	--	1.125	5.147	--	--	0.327	2.499	--	--	--	--
Truck	-0.475	-6.288	-0.434	-4.308	--	--	-0.096	-3.151	-0.044	-1.860	-0.131	-3.694
Truck*nYear4	0.709	4.385	0.428	3.158	--	--	--	--	--	--	--	--
Truck*nYear7	-0.253	-2.184	--	--	--	--	--	--	--	--	--	--
Pick-up	--	--	--	--	--	--	0.044	1.775	--	--	--	--

Variables	Head-on		Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Motorcycle	0.752	11.415	1.269	15.011	0.438	8.095	0.143	6.501	0.952	6.134	0.182	3.863
Motorcycle*nYear4	-0.722	-8.099	-1.602	-8.639	--	--	--	--	-1.138	-5.209	--	--
Motorcycle*nYear7	--	--	0.428	2.878	--	--	--	--	--	--	--	--
Motorized 3-wheelers	0.094	6.853	0.141	5.864	--	--	0.052	2.732	--	--	0.120	3.104
Informal vehicles	0.061	4.022	0.733	5.936	--	--	0.036	2.034	--	--	--	--
Informal vehicles*nYear4	--	--	-0.870	-5.159	--	--	--	--	--	--	--	--
Informal vehicles*nYear16	--	--	1.373	2.127	--	--	--	--	--	--	--	--
Threshold between SI-GI	--	--	--	--	--	--	-0.315	-1.867	--	--	--	--
Threshold between GI-FI			-0.063	-2.690	--	--	--	--	--	--	--	--
Vehicle maneuvering (Base: Straight and others)												
Turning	--	--	--	--	--	--	--	--	0.098	4.467	--	--
Fitness certificate (Base: Not present)												
Present	--	--	--	--	-0.175	-2.668	--	--	--	--	--	--
Roadway Characteristics												
Location type (Base: Rural area)												

Variables	Head-on		Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Urban area	-0.026	-2.324	--	--	--	--	-0.025	-2.132	--	--	--	--
Road class (Base: National highways)												
Regional highways	-0.057	-4.972	--	--	--	--	--	--	--	--	--	--
Feeder roads	-0.079	-5.314	-0.037	-1.694	--	--	--	--	--	--	--	--
Village roads	-0.103	-6.536	-0.111	-2.661	--	--	--	--	--	--	--	--
City roads	-0.060	-3.324	-0.041	-2.563	-0.127	-1.822	--	--	--	--	--	--
Surface quality (Base: Good)												
Rough	-0.065	-2.483	--	--	--	--	--	--	--	--	--	--
Environmental and Weather Characteristics												
Time of the day (Base: Other than late night)												
Late night	0.020	1.685	0.032	2.017	--	--	--	--	--	--	0.223	3.595
Late night*nYear7	--	--	--	--	--	--	--	--	--	--	-0.254	-1.989
Threshold between GI-FI	-0.045	-2.740	--	--	--	--	--	--	--	--	--	--
Season of the year (Base: Summer)												
Rainy	--	--	--	--	--	--	--	--	0.037	1.827	--	--
Light condition (Base: Daylight, dawn/dusk)												

Variables	Head-on		Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**
Night lighted	--	--	--	--	0.211	2.212	--	--	--	--	--	--
Night not lighted	--	--	--	--	--	--	--	--	0.042	1.929	--	--
Weather condition (Base: Clear)												
Rain	0.067	3.997	--	--	--	--	--	--	--	--	--	--
Fog and wind	0.059	2.522	--	--	--	--	--	--	0.119	2.530	--	--
Copula Parameters												
Copula type	None		Gumbel		Gumbel		Frank		None		None	
Constant	--	--	1.232	24.949	1.007	88.976	-6.786	-3.073	--	--	--	--
Divided roads	--	--	1.198	2.201	--	--	--	--	--	--	--	--

Note: "*" Represents the effect of the variable for the base year 2000 (nYear1*Speeding). If the interaction of a variable becomes significant for the base year only, then the slope of the effect of that variable will not change for the rest of the years which implies that the variable impact is linear. For this variable, the coefficient (estimate for "nYear1*variable") is the mean effect for the base year, for the second year the mean effect will be 2*coefficient, for the third year the mean effect will be 3*coefficient, and so on; "--" Represents the variables are not significant at 90% confidence level; NI=No injury, SI=Simple injury, GI=Grievous injury, FI=Fatal injury.

The results further indicate that drivers in pick-ups are likely to sustain severe injuries when involved in sideswipe crashes. This finding is interestingly different than the effect reported in the research for developed countries (Marcoux et al., 2018; Yasmin et al., 2014a). Further, motorcycle drivers are likely to sustain severe injuries for all crash types (Ye et al., 2008). However, the variable shows temporal instability for head-on, rear-end and single-vehicle crashes. Motorized 3-wheeler drivers are likely to experience higher risk for severity for all crash types except right-angle and single-vehicle crashes. The informal vehicle drivers are prone to increased severity propensity for head-on, rear-end and sideswipe crash types. The variable shows temporally varying effect for rear-end crashes. The results also show that informal vehicles influence the threshold between grievous and fatal injury for rear-end crashes and the threshold between simple and grievous injury for sideswipe crashes. The negative signs on the thresholds indicate that this variable further exacerbates the driver injury severity in these crash types. All these findings could be attributable to lower resisting capacity, lack of safety features such as seat belt, higher exposure and vulnerability of drivers compared to 4-wheeler light vehicles (Abegaz et al., 2014; Anowar et al., 2014).

With respect to vehicle maneuvers, turning movement increases the likelihood of driver injury severity for single-vehicle crashes compared to other maneuvers. Further, vehicles with proper fitness decrease the severity in right-angle crashes.

<u>Roadway characteristics</u>

Drivers injured in urban areas are likely to sustain less severe injuries in head-on and sideswipe crashes compared to the rural areas. This is plausible as operating speed is lower in urban areas of Bangladesh. The similar effect was found in developed countries (Abdel-Aty, 2003).

The results also indicate that crashes on regional highways are associated with lower severity for head-on crashes compared to the national highways. Feeder roads, village roads and city roads present reduced severity risk for head-on and rear-end crashes compared to national highways. City roads are also associated with lower severity for right-angle crashes. All these findings could be associated with lower operating speed in the regional, feeder, village and city roads compared to national highways. Similar findings were reported in previous studies (Anowar et al., 2014; Kamruzzaman et al., 2014; Rahman et al., 2021).

The results also show that crashes on rough surfaces decrease the driver injury severity in a head-on crash compared to good and smooth surface conditions.

<u>Environmental and weather characteristics</u>

With regards to the time of the day, crashes during late nighttime period are likely to increase driver injury severity risk for head-on, rear-end and hit-parked-vehicle crashes. The variable shows temporally heterogenous effect for hit-parked-vehicle crashes. The results also indicate that late night variable shifts the threshold between grievous and fatal injury towards left further exacerbating the driver injury severity in head-on crashes. These results are intuitive as the volume of traffic is likely low and operating speeds are likely higher during this period (see Barua and Tay, 2010; Marcoux et al., 2018; Pervaz et al., 2023; Yasmin et al., 2014a for similar results on severity). Among the seasonal effects, rainy season increases the likelihood of severity for single-vehicle crashes.

Crashes occurring during nighttime even with light increases the severity of right-angle crashes while absence of light increases the likelihood of the driver injury severity for single-vehicle crashes.

With respect to weather factors, findings indicate that rainy and foggy conditions increase the likelihood of severe crashes in head-on crashes while foggy condition increases the severity for single-vehicle crashes compared to clear weather conditions (as found in Anowar et al., 2014; Yasmin et al., 2014a). This could be due to the reduced visibility, longer reaction time, and slippery road surface in these weather conditions.

4.3 Dependence Effect

The estimated Gumbel-Frank copula-based joint MNL-GOL model provides the best fit while incorporating the correlation between the crash types and injury severity outcome of the drivers. An examination of the copula parameters presented in the last row panel of Table 4 highlights the presence of common unobserved factors affecting crash type and injury severity for rear-end, right-angle and sideswipe crash types. Our study did not find any statistically significant impact of dependency parameter for head-on and hit-parked-vehicle crash types (please note that the dependence for single-vehicle crashes was found significant in FGM copula, however we selected the Gumbel-Frank copula model due to the best model fit). The positive correlations for rear-end and right-angle crash types indicate that the unobserved factors that increase the likelihood of rear-end, and right-angle crash types also increase the injury severity of the drivers involved in those crashes. On the other hand, the negative sign of copula parameter for sideswipe crash type indicates that the unobserved factors that increase the likelihood of sideswipe crash type decrease the injury severity of the drivers involved in this crash type. We attempted to parameterize the dependency as a function of several exogenous variables in our model system. For rear-end crash type, the copula dependency is characterized by an additional exogenous variable – divided roads. The variables added in the dependency structure allow for dependency to vary across the dataset.

4.4 Predictive Performance of the Model

To demonstrate the performance of the developed model, we undertake a validation exercise using the holdout dataset. The exercise consists of two steps. First, we compare the performance of the developed copula model with the independent model by using BIC values. In this step, we randomly divided the 25,261 observations of the holdout dataset into five distinct validation datasets (four datasets with 5,000 observations each and a dataset with 5,261 observations). The BIC (LL) values of the selected copula model in the validation datasets are 22,937.33 (-10,808.58), 22,719.18 (-10,699.51), 22,740.56 (-10,710.20), 22,867.32 (-10,773.58), 24,073.99 (-11,372.97) and 23,067.71 (-10,872.97) respectively while the values for the independent model are 22,943.55 (-10,811.70), 22,719.10 (-10,699.47), 22,753.96 (-10,716.90), 22,888.17 (-10,784.00), 24,105.79 (-11,388.87) and 23,082.15 (-10,880.19). These values highlight that our developed model shows superior performance (lower BIC) in the four datasets while a very close performance in a dataset. In the second exercise, we compare the observed aggregate shares with the predicted shares across crash type component and injury severity component as shown in Fig. 1.

From the figure, it is clear that the predictions offered by our developed model are very close to observed shares across all comparisons.

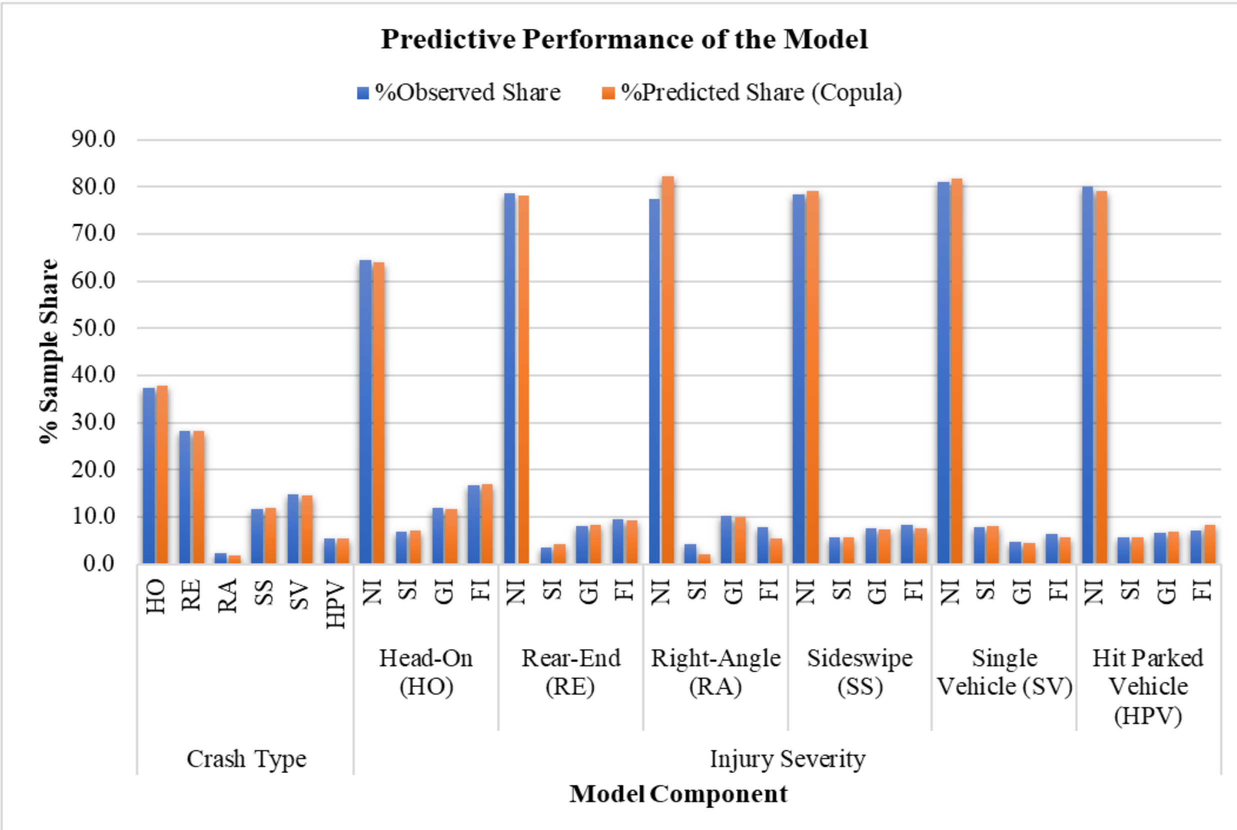

Fig. 1: Predictive performance of the Gumbel-Frank copula model with parameterized dependency

4.5 Elasticity Analysis

The model results shown in Table 3 and Table 4 do not provide the true magnitude of the effects of the exogenous variables on the likelihood of crash type as well as driver injury severity in the crashes. To illustrate the true magnitude of the variables impact, we compute the aggregate level "elasticity effects" for the exogenous variables following the methodology formulated by Eluru and Bhat (2007). The procedure involves computing the aggregate probability for each crash type and severity while modifying the exogenous variable of interest. For any indicator exogenous variable, the elasticity is computed by changing the value of the variable to one for the subsample of observations for which the variable takes a value of zero and to zero for the subsample of observations for which the variable takes a value of one. Subsequently, the shifts in expected aggregate shares in the two subsamples are summed after reversing the sign of the shifts in the second subsample (please see Eluru and Bhat, 2007; Marcoux et al., 2024 for a detailed discussion). The computed elasticity results for crash type component and severity component are presented in Table 5 and Table 6, respectively. The reader would note that for the severity component, we present the elasticity effects only for the lowest and highest injury severity levels (no-injury and fatal injury) across all crash types to conserve on space.

Table 5 shows the elasticity results of the variables for the crash type component. For this component, the computed elasticity can be interpreted as the percentage change in the likelihood of a crash type due to a change in the exogenous variable of interest. For instance, the aggregate elasticity 32.11% for DUI suspect variable for single-vehicle crash type can be interpreted as the likelihood of a driver being involved in a single-vehicle crash under the influence of drug/alcohol is about 32.11% higher than the likelihood of a driver being involved in single-vehicle crash when he/she is not under the influence of drug/alcohol (while other characteristics remain unchanged). The effects of all the variables presented in Table 5 can be interpreted in a similar manner for crash type component. Alternatively, Table 6 shows the elasticity results of the variables on driver injury severity component. For this component, the computed elasticity can be interpreted as the percentage change in the likelihood of an injury severity level for a crash type due to a change in the exogenous variable of interest. For instance, the aggregate elasticity 14.49% for speeding variable for fatal injury in a head-on crash can be interpreted as the likelihood of a speeding driver being fatally injured in a head-on crash is about 14.49% higher than the likelihood of a non-speeding driver being fatally injured while other characteristics being equal. The effects of all the variables presented in Table 6 can be interpreted in a similar manner for injury severity component.

Several insights can be drawn from the elasticity results presented in Table 5 and Table 6. First, the magnitudes of the elasticity for a variable are different across crash types and severities which reinforces the importance of conducting crash type specific injury severity analysis. Second, the most significant variables positively affecting crash types are city road, crossing maneuver, intersection location, divided road, overtaking maneuver, late nighttime driving, driving in dark unlighted conditions, rough road surface, driving under the influence of alcohol and drug and motorized three-wheeler vehicles (as shown in Table 5). Third, the most significant variables increasing fatal injury likelihood are informal vehicles, motorcycles, motorized three-wheelers, foggy and windy weather, turning movement, late nighttime driving, nighttime irrespective of lights, and rainy weather (as shown in Table 6). Fourth, roadway, vehicle, driver and road environmental attributes affect the crash type component while vehicle and road environmental attributes affect the injury severity component significantly.

The insights from the elasticity results can contribute to understanding the road safety situation and facilitate adopting appropriate interventions to improve road safety in the country. Road geometric improvement, installation of effective traffic control systems, intersection improvement policies such as providing dedicated/exclusive turning lanes, signal and signage improvement, installation of resting facilities for nighttime drivers, roadway lighting improvement schemes, maintaining safety standards and fitness of the vehicles, continuous monitoring and targeted enforcement, effective real time messaging and advanced warning systems, improvement of driving behavior for yielding to the signals and signages, improvement of road user behavior through large-scale road safety awareness campaigns, and traffic education could be suitable solutions for addressing the crash types and driver injury severities in the country.

1 **Table 5: Results of the Elasticity Analysis for Crash Type Component**

Variables	*%Head-on*	*%Rear-end*	*%Right-angle*	*%Sideswipe*	*%Single-vehicle*	*%Hit-parked-vehicle*
Driver Characteristics						
DUI suspicion (Base: Not DUI suspect)						
DUI suspect*	-5.87	-5.17	-4.72	-5.55	32.11	-6.20
Vehicle Characteristics						
Vehicle type (Base: 4-wheeler light vehicles)						
Bus	-2.52	-2.05	-1.64	-2.45	13.40	-2.47
Truck	3.50	2.58	1.96	3.36	-27.54	28.71
Motorcycle	19.31	16.47	13.58	18.65	-83.89	-34.81
Motorized 3-wheelers	28.09	-14.22	-34.26	-13.04	-20.64	-23.75
Informal vehicles	-5.62	6.04	-6.16	13.43	-4.89	-5.86
Vehicle maneuvering (Base: Straight and others)						
Overtaking	-10.13	-9.83	-11.39	74.44	-9.95	-9.93
Crossing	-2.33	-3.55	138.98	-3.08	-2.02	-2.78
Turning	-3.22	-2.63	-2.10	-3.14	17.16	-3.17
Fitness certificate (Base: Not present)						

Variables	*%Head-on*	*%Rear-end*	*%Right-angle*	*%Sideswipe*	*%Single-vehicle*	*%Hit-parked-vehicle*
Present	3.94	-4.00	-24.09	4.35	3.54	-16.81
Roadway Characteristics						
Location type (Base: Rural area)						
Urban area	-6.10	30.91	-13.06	-6.88	-33.23	-6.86
Road class (Base: National highways)						
Feeder roads	-12.98	7.69	-12.95	-13.06	35.82	-13.96
Village roads	-3.47	-2.42	-1.82	-3.24	32.54	-43.33
City roads	-13.29	4.85	151.03	-14.39	21.62	-13.97
Presence of divider (Base: Not divided)						
Divided	-45.59	82.70	48.83	2.74	-44.54	0.89
Road geometry (Base: Straight and slope)						
Curve section	16.07	-28.41	20.59	17.60	14.32	-48.27
Facility type (Base: Not at intersection)						
Intersection	-10.25	-11.54	122.50	48.19	-10.14	9.30
Surface quality (Base: Good)						
Rough	-7.08	-5.80	-4.63	-6.90	37.71	-6.96

Variables	***%Head-on***	***%Rear-end***	***%Right-angle***	***%Sideswipe***	***%Single-vehicle***	***%Hit-parked-vehicle***
Road features (Base: None/narrowing/restricted)						
Bridge and culvert	-4.82	-3.94	-3.15	-4.69	25.66	-4.73
Environmental and Weather Characteristics						
Time of the day (Base: Other than late night))						
Late night	-11.72	-10.53	-9.31	-11.38	48.70	30.20
Light condition (Base: Daylight, dawn and dusk)						
Night lighted	-6.80	10.96	-7.73	-7.25	-6.05	24.92
Night not lighted	-6.58	-5.91	-5.09	-6.51	17.10	44.42

Table 6: Results of the Elasticity Analysis for Injury Severity Component

Variables	Head-on		Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal
Driver Characteristics												
Speeding related (Base: Not speeding)												
Speeding*	-6.28	14.49	--	--	--	--	--	--	--	--	-5.72	27.36
Vehicle Characteristics												
Vehicle type (Base: 4-wheeler light vehicles)												
Bus	21.16	-47.58	12.85	-83.99	--	--	41.47	-30.73	5.93	-31.81	14.93	-63.38
Truck	24.11	-52.57	9.81	-69.77	--	--	45.10	-33.41	4.65	-25.01	16.28	-73.27
Pick-up	--	--	--	--	--	--	-18.30	15.11	--	--	--	--
Motorcycle	-71.54	239.29	-38.01	295.35	-48.97	402.21	-52.61	49.38	-47.76	406.01	-30.60	181.42
Motorized 3-wheelers	-22.69	59.37	-11.45	114.20	--	--	-21.39	17.78	--	--	-18.85	100.87
Informal vehicles	-14.21	36.59	-22.49	277.00	--	--	-15.24	26.32	--	--	--	--
Vehicle maneuvering (Base: Straight and others)												
Turning	--	--	--	--	--	--	--	--	-13.41	81.72	--	--

Variables	Head-on		Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal
Fitness certificate (Base: Not present)												
Present	--	--	--	--	10.27	-68.90	--	--	--	--	--	--
Roadway Characteristics												
Location type (Base: Rural area)												
Urban area	5.62	-13.65	--	--	--	--	11.11	-8.60	--	--	--	--
Road class (Base: National highways)												
Regional highways	11.90	-28.38	--	--	--	--	--	--	--	--	--	--
Feeder roads	15.90	-37.08	2.40	-21.76	--	--	--	--	--	--	--	--
Village roads	19.89	-45.24	6.49	-53.40	--	--	--	--	--	--	--	--
City roads	12.40	-29.08	2.71	-24.93	7.71	-57.50	--	--	--	--	--	--
Surface quality (Base: Good)												
Rough	13.24	-30.66	--	--	--	--	--	--	--	--	--	--
Environmental and Weather Characteristics												
Time of the day (Base: Other than late night)												
Late night	-4.52	30.67	-2.24	21.66	--	--	--	--	--	--	-12.14	53.44

Variables	Head-on		Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal	%No-Injury	%Fatal
Season of the year (Base: Summer)												
Rainy	--	--	--	--	--	--	--	--	-4.36	24.75	--	--
Light condition (Base: Daylight, dawn/dusk)												
Night lighted	--	--	--	--	-15.16	90.42	--	--	--	--	--	--
Night not lighted									-5.10	29.14		
Weather condition (Base: Clear)												
Rain	-15.61	41.32	--	--	--	--	--	--	--	--	--	--
Fog and wind	-1.27	3.37	--	--	--	--	--	--	-17.16	113.95	--	--

5 CONCLUSIONS

Road traffic crashes disproportionately affect low and middle-income countries of the world. The unique driver behavior, roadway characteristics, traffic composition, traffic flow, and roadway environment contribute to a fundamentally different system compared to the systems in developed countries. A majority of earlier research examining data from Bangladesh implicitly assumed the entire parameter space to remain the same across the population while completely disregarding temporal stability of parameters over time. To address these critical modeling issues, the current study proposes a joint framework that explicitly models crash type outcomes while allowing for a crash type specific injury severity profile. The approach takes the form of a copula-based temporal multinomial (MNL)-generalized ordered logit (GOL) that allows us to accommodate for the influence of observed and unobserved factors affecting crash type and severity. We also introduce a novel spline approach for incorporating parameter specific variation over time. These newly introduced variables can directly be accommodated within any methodological framework. The study examines six copula structures - Gaussian, Farlie-Gumbel-Morgenstern (FGM), Frank, Clayton, Joe, and Gumbel to consider a wide range of dependency structures. We employ the Bayesian Information Criterion (BIC) to determine the best model among all copula models. We also allow for dependency parameter for crash type and injury severity outcomes to vary across the dataset. The empirical analysis was conducted using police reported crash data drawn from Bangladesh for the years 2000 to 2015 focusing on injury severity sustained by drivers in motor vehicle crashes. We use six crash types (head-on, rear-end, right-angle, sideswipe, single-vehicle and hit-parked-vehicle crashes) and four severity levels (fatal, grievous injury, simple injury and no injury) as our dependent variable categories. A comprehensive set of exogenous variables including driver and vehicle characteristics, roadway attributes, environmental and weather information, and temporal factors is considered for the analysis of the models. The empirical analysis shows that models with temporal heterogeneity outperform the models without temporal heterogeneity. Among the various copula models, the parameterized Gumbel-Frank copula offers the best fit. The model specification results reveal multiple temporally varying parameters in both crash type and severity components. We also conducted a validation exercise using a holdout sample. The results clearly highlight that the model predictions are closely aligned with observed values. The results also highlight various novel variables affecting injury severity in Bangladesh. Further, an elasticity exercise was conducted to illustrate the influence of the exogenous variables on the crash type and injury severity dimensions. It is worthwhile to mention that this study provides a valuable insight into crash and injury severity characteristics, and factors contributing to both dimensions in the context of developing countries.

This research is not without limitations. The empirical analysis was conducted using police reported crash data of Bangladesh. However, in developing countries where crash event reporting and data collection challenges exist, the issue of underreporting and reporting bias in police reported crash data is prevalent. These databases are likely to underreport less severe crashes. Further, victims of road crashes sometimes compromise and mutually settle financial compensation with vehicle owners or drivers without reporting to the police to avoid complex legal proceedings. Due to the lack of adequate officers and trained reporting personnel, data collection and storing processes are also hampered. Recently, several studies relied on alterative data sources such as newspaper reported data and hospital data for their analysis (Bhuiyan et al., 2022; Roy et al., 2021). However, these data might lack details about road attributes, driver, vehicle and weather information and often misclassify the severity of crashes. Future studies in developing countries can explicitly consider underreporting and reporting bias in the analysis and compare the results with the findings of our study. Further, in our research, we explicitly considered the influence of unobserved factors affecting crash type and severity using the copula-based approach. The results clearly highlight the improvement in model fit due to the consideration of these unobserved factors. However, our model structure does not consider the impact of unobserved factors affecting the various parameters (beyond temporal factors). The consideration of random parameters within copula-based approaches can be complex due to the need for simulated likelihood approaches. Future research efforts can build on our framework to accommodate for random parameters in this model system (see Bhowmik et al., 2021 for an approach in a different safety context).

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Shahrior Pervaz, Naveen Eluru, Tanmoy Bhowmik; data collection: Shahrior Pervaz; model estimation and validation: Shahrior Pervaz, Tanmoy Bhowmik, Naveen Eluru; analysis and interpretation of results: Shahrior Pervaz, Tanmoy Bhowmik, Naveen Eluru; draft manuscript preparation: Shahrior Pervaz, Naveen Eluru, Tanmoy Bhowmik. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

Abdel-Aty, M., 2003. Analysis of driver injury severity levels at multiple locations using ordered probit models. J Safety Res 34, 597–603. https://doi.org/10.1016/j.jsr.2003.05.009

Abegaz, T., Berhane, Y., Worku, A., Assrat, A., Assefa, A., 2014. Effects of excessive speeding and falling asleep while driving on crash injury severity in Ethiopia: A generalized ordered logit model analysis. Accid Anal Prev 71, 15–21.

Ahsan, H.M., Raihan, M.A., Rahman, M., 2011. A study on car involvement in road traffic accidents in Bangladesh, in: Proceedings of 4th Annual Paper Meeting and 1st Civil Engineering Congress, Dhaka, Bangladesh. pp. 22–24.

Akter, T., Pervaz, S., 2019. Assessing motorcycle accident and injury characteristics in Dhaka Metropolitan City, in: 1st International Conference on Urban and Regional Planning (ICURP-2019), Dhaka, Bangladesh. pp. 381–390.

Anowar, S., Yasmin, S., Tay, R., 2014. Factors influencing the severity of intersection crashes in Bangladesh. Asian transport studies 3, 143–154.

Aptech, 2015. Aptech Systems Inc.

Barua, U., Tay, R., 2010. Severity of urban transit bus crashes in Bangladesh. J Adv Transp 44, 34–41.

Bham, G.H., Javvadi, B.S., Manepalli, U.R.R., 2012. Multinomial Logistic Regression Model for Single-Vehicle and Multivehicle Collisions on Urban U.S. Highways in Arkansas. J Transp Eng 138, 786–797. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000370

Bhat, C.R., Eluru, N., 2009. A copula-based approach to accommodate residential self-selection effects in travel behavior modeling. Transportation Research Part B: Methodological 43, 749–765. https://doi.org/10.1016/j.trb.2009.02.001

Bhat, C.R., 2011. The maximum approximate composite marginal likelihood (MACML) estimation of multinomial probit-based unordered response choice models. Transportation Research Part B: Methodological, 45(7), 923-939.

Bhowmik, T., Rahman, M., Yasmin, S., Eluru, N. 2021. Exploring analytical, simulation-based, and hybrid model structures for multivariate crash frequency modeling. Anal Methods Accid Res 31, 100167.

Bhuiyan, H., Ara, J., Hasib, K.M., Sourav, M.I.H., Karim, F.B., Sik-Lanyi, C., Governatori, G., Rakotonirainy, A. and Yasmin, S., 2022. Crash severity analysis and risk factors identification based on an alternate data source: a case study of developing country. Scientific reports, 12(1), 21243. https://doi.org/10.1038/s41598-022-25361-5

Eluru, N., Bhat, C.R., 2007. A joint econometric analysis of seat belt use and crash-related injury severity. Accid Anal Prev 39(5), 1037–1049.

Eluru, N., Bhat, C.R., Hensher, D.A., 2008. A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. Accid Anal Prev 40, 1033–1054. https://doi.org/10.1016/j.aap.2007.11.010

Eluru, N., Paleti, R., Pendyala, R.M. and Bhat, C.R., 2010. Modeling injury severity of multiple occupants of vehicles: Copula-based multivariate approach. Transp Res Rec, 2165(1), 1-11.

Eluru, N., Gayah, V. V, 2022. A note on estimating safety performance functions with a flexible specification of traffic volume. Accid Anal Prev 167, 106571. https://doi.org/10.1016/j.aap.2022.106571

Hadiuzzaman, M., Karim, A., Rahman, M., Hasan, T., 2016. Planning level regression models for prediction of the number of crashes on urban arterials in Bangladesh. International journal of transportation engineering 3, 267–275.

Hasanat-E-Rabbi, S., Raihan, M.A., Mahmud, S.M.S., Hoque, M.S., 2022. Pedestrian injury outcomes in the developing urban metropolis: Econometric models for assessing risk factors. IATSS research 46, 269–280.

Hoque, M.M., Mahmud, H., Azad, A., Sohel, S., Sarkar, S., 2009. The risk of children in road traffic accidents in Bangladesh, in: WEB International Conference.

Hoque, M.M., Mahmud, S.M.S., 2010. Promoting vulnerable road users safety towards safe and equitable communities in Bangladesh. Injury Prevention 16, A152–A152.

Hoque, M.M., Mahmud, S.M.S., 2009. Accident Hazards on National Highways in Bangladesh, in: 13th Conference of the Road Engineering Association of Asia and Australasia (REAAA), Songdo Convensia, Incheon, Korea. pp. 23–26.

Hoque, M.M., Mahmud, S.S., Qazi, A.S., 2008. Cycling in Bangladesh. Bicycling in Asia, 81 89.

Hoque, M.M., Pervaz, S., Ashek, A.A.N., 2020. Overview of the highway crashes in Bangladesh, in: Proceedings of the 5th International Conference on Civil Engineering for Sustainable Development (ICCESD 2020), KUET, Khulna, Bangladesh.

Hoque, M.M., Pervaz, S., Paul, A.K., 2016. Safety ratings of complex pedestrian routes in Dhaka metropolitan city, in: 27th ARRB Conference, Melbourne, Victoria, Australia, 16–18 November, 2016.

Hoque, M.M., Roy, K.C., Shah, M.I., 2014. Safety Investigation and Assessment of High Risk Road Sections in Bangladesh, in: 2nd International Conference on Advances in Civil Engineering, CUET, Chittagong, Bangladesh.

Hossain, S., Maggi, E., Vezzulli, A., 2022. Factors associated with crash severity on Bangladesh roadways: empirical evidence from Dhaka city. Int J Inj Contr Saf Promot 29, 300–311.

Hyun, K. (Kate), Mitra, S.K., Jeong, K., Tok, A., 2021. Understanding the effects of vehicle platoons on crash type and severity. Accid Anal Prev 149, 105858. https://doi.org/10.1016/j.aap.2020.105858

Intini, P., Berloco, N., Fonzone, A., Fountas, G., Ranieri, V., 2020. The influence of traffic, geometric and context variables on urban crash types: A grouped random parameter multinomial logit approach. Anal Methods Accid Res 28, 100141. https://doi.org/10.1016/j.amar.2020.100141

Islam, Md.A., Haque, Md.B., Hasan, Md.J., Amin, Md.R., 2022. Frequency Modelling and Risk Evaluation of Road Crashes in Sylhet Region of Bangladesh. International Journal of Intelligent Transportation Systems Research 20, 90–102. https://doi.org/10.1007/s13177-021-00275-0

Kamruzzaman, M.D., Haque, M.M., Washington, S., 2014. Analysis of traffic injury severity in Dhaka, Bangladesh. Transp Res Rec 2451, 121–130.

Lee, L.-F., 1983. Generalized econometric models with selectivity. Econometrica 507–512.

Mahmud, S.M.S., Sarker, A., Hoque, M.M., 2011. Identifications and investigations of hazardous road locations on Dhaka-Aricha Highway, in: Paper Presented on 4th Annual Paper Meet and 1st Civil Engineering Congress, Institute of Engineers, Bangladesh (IEB).

Mannering, F., 2018. Temporal instability and the analysis of highway accident data. Anal Methods Accid Res 17, 1–13. https://doi.org/10.1016/j.amar.2017.10.002

Marcoux, R., Yasmin, S., Eluru, N., Rahman, M., 2018. Evaluating temporal variability of exogenous variable impacts over 25 years: An application of scaled generalized ordered logit model for driver injury severity. Anal Methods Accid Res 20, 15–29. https://doi.org/10.1016/j.amar.2018.09.001

Marcoux, R., Pervaz, S. and Eluru, N., 2024. Assessing non-motorist safety in motor vehicle crashes–a copula-based approach to jointly estimate crash location type and injury severity. Anal Methods Accid Res, 42,100322. https://doi.org/10.1016/j.amar.2024.100322

Paleti, R., Eluru, N., Bhat, C.R., 2010. Examining the influence of aggressive driving behavior on driver injury severity in traffic crashes. Accid Anal Prev 42, 1839–1854. https://doi.org/10.1016/j.aap.2010.05.005

Pervaz, S., Bhowmik, T., Eluru, N., 2024. An integrated multi-resolution framework for jointly estimating crash type and crash severity. Anal Methods Accid Res 42, 100321. https://doi.org/10.1016/j.amar.2024.100321

Pervaz, S., Bhowmik, T., Eluru, N., 2023. An econometric framework for integrating aggregate and disaggregate level crash analysis. Anal Methods Accid Res 39, 100280. https://doi.org/10.1016/j.amar.2023.100280

Pervaz, S., Hazanat-E-Rabbi, S., Newaz, K.M.S., 2016. Pedestrian safety at intersections in Dhaka metropolitan city, in: 17th International Conference Road Safety On Five Continents (RS5C 2016), Rio de Janeiro, Brazil, 17-19 May 2016. Statens väg-och transportforskningsinstitut, pp. 1–11.

Pervaz, S., Mahmud, S.M.S., Raihan, M.A., Uddin, Md.I., 2022. Road crash in Bangladesh: Where we were, where we are, and where we will be, in: Advances in Civil Engineering: Select Proceedings of ICACE 2020. Springer, pp. 301–312.

Pervaz, S., Rahman, Md Mizanur, Hasanat-E-Rabbi, S., Uddin, M.I., Rahman, Md Mahbubur, 2020a. A review of motorcycle safety situation in Bangladesh, in: Proceedings of the 5th International Conference on Civil Engineering for Sustainable Development (ICCESD 2020), KUET, Khulna, Bangladesh. pp. 7–9.

Pervaz, S., Raihan, M.A., Rahman, M.M., Uddin, M.I., 2020b. Urban road safety situation in Bangladesh: A synopsis, in: 5th International Conference on Civil Engineering for Sustainable Development (ICCESD), KUET, Khulna, Bangladesh.

Portoghese, A., Spissu, E., Bhat, C.R., Eluru, N., Meloni, I., 2011. A Copula-Based Joint Model of Commute Mode Choice and Number of Non-Work Stops during the Commute. International Journal of Transport Economics 38, 337–362.

Rahman, M.H., Zafri, N.M., Akter, T., Pervaz, S., 2021. Identification of factors influencing severity of motorcycle crashes in Dhaka, Bangladesh using binary logistic regression model. Int J Inj Contr Saf Promot 28, 141–152.

Rana, T.A., Sikder, S., Pinjari, A.R., 2010. Copula-Based Method for Addressing Endogeneity in Models of Severity of Traffic Crash Injuries: Application to Two-Vehicle Crashes. Transp Res Rec 2147, 75–87. https://doi.org/10.3141/2147-10

Roy, S., Hawlader, M.D.H., Nabi, M.H., Chakraborty, P.A., Zaman, S. and Alam, M.M., 2021. Patterns of injuries and injury severity among hospitalized road traffic injury (RTI) patients in Bangladesh. Heliyon, 7(3). https://doi.org/10.1016/j.heliyon.2021.e06440

Sadeek, S.N., Rifaat, S.M., 2020. Development of district-wise crash prediction model in Bangladesh. Cogent Eng 7, 1762525.

Saha, B., Fatmi, M.R., Rahman, M.M., 2023. Modelling injury severity of victims in collisions involving public transit in Dhaka, Bangladesh. International Journal of Crashworthiness 28, 13–20.

Saha, B., Fatmi, M.R., Rahman, M.M., 2022. Modeling injury severity of unconventional vehicle occupants: hybrid of latent segments and random parameters logit models. Transp Res Rec 2676, 35–47.

Saha, B., Fatmi, M.R., Rahman, M.M., 2021. Pedestrian injury severity in Dhaka, Bangladesh: a latent segmentation-based logit modeling approach. Transportation in developing economies 7, 1–11.

Sarkar, S., Tay, R., Hunt, J.D., 2011. Logistic regression model of risk of fatality in vehicle–pedestrian crashes on national highways in Bangladesh. Transp Res Rec 2264, 128–137.

Shabab, K.R., Bhowmik, T., Zaki, M.H., Eluru, N., 2024. A systematic unified approach for addressing temporal instability in road safety analysis. Anal Methods Accid Res 43, 100335.

Sklar, A., 1973. Random Variable, Joint Distribution Functions, and Copulas. Kybernetika, 9(6)

Srinivasan, K.K., 2002. Injury severity analysis with variable and correlated thresholds: ordered mixed logit formulation. Transp Res Rec 1784, 132–141.

Trivedi, P.K., Zimmer, D.M., 2007. Copula modeling: an introduction for practitioners. Foundations and Trends® in Econometrics 1, 1–111.

Uddin, M.I., Raihan, M.A., Mahmud, S.M.S., Pervaz, S., 2021. Road Safety Status Of Dhaka City: What Does Our Data Tell Us and Priorities for the way Forward, in: 5th International Conference on Advances in Civil Engineering (ICACE 2020), Chattogram, Bangladesh.

World Health Organization (WHO), 2019. Global Health Observatory Data Repository [WWW Document]. URL https://apps.who.int/gho/data/node.main.A997?lang=en (accessed 7.13.23).

Yasmin, S., Eluru, N., Bhat, C.R., Tay, R., 2014a. A latent segmentation based generalized ordered logit model to examine factors influencing driver injury severity. Anal Methods Accid Res 1, 23–38. https://doi.org/10.1016/j.amar.2013.10.002

Yasmin, S., Eluru, N., Pinjari, A.R., Tay, R., 2014b. Examining driver injury severity in two vehicle crashes–A copula based approach. Accid Anal Prev 66, 120–135.

Ye, X., Pendyala, R.M., Al-Rukaibi, F.S., Konduri, K., 2008. Joint model of accident type and severity for two-vehicle crashes. Compendium of Papers CD-ROM, the 87th Annual Meeting of the Transportation Research Board, Washington, DC, USA, 13–17 January 2008.

Zafri, N.M., Prithul, A.A., Baral, I., Rahman, M., 2020. Exploring the factors influencing pedestrian-vehicle crash severity in Dhaka, Bangladesh. Int J Inj Contr Saf Promot 27, 300–307.

APPENDIX

Table A.1: Sample Share of the Selected Variables (%)

Variables	Crash Types					
	Head-on (3,770)	**Rear-end (2,809)**	**Right-angle (196)**	**Sideswipe (1,186)**	**Single-vehicle (1,481)**	**Hit-parked-vehicle (558)**
Injury Severity						
Fatal injury	16.84*	9.36	5.10	7.67	5.54	8.24
Grievous injury	11.67	8.40	9.18	7.59	4.39	7.35
Simple injury	7.03	4.24	2.04	5.48	7.97	5.91
No injury	64.46	78.00	83.67	79.26	82.11	78.49
Driver Characteristics						
Driving Under Influence (drug/alcohol) suspicion						
DUI suspect	11.99	12.14	10.20	12.31	15.60	8.60
Not DUI suspect	88.01	87.86	89.80	87.69	84.40	91.40
Speeding related						
Speeding	48.49	58.17	78.06	50.76	42.47	52.51
Not speeding	51.51	41.83	21.94	49.24	57.53	47.49
Vehicle Characteristics						
Vehicle type						

Variables	Crash Types					
	Head-on (3,770)	**Rear-end (2,809)**	**Right-angle (196)**	**Sideswipe (1,186)**	**Single-vehicle (1,481)**	**Hit-parked-vehicle (558)**
Bus	22.41	21.25	22.96	21.50	33.90	20.61
Truck	26.47	24.81	23.47	27.23	25.05	37.10
4-wheeler light vehicles	17.82	23.07	32.14	19.98	20.19	20.43
Pick-up	4.35	4.31	6.12	3.63	3.44	4.48
Motorcycle	10.53	10.64	7.14	11.21	1.96	5.38
Motorized 3-wheelers	10.69	7.37	4.59	6.16	8.58	6.09
Informal vehicles	6.21	7.12	3.06	8.01	5.33	4.84
Others	1.51	1.42	0.51	2.28	1.55	1.08
Vehicle maneuvering						
Straight	73.82	80.60	79.08	64.00	75.22	54.48
Overtaking	8.20	3.52	8.16	8.18	9.79	3.94
Crossing	4.43	1.32	5.61	5.82	1.69	1.25
Turning	4.83	6.48	3.57	9.87	3.44	3.41
Others	8.73	8.08	3.57	12.14	9.86	36.92
Fitness certificate						
Present	55.89	51.90	47.45	55.31	55.23	52.87
Not present	44.11	48.10	52.55	44.69	44.77	47.13

Variables	Crash Types					
	Head-on (3,770)	Rear-end (2,809)	Right-angle (196)	Sideswipe (1,186)	Single-vehicle (1,481)	Hit-parked-vehicle (558)
Roadway Characteristics						
Location type						
Urban area	23.42	47.85	75.00	31.45	19.72	34.41
Rural area	76.58	52.15	25.00	68.55	80.28	65.59
Road class						
National highways	55.46	42.19	23.98	44.18	47.06	55.02
Regional highways	15.68	11.50	3.57	17.20	14.79	12.19
Feeder roads	11.83	11.11	4.59	13.74	17.56	8.60
Village roads	6.84	3.84	4.08	8.85	9.79	3.23
City roads	10.19	31.36	63.78	16.02	10.80	20.97
Presence of divider						
Divided	8.51	34.25	55.61	15.77	8.17	20.43
Undivided	91.49	65.75	44.39	84.23	91.83	79.57
Road geometry						
Straight	86.68	93.95	97.45	88.28	83.19	94.98
Curve	10.16	3.92	2.04	9.02	9.59	3.76
Slope	1.30	1.03	0.51	0.51	2.36	1.08

Variables	Crash Types					
	Head-on (3,770)	Rear-end (2,809)	Right-angle (196)	Sideswipe (1,186)	Single-vehicle (1,481)	Hit-parked-vehicle (558)
Others	1.62	0.89	0.00	2.11	3.85	0.00
Facility type						
Not at intersection	73.74	69.35	26.02	60.62	76.03	65.23
At intersection	26.26	30.65	73.98	39.38	23.97	34.77
Surface quality						
Good	96.23	96.97	100.00	95.11	90.41	96.59
Rough	2.73	2.35	0.00	3.04	6.48	2.69
Road features						
Bridge-culvert	3.10	2.56	0.00	2.70	4.59	2.51
None/narrowing/restricted	96.90	97.44	100.00	97.30	95.41	97.49
Environmental and Weather Characteristics						
Time of the day						
Late night	15.94	17.48	20.41	13.66	25.05	29.75
Peak morning	13.02	11.14	10.71	12.06	12.02	11.47
Off-peak morning	20.69	20.86	21.43	22.51	18.84	15.59
Off-peak evening	24.96	22.18	25.00	24.62	19.99	15.95
Peak evening	11.46	12.46	9.18	12.48	10.67	9.50

Variables	Crash Types					
	Head-on (3,770)	Rear-end (2,809)	Right-angle (196)	Sideswipe (1,186)	Single-vehicle (1,481)	Hit-parked-vehicle (558)
Late evening	13.93	15.88	13.27	14.67	13.44	17.74
Season of the year						
Winter	25.92	26.37	22.96	27.07	26.74	24.37
Summer	26.45	25.95	30.61	26.89	27.35	27.42
Rainy	25.97	25.28	26.02	23.61	24.17	24.73
Autumn	21.67	22.46	20.41	22.43	21.74	23.48
Light conditions						
Daylight	70.08	67.78	64.80	70.91	61.44	55.73
Dawn/dusk	14.54	11.75	12.24	13.07	16.41	15.95
Night lighted	4.91	12.53	21.43	7.00	6.14	10.57
Night not lighted	10.48	7.94	1.53	9.02	16.00	17.74
Weather conditions						
Clear	91.03	94.80	96.43	92.75	90.01	94.44
Rain	5.73	2.78	2.55	4.13	6.28	3.41
Fog and wind	3.24	2.42	1.02	3.12	3.71	2.15
Temporal Characteristics						
Year						

Variables	Crash Types					
	Head-on (3,770)	**Rear-end (2,809)**	**Right-angle (196)**	**Sideswipe (1,186)**	**Single-vehicle (1,481)**	**Hit-parked-vehicle (558)**
2000	7.08	10.36	11.73	7.34	8.71	6.99
2001	5.36	6.16	8.67	6.16	8.04	8.06
2002	5.97	9.36	10.20	9.36	11.07	9.14
2003	7.67	8.44	10.20	8.60	10.20	11.47
2004	6.39	8.26	7.14	6.91	7.43	6.09
2005	6.68	6.05	9.18	6.75	8.10	4.30
2006	6.37	5.41	8.16	6.49	6.68	7.71
2007	8.49	6.51	6.12	9.11	7.70	5.56
2008	7.32	7.33	7.14	8.85	8.44	8.42
2009	6.92	7.23	7.65	6.16	4.86	7.89
2010	6.39	6.51	3.06	4.64	4.93	5.02
2011	4.91	4.95	3.57	3.96	3.31	3.41
2012	6.21	4.31	2.04	5.14	3.24	4.84
2013	5.04	3.49	1.02	3.29	2.57	3.76
2014	5.07	2.28	1.02	4.22	2.43	3.94
2015	4.14	3.35	3.06	3.04	2.30	3.41

*Column percentage

Table A.2: MNL (Crash Type) Model Estimates with Temporal Heterogeneity (Base: Head-on)

Variables	Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Constant	-0.617	-15.193	-4.084	-26.482	-1.451	-31.366	-1.067	-19.648	-1.993	-26.170
Driver Characteristics										
DUI suspicion (Base: Not DUI suspect)										
DUI suspect*	--	--	--	--	--	--	0.236	5.214	--	--
DUI suspect* nYear4	--	--	--	--	--	--	-0.304	-4.780	--	--
Vehicle Characteristics										
Vehicle type (Base: 4-wheeler light vehicles)										
Bus	--	--	--	--	--	--	0.023	2.880	--	--
Truck	--	--	--	--	--	--	-0.049	-5.247	0.135	1.990
Truck*nYear4	--	--	--	--	--	--	--	--	-0.285	-1.782
Truck*nYear7	--	--	--	--	--	--	--	--	0.344	1.851
Truck*nYear10	--	--	--	--	--	--	--	--	-0.280	-2.132
Motorcycle	--	--	--	--	--	--	-0.655	-5.148	-0.087	-3.767
Motorcycle*nYear4	--	--	--	--	--	--	0.664	3.831	--	--
Motorized 3-wheelers	-0.061	-5.213	-0.114	-2.222	-0.200	-2.532	-0.070	-4.816	-0.073	-3.107

Variables	Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Motorized 3-wheelers* nYear4	--	--	--	--	0.206	1.899	--	--	--	--
Informal vehicles	0.019	2.031	--	--	0.025	2.092	--	--	--	--
Vehicle maneuvering (Base: Straight and others)										
Overtaking	--	--	--	--	0.300	4.317	--	--	--	--
Overtaking*nYear4	--	--	--	--	-0.328	-3.481	--	--	--	--
Crossing	--	--	0.129	4.240	--	--	--	--	--	--
Turning	--	--	--	--	--	--	0.027	2.253	--	--
Fitness certificate (Base: Not present)										
Present	-0.013	-2.523	-0.044	-2.337	--	--	--	--	-0.028	-2.897
Roadway Characteristics										
Location type (Base: Rural area)										
Urban area	0.162	4.872	--	--	--	--	-0.085	-2.990	--	--
Urban area*nYear4	-0.179	-3.973	--	--	--	--	--	--	--	--
Urban area*nYear7	--	--	--	--	--	--	0.303	3.049	--	--
Urban area*nYear10	--	--	--	--	--	--	-0.571	-3.868	--	--
Urban area*nYear13	--	--	--	--	--	--	0.421	2.393	--	--

Variables	Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Road class (Base: National highways)										
Feeder roads	0.038	3.485	--	--	--	--	0.303	7.241	--	--
Feeder roads*nYear4	--	--	--	--	--	--	-0.389	-6.357	--	--
Feeder roads*nYear13	-0.179	-1.727	--	--	--	--	--	--	--	--
Village roads	--	--	--	--	0.162	2.178	0.050	4.142	-0.072	-2.369
Village roads*nYear4	--	--	--	--	-0.186	-1.812	--	--	--	--
City roads	0.028	3.032	0.566	5.414	--	--	0.049	3.463	--	--
City roads*nYear4	--	--	-0.609	-4.157	--	--	--	--	--	--
Presence of divider (Base: Not divided)										
Divided	0.542	13.211	0.442	4.255	0.221	3.976	--	--	0.070	5.087
Divided*nYear4	-0.592	-10.489	-0.467	-3.202	-0.227	-2.998	--	--	--	--
Road geometry (Base: Straight and slope)										
Curve section	-0.073	-6.072	--	--	--	--	--	--	-0.116	-3.934
Facility type (Base: Not at intersection)										
Intersection	--	--	0.558	7.091	0.256	6.640	--	--	0.027	2.661
Intersection*nYear4	--	--	-0.614	-5.688	-0.288	-5.539	--	--	--	--

Variables	Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Surface quality (Base: Good)										
Rough	--	--	--	--	--	--	0.058	3.842	--	--
Road features (Base: None/narrowing/restricted)										
Bridge and culvert	--	--	--	--	--	--	0.039	2.305	--	--
Environmental and Weather Characteristics										
Time of the day (Base: Other than late night))										
Late night	--	--	--	--	--	--	0.336	8.981	0.051	4.469
Late night*nYear4	--	--	--	--	--	--	-0.420	-7.903	--	--
Light condition (Base: Daylight, dawn and dusk)										
Night lighted	0.030	2.868	--	--	--	--	--	--	0.041	2.180
Night not lighted	--	--	--	--	--	--	0.033	3.019	0.185	2.703
Night not lighted*nYear4	--	--	--	--	--	--	--	--	-0.197	-2.032

Note: "*" Represents the effect of the variable for the base year 2000 (nYear1*DUI suspect), If the interaction of a variable becomes significant for the base year only, then the slope of the effect of that variable will not change for the rest of the years which implies that the variable impact is linear. For this variable, the coefficient (estimate for "nYear1*variable") is the mean effect for the base year, for the second year the mean effect will be 2*coefficient, for the third year the mean effect will be 3*coefficient, and so on; "--" Represents the variables are not significant at 90% confidence level.

Table A.3: GOL (Injury Severity) Model Estimates with Temporal Heterogeneity

Variables	Head-on		Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Threshold between NI-SI	0.491	7.016	1.405	16.111	1.578	5.197	1.285	10.818	1.619	16.841	1.514	8.352
Threshold between SI-GI	0.896	15.193	1.810	10.192	1.802	3.078	1.833	4.970	2.338	3.680	1.966	4.662
Threshold between GI-FI	1.779	2.580	2.953	1.976	3.598	2.376	2.764	0.694	3.001	3.313	2.759	1.522
Driver Characteristics												
Speeding related (Base: Not speeding)												
Speeding*	0.075	4.011	--	--	--	--	--	--	--	--	0.045	1.746
Speeding *nYear7	-0.130	-3.539	--	--	--	--	--	--	--	--	--	--
Vehicle Characteristics												
Vehicle type (Base: 4-wheeler light vehicles)												
Bus	-0.100	-7.566	-0.886	-5.641	--	--	-0.526	-3.375	-0.054	-2.752	-0.136	-2.687
Bus*nYear4	--	--	1.028	4.947	--	--	0.597	2.821	--	--	--	--
Truck	-0.475	-6.287	-0.392	-4.309	--	--	-0.165	-4.243	-0.044	-1.861	-0.131	-3.695
Truck*nYear4	0.709	4.384	0.385	3.126	--	--	--	--	--	--	--	--
Truck*nYear7	-0.253	-2.183	--	--	--	--	--	--	--	--	--	--
Pick-up	--	--	--	--	--	--	0.067	1.781	--	--	--	--

Variables	Head-on		Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Motorcycle	0.752	11.415	1.188	13.429	0.416	7.935	0.212	9.913	0.952	6.134	0.182	3.862
Motorcycle*nYear4	-0.722	-8.099	-1.533	-7.733	--	--	--	--	-1.138	-5.208	--	--
Motorcycle*nYear7	--	--	0.477	2.983	--	--	--	--	--	--	--	--
Motorized 3-wheelers	0.094	6.853	0.717	6.652	--	--	0.067	2.392	--	--	0.120	3.104
Informal vehicles	0.061	4.023	-0.857	-5.739	--	--	0.052	2.206	--	--	--	--
Informal vehicles*nYear4	--	--	1.556	2.346	--	--	--	--	--	--	--	--
Informal vehicles*nYear16	--	--	0.717	6.652	--	--	--	--	--	--	--	--
Threshold between SI-GI	--	--	--	--	--	--	-0.303	-1.870	--	--	--	--
Threshold between GI-FI			-0.065	-2.79	--	--	--	--	--	--	--	--
Vehicle maneuvering (Base: Straight and others)												
Turning	--	--	--	--	--	--	--	--	0.098	4.467	--	--
Fitness certificate (Base: Not present)												
Present	--	--	--	--	-0.161	-2.676	--	--	--	--	--	--
Roadway Characteristics												
Location type (Base: Rural area)												

Variables	Head-on		Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**	**Est.**	**t-stat**
Urban area	-0.026	-2.325	--	--	--	--	-0.035	-2.008	--	--	--	--
Road class (Base: National highways)												
Regional highways	-0.057	-4.972	--	--	--	--	--	--	--	--	--	--
Feeder roads	-0.079	-5.313	-0.048	-2.165	--	--	--	--	--	--	--	--
Village roads	-0.103	-6.536	-0.102	-2.350	--	--	--	--	--	--	--	--
City roads	-0.060	-3.325	-0.064	-4.476	-0.129	-1.919	--	--	--	--	--	--
Surface quality (Base: Good)												
Rough	-0.065	-2.483	--	--	--	--	--	--	--	--	--	--
Environmental and Weather Characteristics												
Time of the day (Base: Other than late night)												
Late night	0.020	1.650	0.036	2.177	--	--	--	--	--	--	0.223	3.597
Late night*nYear7											-0.254	-1.990
Threshold between GI-FI	-0.045	-2.740	--	--	--	--	--	--	--	--	--	--
Season of the year (Base: Summer)												
Rainy	--	--	--	--	--	--	--	--	0.037	1.830	--	--
Light condition (Base: Daylight, dawn/dusk)												

Variables	Head-on		Rear-end		Right-angle		Sideswipe		Single-vehicle		Hit-parked-vehicle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Night lighted	--	--	--	--	0.203	2.263	--	--	--	--	--	--
Night not lighted	--	--	--	--	--	--	--	--	0.042	1.928	--	--
Weather condition (Base: Clear)												
Rain	0.067	3.998	--	--	--	--	--	--	--	--	--	--
Fog and wind	0.059	2.522	--	--	--	--	--	--	0.119	2.530	--	--

Note: “*” Represents the effect of the variable for the base year 2000 (nYear1*Speeding), If the interaction of a variable becomes significant for the base year only, then the slope of the effect of that variable will not change for the rest of the years which implies that the variable impact is linear. For this variable, the coefficient (estimate for “nYear1*variable”) is the mean effect for the base year, for the second year the mean effect will be 2*coefficient, for the third year the mean effect will be 3*coefficient, and so on; “--” Represents the variables are not significant at 90% confidence level; NI=No injury, SI=Simple injury, GI=Grievous injury, FI=Fatal injury.