Assessing Non-Motorist Safety in Motor Vehicle Crashes – A Copula-Based Approach to Jointly Estimate Crash Location Type and Injury Severity

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ABSTRACT

Non-motorist injury severity can be affected by various observed and unobserved attributes related to the crash location type (segment or intersection). Recognizing the distinct non-motorist injury severity profiles by crash location type, we propose a joint modeling framework to study crash location type and non-motorist injury severity as two dimensions of the severity process. We employ a copula-based joint framework that ties the crash location type (represented as a binary logit model) and injury severity (represented as a generalized ordered logit model) through a closed form flexible dependency structure to study the injury severity process. The proposed approach also accommodates the potential heterogeneity (across non-motorists) in the dependency structure. The data for our analysis is drawn from the Central Florida region for the years of 2015 to 2021. The model system explicitly accounts for temporal heterogeneity across the two dimensions. A comprehensive set of independent variables including non-motorist user characteristics, driver and vehicle characteristics, roadway attributes, weather and environmental factors, temporal and socio-demographic factors are considered for the analysis. We also conducted an elasticity analysis to show the actual magnitude of the independent variables on non-motorist injury severity for the two locations. The results highlight the importance of examining the effect of various independent variables on non-motorist injury severity outcome by crash location type.

Keywords: Non-motorist, Crash severity, Crash location type, Copula model, Temporal heterogeneity.

1 INTRODUCTION

In the United States, motor vehicle traffic crashes resulted in 42,915 fatalities in 2021 marking the highest single year growth rate (10.5%) in fatalities since 2005 (NHTSA, 2022). In Florida, pedestrian and bicyclist fatalities increased by 16.8% and 16.6% respectively in 2022 compared to 2021 (FLHSMV, 2022) highlighting safety challenges for vulnerable road users in Florida. As transportation agencies and public health professionals promote the adoption of active transportation, it is also important to examine the factors affecting vulnerable road user safety. An important tool for examining the contributing factors to crash occurrence and crash consequences is the application of econometric and statistical models. The current study builds on existing literature contributing to identifying factors affecting crash consequences for active transportation users by developing disaggregate level active user severity models.

The discrete nature of injury severity has resulted in the adoption of discrete outcome models for analysis of motorist and non-motorist injury severity. In these frameworks, the emphasis is on identifying the impact of various observed and unobserved factors on road user injury severity. The host of observed factors examined include road user attributes, driver and vehicle attributes, roadway and traffic attributes, road environmental and weather attributes. The traditional model structures employed include ordered logit/probit model, generalized ordered logit/probit model and multinomial logit model (Islam and Mannering, 2006; Tay et al., 2011; Yasmin et al., 2015). With advancements in modeling, growing number of studies have developed advanced variants of traditional models including random parameter variants with and without heterogeneity in means and variances (Behnood and Mannering, 2016; Eluru et al., 2008; Marcoux et al., 2018; Wang et al., 2022). Generally, in these model systems, there is an implicit assumption that the parameter space to be estimated is universally same i.e., all observations follow the same functional form (simple mean or distribution). To clarify, random parameter models allow for parameters to vary across the dataset. However, the overall distribution of the parameter is still constrained to be the same across the dataset. The imposition of the universal parameter space is relaxed in the latent class models where each class is expected to allow for a different parameter space (Behnood and Mannering, 2016; Chang et al., 2021; Yasmin et al., 2014a). While these models offer enhanced flexibility, these models are complicated to estimate and rarely offer more than two or three segments (Yasmin et al., 2014a).

A more theoretically grounded approach that has gained prominence for addressing the universal parameter space challenge employs well-defined classes of the observation. For example, in analyzing motorist severity, a common approach employed is the partitioning of the observations by crash type – an important crash variable – thus allowing for crash type associated injury severity profiles (Schneider and Savolainen, 2011; Wang et al., 2022). This approach allows for the same parameter to have distinct impact on severity by crash type. This approach, while allowing for additional heterogeneity, can be further enhanced by explicitly modeling crash type variable along with the severity variable in a joint framework. The joint framework enhances the severity model by incorporating additional observed heterogeneity and unobserved heterogeneity across the two decision variables (Eluru et al., 2010; Yasmin et al., 2014b). The joint system can take the form of a bivariate or multivariate model system based on the functional form of the dependent variables of interest. Further, these multivariate models can be examined using traditional multivariate distributions (such as multivariate normal) (Abay et al., 2013; Kabli et al., 2020) or copula distributions that offer enhanced flexibility (Eluru et al., 2010; Wang et al., 2019; Yasmin et al., 2014b).

Following this line of inquiry, in our current research, we focus on understanding non-motorist injury severity recognizing the important role of crash location defined as intersection or segment (Lin and Fan, 2021; Ma et al., 2018; Moore et al., 2011; Tanishita et al., 2023). It is plausible to consider that non-motorist crashes exhibit different severity profiles by crash location type i.e., non-motorist crash severity at segment has a distinct profile than non-motorist crash severity at an intersection. Drivers are more likely to expect non-motorists at intersections and are possibly more well placed to respond to these users. On the other hand, drivers might be less likely to respond appropriately to non-motorists on segments. Further, non-motorists themselves choosing to cross the road on segments are exhibiting different behavior compared to non-motorists' behavior while using intersections. The combination of driver and non-motorist behaviors are likely to mediate the influence of independent variables differently across the two severity profiles. Further, the unobserved factors related to non-motorist location presence are also likely to affect non-motorist crash severity.

Recognizing these important interactions, we employ a copula-based model to examine crash location type and non-motorist injury severity jointly. The crash location type is analyzed as a binary variable employing binary logit model while the severity component is examined using a generalized ordered logit model. The model estimation process begins with the development of separate binary logit and generalized ordered logit components. The reader would note that the severity model is estimated in a pooled manner for pedestrians and bicyclists to estimate a more parsimonious and efficient specification (Bhowmik et al., 2019; Wang et al., 2019). The two components are jointly analyzed using various copula structures including Gaussian, Farlie-Gumbel-Morgenstern (FGM), Frank, Clayton, Joe, and Gumbel to allow for a range of dependency structures (see Bhat and Eluru, 2009 for a detailed description of the copula structures). The dependency parameter in the copula models is parameterized to allow for the influence of unobserved factors to vary across observations. The data for our analysis is drawn from the Central Florida region for the years of 2015 to 2021. As temporal factors are likely to be significant in a multi-year crash dataset (see Mannering, 2018), the model system explicitly accounts for temporal effects. In our model estimation, we consider a comprehensive set of independent variables including non-motorist user characteristics, driver and vehicle characteristics, roadway attributes, weather and environmental factors, temporal and socio-demographic factors.

The rest of the paper is organized as follows. Section 2 provides a review of the literature relevant to the current study. In Section 3, we provide details of the econometric model framework used in the analysis. In Section 4, the data source and variables considered are described. The model results and elasticity effects are presented in Section 5 and Section 6, respectively. Section 7 concludes the paper and presents directions for future research.

2 LITERATURE REVIEW

This section provides an overview of the earlier research relevant to non-motorist injury severity and context of the current study.

2.1 Previous Research Relevant to the Non-motorists' Severity

Transportation safety literature has introduced extensive modeling approaches to gain a comprehensive understanding of the contributing factors to the motorist and non-motorist injury severity (please see Savolainen et al., 2011; Yasmin and Eluru, 2013 for a detailed review). In the current study, we will restrict ourselves to discussing methods employed for analyzing non-motorist injury severity. Researchers have developed non-motorist (pedestrian and/or bicyclist) injury severity models considering non-motorist 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 logit/probit regression models (Lee and Seo, 2022; Sze and Wong, 2007). For polytomous variable, application of ordered models (such as ordered logit/generalized ordered logit) (Ma et al., 2018; Yasmin et al., 2014c) and unordered models (such as multinomial logit) (Islam and Mannering, 2006; Tay et al., 2011) are prevalent in the literature. Many studies also developed random parameter ordered probit/logit models to capture unobserved heterogeneity that possibly exist in the dataset (Behnood and Mannering, 2016; Eluru et al., 2008; Zamani et al., 2021). Several research efforts analyzed the injury severity of pedestrian and bicycle crashes with a focus on a crash location type such as intersection (Bahrololoom et al., 2020; Haleem et al., 2015; Ma et al., 2018) and non-intersection (Toran Pour et al., 2017). In these studies, the data is partitioned by the location of interest and a separate model was developed for the sample of interest. In other studies, data were partitioned and separate models were estimated for intersection and non-intersection (Lin and Fan, 2021; Moore et al., 2011; Tanishita et al., 2023). More recently, a joint model system was developed to examine pedestrian and bicyclist injury severity as a joint process using a random parameters binary logit-generalized ordered logit copula formulation (Phuksuksakul et al., 2023).

From the various studies discussed above, the reported contributing factors relevant to the severity of the non-motorist users include non-motorist user characteristics such as age, gender, position and action (Behnood and Mannering, 2016; Chen and Fan, 2019; Tay et al., 2011; Yasmin et al., 2014c; Zamani et al., 2021), motorist characteristics such as age, gender, alcohol and drug usage, distracted driving, and speeding (Tay et al., 2011; Uddin and Ahmed, 2018), vehicle factors such as vehicle type, vehicle model year, and point of contact (Chen and Fan, 2019; Ma et al., 2018; Tay et al., 2011; Yasmin et al., 2014c), roadway factors such as area type, intersection, presence of traffic control devices, roadway class, speed limit, median, number of lanes, surface conditions, and roadway alignment (Behnood and Mannering, 2016; Chen and Fan, 2019; Uddin and Ahmed, 2018; Yasmin et al., 2014c), road environmental characteristics such as daylight and dark condition (Chen and Fan, 2019; Uddin and Ahmed, 2018; Yasmin et al., 2014c), weather conditions such as rain, cloud, fog and snow (Haleem et al., 2015; Ma et al., 2018; Yasmin et al., 2014c), crash environmental factors such as time of the day, and season (Eluru et al., 2008), crash specific characteristics such as hit-and-run and at-fault (Behnood and Mannering, 2016; Haleem et al., 2015), and land-use characteristics such as residential area, commercial and work zone (Behnood and Mannering, 2016).

2.2 Current Study in Context

The literature clearly highlights the progress made in modeling non-motorist injury severity analysis. Several researchers have recognized that crash location type has a significant impact on non-motorist severity and developed location specific severity models. The econometric models developed so far account for the influence of observed factors. However, these models do not accommodate for the potential relationship between unobserved factors leading to the non-motorist location outcome and the severity outcome. In this study, we address this limitation by incorporating a joint framework that explicitly models crash location type and severity as two dimensions of the outcome process. To be sure, a recent study (Phuksuksakul et al., 2023) developed a similar econometric framework for non-motorist severity analysis. In their analysis the authors focused on active travelers while not explicitly accounting for crash location. Thus, in their study, injury severity profiles were partitioned only on the basis of active traveler and not based on the crash location. The current study proposes a copula-based model to examine the joint process between the crash location type and the injury severity sustained by the non-motorists in a traffic crash. Specifically, the study proposes a copula-based joint binary logit (BL)-pooled generalized ordered logit (GOL) model to consider the dependence between the location types and crash severity sustained by pedestrian and bicyclist in a single motor vehicle crash. In the first stage of modeling, the study developed a binary logit to model crash location type and a pooled GOL to model pedestrian and bicyclist injury severity. Such pooled model offers significant advantages over un-pooled (separate model for pedestrian and bicyclist) in terms of parsimonious estimation and data fit while also accounting for variable specific (pedestrian and bicyclist) effects (Bhowmik et al., 2019; Wang et al., 2019). In the second stage, built on binary logit and pooled GOL, the study examines six copula structures - Gaussian, Farlie-Gumbel-Morgenstern (FGM), Frank, Clayton, Joe, and Gumbel to consider a wide range of dependency structures, including radial symmetry and asymmetry, and asymptotic tail dependence between location type and crash severity variables. The Bayesian Information Criteria (BIC) is used to select the best fitted model among the estimated models. Further, we parameterize the copula dependence parameter in the best fitted model to obtain a direct effect of exogenous variables on dependence structure. For the empirical analysis of the proposed model, the current study uses pedestrian and bicycle crash data drawn from the Central Florida region for the years of 2015 to 2021. In our analysis, we focus on motor vehicle crashes where a motor vehicle and a non-motorist (pedestrian or bicyclist) were involved. To account for the presence of data from multiple years, we used various spline functional forms (year spline variables and independent variables interacted with year spline variables) that account for potential temporal instability in parameter estimates (more details are provided in the variables considered section).

In summary, the contributions of the current research effort to safety literature are twofold. First, methodologically we formulate a copula-based binary logit (BL)-generalized ordered logit (GOL) model to jointly estimate crash location type and injury severity sustained by pedestrians and bicyclists in a single motor vehicle crash by explicitly accounting for temporal heterogeneity of the parameters using a spline formulation approach. The model system allows us to capture potential dependency of the unobserved factors between two dimensions while also allowing the dependency to vary across pedestrians and bicyclists. Second, empirically, by using the pedestrian and bicycle crash data from the Central Florida region, we investigate the contributing factors to pedestrian and bicycle injury severity at intersections and segments that will guide and assist safety professionals to improve non-motorist safety in the region.

3 MODEL FRAMEWORK

The focus of our study is to jointly model the crash location type and injury severity outcome of non-motorists in single motor vehicle crashes using a copula-based joint binary logit-pooled generalized ordered logit modeling framework. In this section, econometric formulation for the joint model is presented.

3.1 The Crash Location Type Model Component

Let q $(q = 1,2, \dots \dots, Q)$ be the indices to represent non-motorist (pedestrian and bicyclist) and k $(k = 1,2, \dots \dots, K)$ represents crash locations (here, K=2). Let j be the index for the discrete outcome that corresponds to the injury severity level j $(j = 1,2, \dots \dots, J)$ of non-motorist q. In this study, j takes five severity levels: $j = 1$ for no injury (NI), $j = 2$ for possible injury (PI), $j = 3$, for non-incapacitating injury (NII), $j = 4$ for incapacitating injury (II), and $j = 5$ for fatal injury (FI). The propensity of a non-motorist q involving in a crash at location type k takes the form of:

$$u_{qk}^{*} = \beta_k x_{qk} + \xi_{qk} \tag{1}$$

where, x_{qk} is a column vector of exogenous variable, β_k is a row vector of unknown parameters specific to location 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 location type k. A non-motorist q is assumed to be involved in a crash of location type k if and only if q is associated with the maximum propensity among all k crash location types, that is if the following condition holds:

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

The condition demonstrated in Equation 2 can be expressed as a series of binary outcome models for each location type k (Lee, 1983). Let η_{qk} be a dichotomous variable with $\eta_{qk} = 1$ if a non-motorist q ends up in a crash at location type k and $\eta_{qk} = 0$ otherwise. Thus, the condition presented in Equation 2 can be defined with a stochastic term v_{qk} as follows:

$$v_{qk} = \xi_{qk} - \left\{ \max_{l=1,2,\ldots,k,\ \ l\neq k} u_{ql}^{*} \right\} \tag{3}$$

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 a detailed discussion).

By substituting the right side for u_{qk}^{*} from Equation 1 in Equation 2, we can write:

$$\eta_{qk} = 1 \ \ if \ \ \beta_k x_{qk} + v_{qk} > 0 \tag{4}$$

In Equation 4, the probability expression of crash location outcome 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 discrete outcome (crash location type) model resembles the binary logit probability expression as follows:

$$\Lambda_k(\beta_k x_{qk}) = Pr(v_{qk} > -\beta_k x_{qk}) = \frac{\sum_{l\neq k} exp\ (\beta_k x_{ql})}{exp\ (\beta_k x_{qk}) + \sum_{l\neq k} exp\ (\beta_k x_{ql})} \tag{5}$$

3.2 The Injury Severity Model Component

In the joint model framework, the modeling of non-motorist injury severity is undertaken using a 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:

$$y_{qk}^{*} = \alpha_k z_{qk} + \varepsilon_{qk}\ ,\ \ y_{qk} = j_k, if\ \tau_{k,j-1} < y_{qk}^{*} < \tau_{k,j} \tag{6}$$

where, y_{qk}^{*} is the latent injury risk propensity for non-motorist q if he/she was involved in a crash at location 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 location type k, with the following ordering conditions: $\left(-\infty < \tau_{k,1} < \tau_{k,2} <\ \dots\dots\dots < \tau_{k,J-1} < +\infty\right)$.

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). In order to ensure the ordering of observed discrete injury severity levels, we employ the following parametric form followed by Eluru et al. (2008) (Eluru et al., 2008):

$$\tau_{k,j} = \tau_{k,j-1} + exp(\phi_{kj} + \delta_{kj}'\, \mathrm{G}_{kj}) \tag{7}$$

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 non-motorist q sustaining an injury severity level j in a crash at location type k take the following form:

$$\begin{aligned} Pr(y_{qk} = j_k) = \Lambda_k\big(\tau_{k,j-1} + exp(\phi_{kj} + \delta_{kj}'\, \mathrm{G}_{kj}) - \alpha_k z_{qk}\big) - \Lambda_k\big(\tau_{k,j-2} \\ + exp(\phi_{kj-1} + \delta_{kj-1}'\, \mathrm{G}_{kj-1}) - \alpha_k z_{qk}\big) \end{aligned} \tag{8}$$

where, $\Lambda_{\mathrm{k}}(.)$ is the standard logistic cumulative distribution function. The probability expression of Equation 8 represents the independent injury severity model for a crash location type k.

3.3 The Joint Model: A Copula-based Approach

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

$$\begin{aligned} \eta_{qk} = 1\ \ if\ \ \beta_k x_{qk} > -v_{qk} \\ y_{qk}^{*} = \alpha_k z_{qk} + \varepsilon_{qk}\ ,\ \ y_{qk} = 1\big[\eta_{qk} = 1\big] y_{qk}^{*} \end{aligned} \tag{9}$$

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

However, the level of dependency between the underlying location type outcome and the injury severity level of non-motorist 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 (please see Bhat and Eluru, 2009 for a detailed description of the copula approach). In constructing the dependency with the copula structure, the stochastic terms (v_{qk} and ε_{qk}) are transformed into uniform distribution by using their inverse cumulative distribution functions. Further, these uniform distributed functions are coupled as a multivariate joint distribution function using the copula framework. 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:

$$\begin{aligned}\Lambda_{vk,\varepsilon k}(v,\varepsilon) &= Pr(v_{qk} < v, \varepsilon_{qk} < \varepsilon)\\ &= [\Lambda_{vk}^{-1}(U_1) < v, \Lambda_{\varepsilon k}^{-1}(U_2) < \varepsilon\,]\\ &= [U_1 < \Lambda_{vk}(v), U_2 < \Lambda_{\varepsilon k}(\varepsilon)\,]\end{aligned} \tag{10}$$

The joint distribution (of uniform marginal variable) in Equation 10 can be generated by a function $C_{\theta q}(.,.)$ (Sklar, 1973), such that:

$$\Lambda_{vk,\varepsilon k}(v,\varepsilon) = C_{\theta q}(U_1 = \Lambda_{vk}(v), U_2 = \Lambda_{\varepsilon k}(\varepsilon)) \tag{11}$$

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

$$\theta_q = fn(\gamma_k s_{qk}) \tag{12}$$

where, s_{qk} is a column vector of exogenous variable, γ_k is a row vector of unknown parameters (including a constant) specific to location 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 $\theta_q = 1 + exp\,(\gamma_k s_{qk})$.

3.4 Estimation Procedure

The joint probability that the non-motorist q gets involved in a crash at location type k and sustaining injury severity level j, from Equation 5 and Equation 8, can be written as:

$$\begin{aligned}&Pr(\eta_{qk} = 1, y_{qk} = j_k)\\ &= Pr\left\{(\beta_k x_{qk} > -v_{qk}), \begin{pmatrix}(\tau_{k,j-2} + \exp(\phi_{k,j-1} + \delta'_{k,j-1}\,\mathrm{G}_{k,j-1}) - \alpha_k z_{qk})\\ < \varepsilon_{qk} < (\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\,\mathrm{G}_{kj}) - \alpha_k z_{qk})\end{pmatrix}\right\}\\ &= \Lambda_{\varepsilon k}(\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\,\mathrm{G}_{kj}) - \alpha_k z_{qk}) - \Lambda_{\varepsilon k}(\tau_{k,j-2} + \\ &exp(\phi_{k,j-1} + \delta'_{k,j-1}\,\mathrm{G}_{k,j-1}) - \alpha_k z_{qk}) - (Pr[v_{qk} < -\beta_k x_{qk}\,, \varepsilon_{qk} < (\tau_{k,j-1} + \\ &exp(\phi_{kj} + \delta'_{kj}\,\mathrm{G}_{kj}) - \alpha_k z_{qk})] - Pr[v_{qk} < -\beta_k x_{qk}\,, \varepsilon_{qk} < (\tau_{k,j-2} + \\ &exp(\phi_{k,j-1} + \delta'_{k,j-1}\,\mathrm{G}_{k,j-1}) - \alpha_k z_{qk})]\,)\end{aligned} \tag{13}$$

The joint probability of Equation 13 can be expressed by using the copula function in Equation 11 as:

$$\begin{aligned} Pr(\eta_{qk} = 1, y_{qk} = j_k) &= \Lambda_{\varepsilon k}\big(\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\, \mathrm{G}_{kj}) - \alpha_k z_{qk}\big) \\ &- \Lambda_{\varepsilon k}\big(\tau_{k,j-2} + exp(\phi_{k,j-1} + \delta'_{k,j-1}\, \mathrm{G}_{k,j-1}) - \alpha_k z_{qk}\big) \\ &- \left[C_{\theta q}\big(U^k_{q,j}, U^k_q\big) - C_{\theta q}\big(U^k_{q,j-1}, U^k_q\big)\right] \end{aligned} \tag{14}$$

where $U^k_{q,j} = \Lambda_{\varepsilon k}\big(\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\, \mathrm{G}_{kj}) - \alpha_k z_{qk}\big), \quad U^k_q = \Lambda_{\nu k}\big(-\beta_k x_{qk}\big)$ (15)

Thus, the likelihood function with the joint probability expression in Equation 14 for location type and non-motorist injury severity outcomes can be expressed as:

$$L = \prod_{q=1}^{Q}\left[\prod_{k=1}^{K}\prod_{j=1}^{J}\{Pr(\eta_{qk} = 1, y_{qk} = j_k)\}^{\omega_{qkj}}\right] \tag{16}$$

where, ω_{qkj} is dummy with $\omega_{qkj} = 1$ if the non-motorist q sustains crash at location 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 BL component, α_k and $\tau_{k,j}$, ϕ_{kj}, δ'_{kj} in GOL component, and finally γ_k in the dependency component. We use GAUSS matrix programming software to run the models.

4 DATA PREPARATION

The current research effort examined crash data involving pedestrian and bicyclist crashes from the Central Florida region. These data were collected from the Signal Four Analytics (S4A) database for the years of 2015 to 2021. For this study period, a total of 10,013 pedestrian and 6,597 bicycle crash records were found in the database. After cleaning the missing information, a total of 9,241 pedestrian and 6,237 bicycle crash records were retained. The injury severity is classified according to a five-point severity scale. The distribution of the severity of the overall non-motorists is 12.2% no injury (NI), 27.7% possible injury (PI), 37.3% non-incapacitating injury (NII), 16.7% incapacitating injury (II), and 6.1% fatal injury (FI). Out of the total 15,478 pedestrian and bicycle crash records, this study randomly considered 10,000 records for model estimation and the remaining 5,478 crash records were set aside for validation purpose.

4.1 Variables Considered

The variables for the analysis were collected from different data sources including Signal Four Analytics (S4A), US Census Bureau and American Community Survey, and Florida Geographic Data Library databases. The dependent variables considered in this study can be categorized into two dimensions. In the first dimension of modeling, this study considers the crash location type (segment and intersection) as the dependent variable while in the second dimension, the injury severity sustained by pedestrians and bicyclists is considered according to the five-point injury severity scale. For the independent variables, this study considers an exhaustive set of variables including non-motorist characteristics (such as age and sex), driver and vehicle characteristics (such as driving under influence, distraction, vehicle type, and model year), roadway characteristics (such as road class, shoulder type, speed limit, and number of lanes), weather and environmental factors (such as clear, rainy, light conditions, time of the day, and season), temporal factors (such as year of the crash) and socio-demographic characteristics (such as population density, income, means of transport, and population group by different races) of the census block groups where crashes occurred. We use ArcGIS to combine the crash records, census data and census block group geography to obtain the socio-demographic information at the crash record resolution.

In our study, we tested the temporal instability of the variables by using a spline formulation approach that includes year spline variables, and the interactions of year splines and other exogenous variables. In this approach, multiple spline variables were computed for the year variable including "$nYear_1$", "$nYear_2$" … "$nYear_6$" and "$nYear_7$" where $nYear_i$ represents the spline for the year and is defined as the following approach:

$$nYear_1 = Max(Year_{record} - Year_{base}, 0) \tag{17}$$

$$nYear_2 = Max(Year_{record} - Year_{base} - 1, 0) \tag{18}$$

… … …

$$nYear_i = Max(Year_{record} - Year_{base} - (i-1), 0) \tag{19}$$

where $Year_{record}$ corresponds to year of the observation, $Year_{base}$ corresponds to the year of data prior to the first year used for analysis (in this study, $Year_{base} = 2014$), and i $(1, 2, \dots, i)$ represents the years starting from 2015. The approach effectively serves as a piecewise linear formulation for each parameter over the years. For example, if the estimates for DUI variable are found 0.30 (estimate of DUI*$nYear_1$), -0.45 (estimate of DUI*$nYear_3$), and 0.25 (estimate of DUI*$nYear_6$) for the year 2015, 2017 and 2020 respectively, the overall impact of DUI is 0.30 for the year 2015, (0.30*2) for 2016, (0.30*3-0.45) for 2017, (0.30*4-0.45*2) for 2018, (0.30*5-0.45*3) for 2019, (0.30*6-0.45*4+0.25) for 2020, and (0.30*7-0.45*5+0.25*2) for 2021. To be specific, this spline approach represents the year threshold points where the slope for a variable is expected to change (see Eluru and Gayah, 2022; Shabab et al., 2023 for an application of the approach).

In estimating the model, several functional forms, and combination of variables were considered and those that provide the best fit were retained in the final specification. The final specification of the model was based on removing the statistically insignificant variables in a systematic process based on 90% confidence level. The sample share of the variables considered for the final model estimation is presented in Table A.1 in the Appendix section.

5 EMPIRICAL ANALYSIS

5.1 Model Specification and Overall Measures of Fit

The empirical analysis involves a series of model estimation. The model estimation process started with the development of a binary logit (BL) to model crash location type and separate ordered logit (OL) models to analyze pedestrian and bicyclist severity for each location type. Then, we developed a pooled OL model for each location type that examines if parameter differences between pedestrian and bicyclist components are statistically different. The reader would note that in this pooled modeling approach, we tested the statistical significance of an exogenous variable from pooled dataset and an interaction of that variable with pedestrian/bicyclist indicator variable to examine the potential deviation of the variable effect across pedestrians and bicyclists. An insignificant effect of the interaction variable indicates no significant deviation of the effect of the main variable across two users resulting in the same coefficient and t-statistic for pedestrians and bicyclists. It is worthwhile to mention that this pooled modeling approach offers significant advantages in terms of dimensionality and model performance relative to the separate models for pedestrians and bicyclists (see for previous examples of such pooled models Wang et al., 2019, Marcoux et al., 2018). Subsequently, we tested the temporal instability of the variables by using year spline variables, and the interactions of year splines and other exogenous variables in both BL and pooled OL models. Next, we parametrized the thresholds to relax the monotonic effect of the pooled OL model and developed a pooled GOL model with temporal heterogeneity. 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. Based on the significance of copula dependence parameter for each location type, copula models that allow for different dependency structures for different location types and injury severity combinations were estimated.

The alternative copula models estimated are non-nested and hence, cannot be tested using the traditional log-likelihood ratio test (Eluru et al., 2010). 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:

$$BIC = -2LL + N_p \, ln(Q) \tag{20}$$

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 is the preferred model.

The LL and BIC values of the estimated models are presented in Table 1. From Table 1, it is clear that the pooled model system offers improved data fit (with lower BIC value) compared to the separate models supporting the findings of earlier research (Wang et al., 2019). Further, the values indicate that capturing temporal heterogeneity and parameterizing the threshold values improved the model performance compared to the models without temporal heterogeneity and unparameterized threshold values. The comparison exercise among copula models shows that with exclusively a single copula dependency structure, all the copula structures show better performance than the independent copula model. However, only three copula structures – Gaussian, Clayton and Joe show significant dependence parameters for both segment and intersection locations. The FGM and Frank structures show significant dependence parameter only for segment location while the Gumbel structure shows significant dependence parameter only for intersection location. We also tested the performance of the combinations such as Gaussian-Gumbel, and Frank-Gaussian, structure. However, the lowest BIC value was obtained for the single Gaussian structure as shown in Table 1. For this model, we find that parameterizing the dependence structure provides further improved BIC (lower) compared to the model structure without parameterization[1]. Thus, the Gaussian copula with parameterized dependence was finalized for our analysis[2].

TABLE 1 Comparison of the Model Performance

Model	Log-Likelihood	Number of Parameters	BIC
Independent models (BL and separate OL models)	-20,417.4	93	41,691.4
Independent models (BL and pooled OL models)	-20,418.1	75	41,527.0
Independent models with temporal heterogeneity (BL and pooled OL models)	-20,254.2	94	41,374.2
Independent models with temporal heterogeneity (BL and pooled GOL models)	-20,214.5	98	41,331.6
Gaussian copula model	-20,191.9	94	41,249.6
FGM copula model	-20,197.2	94	41,260.2
Frank copula model	-20,206.6	92	41,260.6
Clayton copula model	-20,223.2	96	41,330.6
Joe copula model	-20,193.6	94	41,253.0
Gumbel copula model	-20,215.9	97	41,325.2
Gaussian-Gumbel copula model	-20,193.5	94	41,252.8
Frank-Gaussian copula model	-20,202.9	94	41,271.6
Gaussian copula model with parameterized dependence	-20,178.0	96	41,240.2

5.2 Estimation Results

The estimation results of the Gaussian copula model with parameterized dependency are shown in Table 2. The results of the independent copula model are shown in Table A.2 of the Appendix. For the ease of presentation, the location type component and injury severity component are discussed separately. The copula parameters are presented in the last row panel of Table 2.

---

[1] We conducted a comparison exercise between the performance of a separate model system (composed of a crash location type model (BL) and a single injury severity model (OL) with crash location type exogenous variable - intersection vs segment for pedestrians and bicyclists by using pooled dataset) with the performance of proposed copula-based model. The comparison exercise showed that our proposed copula-based model offers superior performance than the separate model system in terms of BIC and LL values. The BIC (LL) values of separate model system and proposed copula-based model are 41,536.55 (-20,565.65) and 41,240.19 (-20,178.00) respectively. This finding further reinforces the rationale for developing the joint model structure with crash location types as a dependent variable linked through copula structure.
[2] In an effort to further assess the predictive performance of the proposed copula-based joint model, a validation exercise is carried out using the holdout sample. We compare the predictive log-likelihood of the proposed copula-based joint model with the independent model system. The predictive BIC (LL) of the proposed model and independent model system are 23,921.37 (-11,556.08) and 23,957.85 (-11,557.11) respectively. This result further highlights the enhanced performance of the proposed copula model.

5.2.1 Location Type Component

The results of the location type model component are presented in the first column panel of Table 2. The reader would note that a positive (negative) sign for a variable in Table 2 signifies that an increase in the variable is likely to result in a higher (lower) likelihood of segment crash (compared to intersection crash) given that a crash occurred. For the ease of discussion, in the following sections, the impacts of the variables are discussed by variable characteristics separately.

<u>Non-motorist characteristics</u>

The age variable impacts suggest that non-motorists under the age of 20 are less likely to be involved in segment crashes while senior non-motorists (age ≥65) are more likely to be crash prone on segments. The results might suggest that senior individuals are unable to respond in time to prevent crashes on segments. On the other hand, for younger non-motorists, intersections offer complexity that cannot be overcome by their agility. The reader would note that crash location type variable (intersection versus segment) as considered in our analysis has not been examined in earlier work on severity analysis. Thus, it is not possible to compare our findings with earlier research efforts.

<u>Driver characteristics</u>

Drivers under the influence of alcohol and drug are more likely to be involved in crashes on segments. Drivers under influence are likely to react slower and are unlikely to identify objects adequately. On the other hand, distracted drivers are more likely to be involved in crashes at intersections. Non-motorist exposure is typically higher at intersections, and distraction while driving might increase the crashes at intersections compared to segment locations.

<u>Vehicle characteristics</u>

With respect to vehicle characteristics, vehicles of model year earlier than 2006 are more likely to be involved in segment crashes compared to the vehicles of model year after 2006. This is probably a result of technological safety advancements in motor vehicles over the years in relation to assisted driving, assisted breaking, and lane departure avoidance.

<u>Roadway characteristics</u>

Several roadway characteristics were tested in the model. The results indicate that on rural roads, non-motorist crashes are more likely to be segment crashes. The results probably reflect the low density of intersections and non-motorists crossing along non-intersection locations. Further, the results show that the effect of this variable is not stable over the years. The negative sign of the variable “Rural roads*nYear3” implies that the impact decreases in 2017 and slope of the impact changes over time starting from 2017.

Table 2 also suggests that the presence of curb shoulder reduces the likelihood of segment crashes as this shoulder type typically includes a sidewalk and possibly higher intersection density for crossing. Interestingly, the slope of the effect further increases in 2017 and then decreases in 2020 as indicated by “Curb shoulder*nYear3” and “Curb shoulder*nYear6” variables respectively.

TABLE 2 Estimation Results of the Gaussian Copula Model with Parameterized Dependence

Variables	Location Type Model (Base: Intersection)		Intersection Severity Model				Segment Severity Model			
			Pedestrian		Bicycle		Pedestrian		Bicycle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Constant	0.172	4.244	--	--	--	--				
Threshold between NI-PI	--	--	-2.406	-18.019	-1.962	-15.284	-2.545	-40.478	-2.410	-35.561
Threshold between PI-NII	--	--	-0.690	-13.355	-0.434	-10.919	-1.096	-13.572	-0.961	-13.572
Threshold between NII-II	--	--	0.965	11.455	1.308	11.329	0.240	8.707	0.442	8.028
Threshold between II-FI	--	--	2.264	3.485	3.122	6.014	1.322	1.656	1.571	1.657
Non-motorist Characteristics										
Age (Base: Other age group)										
Age <20*	-0.065	-4.816	-0.069	-2.479	--	--	--	--	--	--
Age ≥ 65	0.029	2.079	0.196	3.953	0.196	3.953	0.083	5.656	0.083	5.656
*Age ≥ 65*nYear4*	--	--	-0.184	-1.801	-0.184	-1.801	--	--	--	--
Driver Characteristics										
DUI related (Base: Not DUI driving)										
DUI driving	0.143	2.984	0.483	6.606	0.483	6.606	0.122	2.901	0.290	3.574
Distracted related (Base: Not distracted driving)										
Distracted driving	-0.051	-4.334	--	--	--	--	--	--	--	--
Movement pattern (Base: Straight and others)										
Turning	--	--	-0.045	-3.628	-0.045	-3.628	-0.297	-2.928	-0.252	-2.478
Turning*nYear2	--	--	--	--	--	--	0.299	2.411	0.299	2.411
Threshold between II-FI	--	--	--	--	--	--	0.062	2.645	0.062	2.645
Vehicle Characteristics										
Vehicle type (Base: Car and others)										
SUV	--	--	--	--	--	--	0.302	2.995	0.302	2.995
*SUV*nYear2*	--	--	--	--	--	--	-0.363	-2.864	-0.363	-2.864
*SUV*nYear7*	--	--	--	--	--	--	0.398	2.668	0.398	2.668
Pickup	--	--	--	--	--	--	0.036	2.851	0.036	2.851
Vehicle model year (Base: Model 2006-2021)										
Model < 2006	0.033	3.235	--	--			--	--	--	--
Point of impact (Base: Front impact)										
Left impact	--	--	-0.083	-3.355	-0.083	-3.355	-0.095	-5.966	-0.095	-5.966
Rear impact	--	--	--	--	--	--	-0.083	-4.095	--	--
Right impact	--	--	-0.046	-2.411	-0.046	-2.411	-0.164	-8.243	-0.097	-4.502
*Right impact*nYear6*	--	--	--	--	--	--	0.306	3.643	0.306	3.643

Variables	Location Type Model (Base: Intersection)		Intersection Severity Model				Segment Severity Model			
			Pedestrian		Bicycle		Pedestrian		Bicycle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Roadway Characteristics										
Road class (Base: Urban roads)										
Rural roads	0.149	4.292	0.424	4.753	0.424	4.753	0.065	1.845	0.065	1.845
*Rural roads*nYear2*	--	--	-0.420	-3.803	-0.420	-3.803	--	--	--	--
*Rural roads*nYear3*	-0.126	-2.336	--	--	--	--	-0.111	-2.043	-0.111	-2.043
Road system identifier (Base: Local roads and others)										
State roads	--	--	--	--	--	--	0.056	3.777	--	--
US roads	--	--	--	--	--	--	0.787	6.192	0.787	6.192
*US roads*nYear2*	--	--	--	--	--	--	-0.909	-5.826	-0.909	-5.826
Parking lots	--	--	--	--	-0.198	-1.888	-0.045	-3.714	-0.045	-3.714
Shoulder type (Base: Other types)										
Curb shoulder	-0.240	-7.368	--	--	--	--	--	--	--	--
*Curb shoulder*nYear3*	0.319	5.624	--	--	--	--	--	--	--	--
*Curb shoulder*nYear6*	-0.113	-1.860	--	--	--	--	--	--	--	--
Speed limit (Base: SL ≤ 25 mph)										
SL 26-40	--	--	--	--	--	--	0.331	4.201	0.331	4.201
*SL 26-40*nYear2*	--	--	--	--	--	--	-0.353	-3.698	-0.353	-3.698
SL ≥ 41	0.042	3.210	0.412	3.706	0.412	3.706	0.081	5.817	0.081	5.817
*SL ≥ 41*nYear2*	--	--	-0.436	-3.179	-0.436	-3.179	--	--	--	--
Number of lanes (Base: Lane ≤ 2)										
Lane 3	-0.427	-4.298	--	--	--	--	--	--	--	--
*Lane 3*nYear3*	0.514	3.318	--	--	--	--	--	--	--	--
Lane 4	-0.058	-4.646	0.051	2.841	0.051	2.841	0.066	4.253	--	--
Lane ≥ 5	-0.029	-1.817	0.080	3.753	0.080	3.753	0.049	2.687	--	--
Traffic control device (Base: No control)										
Traffic signs	--	--	-0.047	-3.249	-0.047	-3.249	-0.041	-1.975	-0.041	-1.975
Traffic signals	--	--	-0.035	-2.253	-0.035	-2.253	--	--	--	--
Threshold between NII-II	--	--	0.030	2.922	0.030	2.922	--	--	--	--
Threshold between II-FI	--	--	0.223	4.557	0.223	4.557	--	--	--	--
Weather and Environmental Characteristics										
Weather condition (Base: Clear)										
Cloudy	0.032	2.706	--	--	--	--	--	--	--	--
Light condition (Base: Daylight)										
Dawn and dusk	0.031	1.846	--	--	--	--	--	--	--	--

Variables	Location Type Model (Base: Intersection)		Intersection Severity Model				Segment Severity Model			
			Pedestrian		Bicycle		Pedestrian		Bicycle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Dark lighted	0.056	5.018	0.114	7.076	0.114	7.076	--	--	--	--
Dark not lighted	0.706	8.527	1.097	5.441	1.097	5.441	--	--	--	--
*Dark not lighted*nYear2*	--	--	-1.090	-4.430	-1.090	-4.430	--	--	--	--
*Dark not lighted*nYear3*	-1.155	-4.358	--	--	--	--	--	--	--	--
*Dark not lighted*nYear4*	0.365	1.658	--	--	--	--	--	--	--	--
Time of the day (Off-peak and peak evening)										
Late night (00:00-6:30)	--	--	--	--	--	--	0.494	4.579	0.494	4.579
*Late night*nYear2*	--	--	--	--	--	--	-0.535	-4.034	-0.535	-4.034
Peak morning (6:30:9:00)	-0.057	-5.008	--	--	--	--	--	--	--	--
Off-peak morning (9:00-12:00)	--	--	--	--	0.070	2.923	--	--	--	--
Late evening (18:30-24:00)	--	--	--	--	--	--	0.030	2.387	--	--
Socio-demographic Characteristics										
Proportion of public transportation means	0.174	2.065	--	--	--	--	--	--	--	--
Dependence Parameter										
Constant			-0.443	-4.348	-0.443	-4.348	-0.857	-34.285	-0.857	-34.285
Curb shoulder			--	--	--	--	0.086	4.069	0.086	4.069
SUV			0.123	2.856	0.123	2.856	--	--	--	--
Log-likelihood: -20,178.00; Number of parameters: 96; BIC: 41,240.19										

Note: "*" Represents the effect of the variable for the year 2015 (nYear1*Age <20); "--" Represents the variables are not significant at 90% confidence level; NI=No injury, PI=Possible injury, NII=Non-incapacitating injury, II=Incapacitating injury, FI=Fatal injury.

The results also indicate that crashes occurring on roadways with higher posted speed limit (speed limit ≥41mph) are likely to be segment crashes. Model results also imply that crashes occur on roadways with 3 lanes, 4 lanes, or more than 5 lanes are less likely to be segment crashes compared to 2 lane roads. Typically segments with higher number of lanes increase the distance that non-motorists have to traverse substantially and thus discouraging non-motorist crossings. Further, the results show that the impact of the 3-lane variable is not stable over time and the effect increases from 2017.

<u>Weather and environmental characteristics</u>

Among the weather conditions, cloudy weather shows positive impact on segment crashes. Compared to daylight conditions, crashes occurring at dawn/dusk and dark conditions irrespective of lights are more likely to be segment crashes. This is plausible as segments have lower lighting facilities compared to intersections and hence crashes occurring at dawn/dusk or dark conditions are more likely to occur on segments. The results also indicate that the impact of the dark not lighted variable is not stable over time, and the impact changes during 2017 and 2018.

With regards to the time of the day, the model results show that crashes occurring during morning peak are less likely to be segment crashes compared to other times of the day. As the exposure of non-motorists is typically higher at intersections, more activities such as crossings are likely to be higher at peak times which might increase intersection crashes.

<u>Socio-demographic characteristics</u>

A higher proportion of public transportation adoption is associated with higher segment crash likelihood. The result is intuitive as public transit stops are found on mid-blocks and are usually away from intersection for traffic management reasons. Hence, transit riders trying to cross the road might be obscured by the bus and are likely to be subject to higher crash risk.

5.2.2 Severity Component

The results of the severity component are presented in the last column panels of Table 2. The reader would note that a positive (negative) sign for a variable in Table 2 signifies that an increase in the variable is likely to result in higher (lower) severity in a crash. We present the discussion for severity component for segment and intersection by variable group together.

<u>Non-motorist characteristics</u>

For intersection crashes, younger pedestrians are likely to sustain less severe injury. For senior non-motorists, the results show that pedestrians and bicyclists of age 65 and older have a higher likelihood of severity in a crash compared to other age groups with slightly higher magnitude for intersections. The results are consistent with many previous studies (Bahrololoom et al., 2020; Ma et al., 2018). For intersection crashes, the impact of the variable Age ≥65 is found to decrease from the year 2018 as shown in Table 2.

<u>Driver and vehicle characteristics</u>

As expected, driving under influence increases the likelihood of pedestrian and bicyclist severity in intersection and segment crashes (Chen and Fan, 2019; Eluru et al., 2008; Tay et al., 2011). The magnitude of the impact is higher for intersection crashes. At both locations, turning maneuvers decrease the severity of the pedestrian and bicycle crashes compared to other maneuvers. In addition, for this variable, the impact is found to increase starting from 2016 for segment location. The results also indicate that this variable further reduces the likelihood of severity at segments as it shifts the threshold between fatal and incapacitating injury towards right resulting in further decrease in the probability of severe crashes.

Vehicle type of the motor vehicle involved in the crash has a significant impact on severity at segment location. Specifically, severity of crash is exacerbated for SUV and Pickup vehicle types. Further, the magnitude of the impact of SUV decreases from the year 2016 and increases again in the year 2021. Notably, the results did not find significant impact of heavy vehicle in crash severity in our study area. The direction of impact offers expected results with front impact that most risky while left and right impact reduce severity across locations for non-motorists (Zamani et al., 2021). The effect of the right impact variable is found to be unstable over the years and the slope of the impact increases from the year 2020 at segment location. The rear impact direction on segments is observed to reduce severity only for pedestrians. The result warrants further investigation.

Roadway characteristics

The parameters estimated for rural roads variable highlight the increased risk for non-motorists at both locations on rural roads. Further, the impact of the parameters is found to change from the year 2016 and 2017 at the intersection and segment location, respectively.

With respect to state roads, the segment severity model results highlight an increased severity risk for pedestrians. On US roads, at segment location, there is an increased severity risk of the non-motorists, and the impact is found to decrease from the year 2016.

As expected, crashes in parking lots are less likely to be severe for bicyclists across both locations and for pedestrians at segment location. In terms of posted speed limit, higher speeds (greater than 40mph) are associated with severe injuries across locations (Chen and Fan, 2019; Pervaz et al., 2023). On the other hand, the speed limit 26-40mph also shows higher severity for segment location compared to the speed limit ≤25mph and the impact of this variable is found to decrease starting from 2016. For intersection location, the impact of the SL ≥41 variable also indicates variable impact starting from the year 2016. Across both locations, crashes on facilities with 4 or 5 lanes and higher are associated with higher pedestrian injury severity while the variables show higher severity for bicyclists at intersection location only (Haleem et al., 2015; Yasmin et al., 2014c).

The presence of traffic signs is associated with reduced severity for non-motorists across locations. Traffic signals variables, unsurprisingly, exert influence on intersection location. The three parameters estimated – propensity, thresholds between fatal and incapacitating injury, and incapacitating and non-incapacitating injury – highlight how traffic signals reduce non-motorist injury severity at intersections (Eluru et al., 2008; Toran Pour et al., 2017).

Weather and environmental characteristics

Among road environmental variables, the interaction of natural light and lighting conditions offers interesting results. Dark conditions irrespective of light are associated with higher non-motorist severity for intersection facilities. It is also interesting to note that the impact of the dark not lighted variable has changed from the year 2016. The findings are in general consistent with earlier studies (see Chen and Fan, 2019; Uddin and Ahmed, 2018).

Segment crashes occurring during late night period are associated with increased non-motorist severity and the impact is found to decrease from the year 2016. Bicycle crashes occurring at intersection during off peak morning time have a higher impact on severity compared to the other times of the day (see Eluru et al., 2008; Phuksuksakul et al., 2023 for similar findings). The findings also indicate that pedestrian injury severity is likely to be higher for crashes in the late evening period.

5.2.3 Dependence Effect

As indicated earlier, the estimated Gaussian copula-based joint BL-pooled GOL model provides the best fit in incorporating the correlations between the crash location type and injury severity outcome of the pedestrian and bicycle crashes. An examination of the copula parameters presented in the last row panel of Table 2 highlights the presence of common unobserved factors affecting crash location type and injury severity. The reader would note that in our dataset, the copula parameters did not offer statistically significant differences for pedestrians and bicyclists between the crash location types and injury severity outcomes. The negative correlations indicate that the unobserved factors that increase the likelihood of segment and intersection crashes decrease the injury severity of the pedestrians and bicyclists involved in those crashes. We parameterized the dependency by exogenous factors in our model system. For intersection location, the copula dependency is characterized by an additional exogenous variable – SUV for both pedestrian and bicycle crashes while for segment location, the copula dependency is characterized by an additional variable – curb shoulder type. The findings indicate that for intersection location, the dependency parameter θ_q varies across the pedestrians and bicyclists with the SUV variable i.e., for crashes involving SUV's at the intersection, the dependency between crash location type and severity increases relative to other crashes. For segment location, the presence of curb shoulder type increases θ_q compared to crashes without curb shoulder. This provides support to our hypothesis that the dependency structures are not constant across the entire database.

6 ELASTICITY EFFECT ANALYSIS

The model results shown in Table 2 do not provide the true magnitude of the effects of the exogenous variables on the probability of crashes across location types as well as the probability of the crash severity sustained by pedestrians and bicyclists. To demonstrate the actual 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). According to the methodology, for any indicator exogenous variable, the elasticity can be 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 and the percentage change in expected aggregate shares in the entire sample due to change in the indicator variable from 0 to 1 is obtained. For mathematical expressions, let's consider an exogenous indicator variable DUI driving (where DUI is 1 if a driver is under the influence of drug/alcohol and 0 otherwise) for which elasticity will be computed. From equation 8, probability expressions for non-motorist q sustaining an injury severity level j in a crash at location type k is (base probability as estimated in the model),

$$\begin{aligned} Pr_{base} &= Pr(y_{qk} = j_k) \\ &= \Lambda_k\big(\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\, \mathrm{G}_{kj}) - \alpha_k z_{qk}\big) - \Lambda_k\big(\tau_{k,j-2} \\ &\quad + exp(\phi_{kj-1} + \delta'_{kj-1}\, \mathrm{G}_{kj-1}) - \alpha_k z_{qk}\big) \end{aligned} \tag{21}$$

According to the discussions presented above, we compute the probability again by changing the DUI driving variable value to 0 (where the value is 1) and to 1 (where the value is 0) while keeping all other characteristics unchanged by following expression,

$$
\begin{aligned}
Pr_{New} = Pr(y_{qk} = j_k) \\
&= \Lambda_k\big(\tau_{k,j-1} + exp(\phi_{kj} + \delta'_{kj}\,\mathrm{G}_{kj}) - \alpha_k z_{qk}\big) - \Lambda_k\big(\tau_{k,j-2} \\
&+ exp(\phi_{kj-1} + \delta'_{kj-1}\,\mathrm{G}_{kj-1}) - \alpha_k z_{qk}\big)
\end{aligned}
\tag{22}
$$

Now, aggregate elasticity effects for DUI driving variable can be computed as,

$$
Aggregate\ Elasticity_{(y_{qk}=j_k)} = \frac{\sum_q((Pr_{New} - Pr_{base}) \times Sign) \times 100}{\sum_q Pr_{base}} \tag{23}
$$

Where “sign” takes the value of “1” for the individual for which value changes from 0 to 1 and (-1) for the individual for which value changes from 1 to 0.

For the severity component, the computed elasticity can be interpreted as the percentage change in the likelihood of an injury severity level j for a crash at location type k due to a change in the DUI driving variable from 0 to 1. For instance, the aggregate elasticity 60% for DUI driving variable for fatal injury at a segment can be interpreted as the likelihood of a non-motorist being fatally injured in a segment crash by a driver under the influence of drug/alcohol is about 60% higher than the likelihood of a non-motorist being fatally injured by a driver not under the influence of drug/alcohol while other characteristics being equal.

The results of the measured elasticity for crashes by location types, intersection crash severity and segment crash severity are presented in Table 3, Table 4 and Table 5, respectively. Table 3 shows the percentage change in the likelihood of crashes by location type while Table 4 and Table 5 show the percentage change in the likelihood of injury severities due to the changes in the exogenous variable of interest across location types. The findings from the tables indicate that the elasticity effects of the variables for both crash location type and injury severity components are consistent with the effects presented in Table 2. For example, the elasticity estimate for the senior non-motorist related variable (Age ≥65) indicates that senior non-motorists decrease the likelihood of intersection crashes by 6.11% and increase the likelihood of segment crashes by 4.83% (see Table 3) while increase the likelihood of the fatal injury by 48.36% at intersection location (see Table 4) and by 25.02% at segment location (see Table 5). The effects of all the variables presented in Table 3, Table 4 and Table 5 can be interpreted in a similar fashion.

The results from Table 3 imply that higher number of lanes, curb shoulder type, young non-motorists, peak morning period and distracted driving are the significant factors that contribute to intersection crashes while dark conditions without lighting, driving under the influence of drug and alcohol, higher public transportation means of transport and rural roads are the significant contributing factors for segment crashes.

The elasticity results from Table 4 highlight that, for intersection location, the most significant variables with respect to an increase in the non-motorist fatal injury risk at intersection location are DUI related, dark not lighted, senior non-motorists, dark lighted, rural roads, higher speed limit and higher number of lanes in the roadways. The variables describing traffic signals, left impacts, traffic signs, turning movement and right impacts reduce the non-motorist fatal injury risks at intersection location. Further, pedestrians of age less than 20 reduce the fatal injury risks at intersection location while bicyclists involved in crashes at off-peak morning increase the fatal injury risk.

The results from Table 5 show that for segment location, the most significant variables with respect to an increase in the non-motorist fatal injury risk at segment location are DUI related, US roads, late night, senior non-motorists, higher speed limit, SUV and pickup vehicle. The variables describing turning movement, right impacts, left impacts, and traffic signs reduce the non-motorist fatal injury risks at segment location. Further, the higher number of lanes in segment increases the pedestrian fatal injury risks at segment location.

TABLE 3 Elasticity Effects of the Variables for Crash Location Type Component

Variables	**Location Type Model**	
	Intersection Crash	**Segment Crash**
Non-motorist Characteristics		
Age (Base: Other age group)		
Age <20	14.21	-11.23
Age $\geq$ 65	-6.11	4.83
Driver Characteristics		
DUI related (Base: Not DUI driving)		
DUI driving	-28.52	22.55
Distracted related (Base: Not distracted driving)		
Distracted driving	11.02	-8.71
Vehicle Characteristics		
Vehicle model year (Base: Model 2006-2021)		
Model < 2006	-7.08	5.60
Roadway Characteristics		
Road class (Base: Urban roads)		
Rural roads	-17.23	13.63
Shoulder type (Base: Other types)		
Curb shoulder	17.19	-13.59
Speed limit (Base: SL $\leq$ 25 mph)		
SL $\geq$ 41	-8.99	7.11
Number of lanes (Base: Lane $\leq$ 2)		
Lane 3	31.98	-25.28
Lane 4	12.46	-9.85
Lane $\geq$ 5	6.20	-4.90
Weather and Environmental Characteristics		
Weather condition (Base: Clear)		
Cloudy	-6.75	5.34
Light condition (Base: Daylight)		
Dawn and dusk	-6.55	5.18
Dark lighted	-11.98	9.47
Dark not lighted	-42.85	33.88
Time of the day (Off-peak and peak evening)		
Peak morning (6:30:9:00)	12.30	-9.73
Socio-demographic Characteristics		
Proportion of public transportation means	-20.21	15.98

TABLE 4 Elasticity Effects of the Variables for Intersection Crash Severity

Variables	Intersection Crash Severity Model									
	Pedestrian					Bicycle				
	NI	**PI**	**NII**	**II**	**FI**	**NI**	**PI**	**NII**	**II**	**FI**
Non-motorist Characteristics										
Age (Base: 20-64)										
Age<20	28.26	15.01	-2.13	-14.57	-20.11	--	--	--	--	--
Age ≥ 65	-39.31	-28.27	-2.70	29.45	48.36	-39.31	-28.27	-2.70	29.45	48.36
Driver Characteristics										
DUI related (Base: Not DUI driving)										
DUI driving	-77.83	-70.90	-43.05	69.96	268.40	-77.83	-70.90	-43.05	69.96	268.40
Movement pattern (Base: Straight and others)										
Turning	16.48	10.08	-0.51	-10.02	-14.47	16.48	10.08	-0.51	-10.02	-14.47
Vehicle Characteristics										
Point of impact (Base: Front impact)										
Left impact	34.52	17.84	-2.78	-17.34	-23.66	34.52	17.84	-2.78	-17.34	-23.66
Right impact	18.01	10.17	-1.06	-9.94	-14.00	18.01	10.17	-1.06	-9.94	-14.00
Roadway Characteristics										
Road class (Base: Urban roads)										
Rural roads	-37.04	-24.36	0.06	24.54	36.51	-37.04	-24.36	0.06	24.54	36.51
Road system identifier (Base: Local roads and others)										
Parking lots	--	--	--	--	--	103.91	37.58	-13.06	-37.73	-46.31
Speed limit (Base: SL ≤ 25 mph)										
SL ≥ 41	-27.41	-18.91	-0.69	19.63	28.76	-27.41	-18.91	-0.69	19.63	28.76
Number of lanes (Base: Lane ≤ 3)										
Lane 4	-17.40	-11.21	0.06	11.31	16.97	-17.40	-11.21	0.06	11.31	16.97
Lane ≥ 5	-25.86	-17.60	-0.80	18.09	28.23	-25.86	-17.60	-0.80	18.09	28.23
Traffic control device (Base: No control)										
Traffic signs	17.67	10.24	-0.78	-9.97	-14.95	17.67	10.24	-0.78	-9.97	-14.95
Traffic signals	12.96	7.68	10.03	9.04	-98.11	12.96	7.68	10.03	9.04	-98.11
Environmental Characteristics										
Light condition (Base: Daylight)										
Dark lighted	-35.74	-25.14	-1.62	26.24	40.26	-35.74	-25.14	-1.62	26.24	40.26
Dark not lighted	-67.30	-55.57	-16.58	62.16	123.72	-67.30	-55.57	-16.58	62.16	123.72
Time of the day (Base: Other times)										
Off-peak morning	--	--	--	--	--	-23.00	-15.29	-0.52	15.41	25.04

TABLE 5 Elasticity Effects of the Variables for Segment Crash Severity

Variables	Segment Crash Severity Model									
	Pedestrian					Bicycle				
	NI	PI	NII	II	FI	NI	PI	NII	II	FI
Non-motorist Characteristics										
Age (Base: 20-64)										
Age ≥ 65	-27.91	-21.60	-9.46	6.28	25.02	-27.91	-21.60	-9.46	6.28	25.02
Driver Characteristics										
DUI related (Base: Not DUI driving)										
DUI driving	-36.52	-29.91	-15.45	6.61	38.76	-63.70	-57.30	-39.97	-2.70	99.11
Movement pattern (Base: Straight and others)										
Turning	66.93	22.59	2.24	5.79	-39.00	53.46	11.04	-1.38	11.14	-29.52
Vehicle Characteristics										
Vehicle type (Base: Car and others)										
SUV	-14.43	-11.23	-4.75	3.51	12.57	-14.43	-11.23	-4.75	3.51	12.57
Pickup	-12.93	-9.63	-3.76	3.14	10.45	-12.93	-9.63	-3.76	3.14	10.45
Point of impact (Base: Front impact)										
Left impact	43.46	27.55	6.60	-11.23	-24.67	43.46	27.55	6.60	-11.23	-24.67
Rear impact	37.48	24.15	6.04	-9.75	-21.84	--	--	--	--	--
Right impact	84.39	47.37	7.91	-20.44	-39.90	44.50	27.88	6.68	-11.40	-25.05
Roadway Characteristics										
Road class (Base: Urban roads)										
Rural roads	-1.53	-1.35	-0.58	0.48	1.41	-1.53	-1.35	-0.58	0.48	1.41
Road system identifier (Base: Local roads and others)										
State roads	-19.47	-14.94	-6.30	4.68	16.75	--	--	--	--	--
US roads	-30.43	-25.33	-12.98	6.42	31.79	-30.43	-25.33	-12.98	6.42	31.79
Parking lots	18.36	12.91	4.09	-4.87	-12.54	18.36	12.91	4.09	-4.87	-12.54
Speed limit (Base: SL ≤ 25 mph)										
SL 26-40	-22.50	-17.27	-6.96	5.68	18.73	-22.50	-17.27	-6.96	5.68	18.73
SL ≥ 41	-28.61	-22.08	-9.19	7.23	24.28	-28.61	-22.08	-9.19	7.23	24.28
Number of lanes (Base: Lane ≤ 3)										
Lane 4	-22.66	-17.58	-7.60	5.41	19.95	--	--	--	--	--
Lane ≥ 5	-17.09	-13.04	-5.40	4.13	14.49	--	--	--	--	--
Traffic control device (Base: No control)										
Traffic signs	17.06	11.60	3.49	-4.39	-11.19	17.06	11.60	3.49	-4.39	-11.19
Environmental Characteristics										
Time of the day (Base: Other times)										

Variables	Segment Crash Severity Model									
	Pedestrian					Bicycle				
	NI	PI	NII	II	FI	NI	PI	NII	II	FI
Late night	-29.60	-23.68	-10.88	6.95	27.68	-29.60	-23.68	-10.88	6.95	27.68
Late evening	-10.95	-8.11	-3.08	2.75	8.61	--	--	--	--	--

Note: NI=No injury, PI=Possible injury, NII=Non-incapacitating injury, II=Incapacitating injury, FI=Fatal injury

From the aforementioned elasticity effects, it can be highlighted that the influence of driver, road environmental and non-motorists related variables are found to be substantially larger than the influence of roadway and vehicle characteristics. Further, the elasticity values clearly highlight that each crash location type has a fundamentally distinct injury severity profile underscoring the importance of examining the effect of various exogenous variables on pedestrian and bicyclist injury severity outcome by different non-motorist location.

7 CONCLUSIONS

Traditional models of crash frequency or severity analysis implicitly assume that the parameter space to be estimated is universally same i.e., all observations follow the same functional form (simple mean or distribution). However, several research efforts have highlighted the value of allowing for distinct crash severity profiles by various attribute categories. In modeling non-motorist injury severity, the crash location variable offers an attribute that can potentially mediate the impact of independent variables affecting severity. We build a mathematical framework that accommodates for observed and unobserved factors associated with crash location type impacting non-motorist crash severity. Specifically, we employed a copula-based model to examine crash location type and non-motorist injury severity jointly. In this model, the crash location type is analyzed as a binary variable employing binary logit (BL) model while the severity component is examined using a generalized ordered logit (GOL) model. The copula structures considered that represent a range of dependency structures include Gaussian, Farlie-Gumbel-Morgenstern (FGM), Frank, Clayton, Joe, and Gumbel. Several Copula models including those that allow for varying copulas across the two locations are also considered. The copula parameter was also allowed to vary across the data. Bayesian Information Criterion (BIC) was employed to determine the best model among all copula models tested. For the empirical analysis of the models, we used pedestrian and bicycle crash data drawn from the Central Florida region for the years of 2015 to 2021. A total of 15,478 non-motorist crash records (9,241 pedestrians and 6,237 bicyclists) were used for the analysis. To obtain accurate estimates, we explicitly accounted for temporal heterogeneity in our developed model system. We considered a comprehensive set of exogenous variables including non-motorist user characteristics, driver and vehicle characteristics, roadway attributes, weather and environmental factors, temporal and socio-demographic factors for the analysis of the models.

The results of the empirical analysis show that a Gaussian copula model with parameterized dependence term offered the best fit. Further, we assessed the predictive performance of the developed copula-based joint model by conducting a validation exercise. The validation exercise further highlighted the enhanced performance of the developed model. We also conducted an elasticity analysis to show the magnitude of the variables on pedestrian and bicyclist injury severity at two locations. The elasticity results highlight that each crash location type has a fundamentally distinct injury severity profile underscoring the importance of examining the effect of various exogenous variables on pedestrian and bicyclist injury severity outcome by different non-motorist location. Finally, it is worthwhile to highlight that our study investigated the contributing factors to pedestrian and bicycle injury severity at crash locations that will guide the policymakers and transportation agencies to devise appropriate countermeasures to promote adoption of active transportation, particularly for the Central Florida region.

This study uses the information of age and sex of the pedestrians and bicyclists as non-motorist characteristics during empirical analysis. As a specific direction of research, future efforts can investigate the effect of the several pedestrian and bicyclist related factors (such as distraction, failure to yield traffic signs/signals, jaywalking/crossing and other non-motorist activities) if such variables are available in the crash dataset. Furthermore, we recognize that crash location type variable is one possible dimension that potentially mediates crash severity. In future efforts, other mediating variables such as rural and non-rural environments can be considered to mediate crash severity outcome. The analysts should exhibit caution in selecting the variable for partitioning the data – as a large number of categories can result in a very small share for each category. For appropriately selected variables, in future research efforts, it would be interesting to consider a series of joint models to identify the optimal mediating variable for the dataset.

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APPENDIX

TABLE A.1 Sample Characteristics of the Variables across Different Location Types

Variables	Intersection Crashes			Segment Crashes		
	Pedestrian (N=3,270)	**Bicycle (N=3,544)**	**Total (N=6,814)**	**Pedestrian (N=5,971)**	**Bicycle (N=2,693)**	**Total (N=8,664)**
Severity Class						
No injury (NI)	360 (11.01)	568 (16.03)	928 (13.62)	587 (9.83)	376 (13.96)	963 (11.11)
Possible injury (PI)	937 (28.65)	1,071 (30.22)	2,008 (29.47)	1,520 (25.46)	755 (28.04)	2,275 (26.26)
Non-incapacitating injury (NII)	1,231 (37.65)	1,391 (39.25)	2,622 (38.48)	2,110 (35.34)	1,041 (38.66)	3,151 (36.37)
Incapacitating injury (II)	540 (16.51)	459 (12.95)	999 (14.66)	1,157 (19.38)	428 (15.89)	1,585 (18.29)
Fatal injury (FI)	202 (6.18)	55 (1.55)	257 (3.77)	597 (10.00)	93 (3.45)	690 (7.96)
Non-motorist Characteristics						
Age <20	376 (11.50)	473 (13.35)	849 (12.46)	446 (7.47)	276 (10.25)	722 (8.33)
Age ≥ 65	444 (13.58)	324 (9.14)	768 (11.27)	819 (13.72)	237 (8.80)	1,056 (12.19)
Other age group	2,450 (74.92)	2,747 (77.51)	5,197 (76.27)	4,706 (78.81)	2,180 (80.95)	6,886 (79.48)
Driver Characteristics						
DUI driving	40 (1.22)	17 (0.48)	57 (0.84)	107 (1.79)	32 (1.19)	139 (1.60)
Not DUI driving	3,230 (98.78)	3,527 (99.52)	6,757 (99.16)	5,864 (98.21)	2,661 (98.81)	8,525 (98.40)
Distracted driving	399 (12.20)	550 (15.52)	949 (13.93)	547 (9.16)	315 (11.7)	862 (9.95)
Not distracted driving	2,871 (87.80)	2,994 (84.48)	5,865 (86.07)	5,424 (90.84)	2,378 (88.30)	7,802 (90.05)
Movement pattern						
Straight	1,265 (38.69)	1,192 (33.63)	2,457 (36.06)	3,630 (60.79)	1,438 (53.40)	5,068 (58.49)
Turning	1,522 (46.54)	1,920 (54.18)	3,442 (50.51)	703 (11.77)	659 (24.47)	1,362 (15.72)
Lane changing and overtaking	63 (1.93)	56 (1.58)	119 (1.75)	240 (4.02)	144 (5.35)	384 (4.43)
Others	420 (12.84)	376 (10.61)	796 (11.68)	1,398 (23.41)	452 (16.78)	1,850 (21.35)
Vehicle Characteristics						
Vehicle type						
Car	1,605 (49.08)	1,718 (48.48)	3,323 (48.77)	2,744 (45.96)	1,224 (45.45)	3,968 (45.8)
SUV	581 (17.77)	711 (20.06)	1,292 (18.96)	1,088 (18.22)	504 (18.72)	1,592 (18.37)
Pickup	391 (11.96)	423 (11.94)	814 (11.95)	721 (12.08)	359 (13.33)	1,080 (12.47)
Heavy vehicle	96 (2.94)	103 (2.91)	199 (2.92)	185 (3.10)	79 (2.93)	264 (3.05)
Other vehicles	597 (18.26)	589 (16.62)	1,186 (17.41)	1,233 (20.65)	527 (19.57)	1,760 (20.31)
Vehicle model year						
Model < 2006	676 (20.67)	831 (23.45)	1,507 (22.12)	1,524 (25.52)	623 (23.13)	2,147 (24.78)
Model 2006-2010	580 (17.74)	688 (19.41)	1,268 (18.61)	1,048 (17.55)	471 (17.49)	1,519 (17.53)
Model 2011-2015	872 (26.67)	967 (27.29)	1,839 (26.99)	1,392 (23.31)	704 (26.14)	2,096 (24.19)

Variables	Intersection Crashes			Segment Crashes		
	Pedestrian (N=3,270)	**Bicycle (N=3,544)**	**Total (N=6,814)**	**Pedestrian (N=5,971)**	**Bicycle (N=2,693)**	**Total (N=8,664)**
Model 2016-2021	605 (18.5)	648 (18.28)	1,253 (18.39)	1,037 (17.37)	504 (18.72)	1,541 (17.79)
Point of impact						
Front impact	2,120 (64.83)	2,261 (63.8)	4,381 (64.29)	3,142 (52.62)	1,478 (54.88)	4,620 (53.32)
Left impact	228 (6.97)	231 (6.52)	459 (6.74)	446 (7.47)	155 (5.76)	601 (6.94)
Rear impact	19 (0.58)	19 (0.54)	38 (0.56)	429 (7.18)	68 (2.53)	497 (5.74)
Right impact	298 (9.11)	519 (14.64)	817 (11.99)	777 (13.01)	576 (21.39)	1,353 (15.62)
Others	605 (18.5)	514 (14.5)	1,119 (16.42)	1,177 (19.71)	416 (15.45)	1,593 (18.39)
Roadway Characteristics						
Road class						
Urban roads	2,183 (66.76)	2,018 (56.94)	4,201 (61.65)	3,126 (52.35)	1,401 (52.02)	4,527 (52.25)
Rural roads	1,087 (33.24)	1,526 (43.06)	2,613 (38.35)	2,845 (47.65)	1,292 (47.98)	4,137 (47.75)
Road system identifier						
Inter-state roads	19 (0.58)	14 (0.40)	33 (0.48)	76 (1.27)	7 (0.26)	83 (0.96)
State roads	764 (23.36)	781 (22.04)	1,545 (22.67)	1,021 (17.10)	539 (20.01)	1,560 (18.01)
US roads	341 (10.43)	252 (7.11)	593 (8.70)	595 (9.96)	260 (9.65)	855 (9.87)
County roads	523 (15.99)	658 (18.57)	1,181 (17.33)	830 (13.9)	566 (21.02)	1,396 (16.11)
Local roads	1,523 (46.57)	1,736 (48.98)	3,259 (47.83)	1,986 (33.26)	950 (35.28)	2,936 (33.89)
Parking lots	55 (1.68)	53 (1.50)	108 (1.58)	1145 (19.18)	262 (9.73)	1,407 (16.24)
Private roads	33 (1.01)	38 (1.07)	71 (1.04)	184 (3.08)	67 (2.49)	251 (2.90)
Other roads	11 (0.34)	12 (0.34)	23 (0.34)	134 (2.24)	42 (1.56)	176 (2.03)
Shoulder type						
Curb shoulder	1,952 (59.79)	2,220 (62.64)	4,177 (61.30)	2,892 (48.43)	1,400 (51.99)	4,292 (49.54)
Other shoulder types	1,313 (40.21)	1,324 (37.36)	2,637 (38.70)	3,079 (51.57)	1,293 (48.01)	4,372 (50.46)
Speed limit in mph						
SL ≤ 25	1,263 (38.62)	1,608 (45.37)	2,871 (42.13)	2,865 (47.98)	1,152 (42.78)	4,017 (46.36)
SL 26-40	1,171 (35.81)	1,218 (34.37)	2,389 (35.06)	1,447 (24.23)	722 (26.81)	2,169 (25.03)
SL ≥ 41	836 (25.57)	718 (20.26)	1,554 (22.81)	1,659 (27.78)	819 (30.41)	2,478 (28.60)
Number of lanes						
Lane ≤ 2	1,814 (55.47)	2,358 (66.53)	4,172 (61.23)	3,860 (64.65)	1,764 (65.50)	5,624 (64.91)
Lane 3	160 (4.89)	149 (4.20)	309 (4.53)	144 (2.41)	68 (2.53)	212 (2.45)
Lane 4	808 (24.71)	695 (19.61)	1,503 (22.06)	1,123 (18.81)	575 (21.35)	1,698 (19.60)
Lane ≥5	488 (14.92)	342 (9.65)	830 (12.18)	844 (14.13)	286 (10.62)	1,130 (13.05)
Traffic control devices						
Traffic signs	1,236 (37.8)	1,061 (29.94)	2,297 (33.71)	211 (3.53)	148 (5.5)	359 (4.14)
Traffic signals	721 (22.05)	1,277 (36.03)	1,998 (29.32)	395 (6.62)	520 (19.31)	915 (10.56)

Variables	Intersection Crashes			Segment Crashes		
	Pedestrian (N=3,270)	**Bicycle (N=3,544)**	**Total (N=6,814)**	**Pedestrian (N=5,971)**	**Bicycle (N=2,693)**	**Total (N=8,664)**
No control device	1,313 (40.15)	1,206 (34.03)	2,519 (36.97)	5,365 (89.85)	2,025 (75.19)	7,390 (85.3)
Weather Characteristics						
Clear	2,682 (82.02)	2,940 (82.96)	5,622 (82.51)	4,791 (80.24)	2,202 (81.77)	6,993 (80.71)
Rainy	162 (4.95)	111 (3.13)	273 (4.01)	290 (4.86)	94 (3.49)	384 (4.43)
Cloudy	407 (12.45)	482 (13.6)	889 (13.05)	849 (14.22)	382 (14.18)	1,231 (14.21)
Others	19 (0.58)	11 (0.31)	30 (0.44)	41 (0.69)	15 (0.56)	56 (0.65)
Environmental Characteristics						
Light condition						
Daylight	1,938 (59.27)	2,772 (78.22)	4,710 (69.12)	3,053 (51.13)	1,917 (71.18)	4,970 (57.36)
Dawn and dusk	197 (6.02)	210 (5.93)	407 (5.97)	354 (5.93)	164 (6.09)	518 (5.98)
Dark lighted	848 (25.93)	410 (11.57)	1,258 (18.46)	1,413 (23.66)	316 (11.73)	1,729 (19.96)
Dark not lighted	284 (8.69)	150 (4.23)	434 (6.37)	1,132 (18.96)	294 (10.92)	1,426 (16.46)
Time of the day						
Late night (00:00-6:30)	286 (8.75)	151 (4.26)	437 (6.41)	714 (11.96)	179 (6.65)	893 (10.31)
Peak morning (6:30:9:00)	514 (15.72)	566 (15.97)	1,080 (15.85)	580 (9.71)	321 (11.92)	901 (10.40)
Off-peak morning (9:00-12:00)	380 (11.62)	593 (16.73)	973 (14.28)	608 (10.18)	408 (15.15)	1,016 (11.73)
Off-peak evening (12:00-16:00)	645 (19.72)	1,003 (28.30)	1,648 (24.19)	1,202 (20.13)	738 (27.40)	1,940 (22.39)
Peak evening (16:00-18:30)	539 (16.48)	692 (19.53)	1,231 (18.07)	902 (15.11)	494 (18.34)	1,396 (16.11)
Late evening (18:30-24:00)	906 (27.71)	539 (15.21)	1,445 (21.21)	1,965 (32.91)	553 (20.53)	2,518 (29.06)
Temporal Characteristics						
Year						
2015	400 (12.23)	581 (16.39)	981 (14.4)	808 (13.53)	390 (14.48)	1,198 (13.83)
2016	415 (12.69)	520 (14.67)	935 (13.72)	750 (12.56)	363 (13.48)	1,113 (12.85)
2017	422 (12.91)	511 (14.42)	933 (13.69)	780 (13.06)	354 (13.15)	1,134 (13.09)
2018	532 (16.27)	533 (15.04)	1,065 (15.63)	880 (14.74)	420 (15.6)	1,300 (15.00)
2019	516 (15.78)	523 (14.76)	1,039 (15.25)	1,016 (17.02)	397 (14.74)	1,413 (16.31)
2020	470 (14.37)	451 (12.73)	921 (13.52)	788 (13.20)	359 (13.33)	1,147 (13.24)
2021	515 (15.75)	425 (11.99)	940 (13.8)	949 (15.89)	410 (15.22)	1,359 (15.69)
Socio-demographic Characteristics						
Proportion of public transportation means: Mean	0.023	0.021	0.022	0.023	0.021	0.023
Proportion of public transportation means: Std. Dev	0.049	0.044	0.046	0.048	0.047	0.047
Proportion of public transportation means: Min	0.000	0.000	0.000	0.000	0.000	0.000
Proportion of public transportation means: Max	0.602	0.494	0.602	0.602	0.511	0.602

*The numbers in parenthesis correspond to column percentages within each category

TABLE A.2 Estimation Results of Independent Copula Model

Variables	Location Type Model (Base: Intersection)		Intersection Severity Model				Segment Severity Model			
			Pedestrian		Bicycle		Pedestrian		Bicycle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Constant	0.256	5.942	--	--	--	--				
Threshold between NI-PI	--	--	-1.874	-22.189	-1.446	-19.240	-1.756	-24.271	-1.536	-19.666
Threshold between PI-NII	--	--	-0.165	-14.164	0.092	12.435	-0.130	-19.864	0.090	19.864
Threshold between NII-II	--	--	1.586	16.725	1.985	18.987	1.641	21.628	2.073	18.785
Threshold between II-FI	--	--	3.059	6.655	4.154	10.173	3.175	11.307	3.849	8.455
Non-motorist Characteristics										
Age (Base: Other age group)										
Age <20*	-0.070	-4.382	-0.052	-1.825	--	--	-0.050	-1.839	--	--
Age ≥ 65	0.028	2.028	0.202	3.890	0.202	3.890	0.123	7.569	0.123	7.569
*Age ≥ 65*nYear4*	--	--	-0.208	-1.936	-0.208	-1.936	--	--	--	--
Driver Characteristics										
DUI related (Base: Not DUI driving)										
DUI driving	0.131	2.681	0.452	6.199	0.452	6.199	0.222	5.057	0.466	5.356
Distracted related (Base: Not distracted driving)										
Distracted driving	-0.072	-5.116	--	--	--	--	--	--	--	--
Movement pattern (Base: Straight and others)										
Turning	--	--	-0.044	-3.355	-0.044	-3.355	-0.470	-3.593	-0.401	-3.056
Turning*nYear2	--	--	--	--	--	--	0.472	2.946	0.472	2.946
Threshold between II-FI	--	--	--	--	--	--	0.106	4.114	0.106	4.114
Vehicle Characteristics										
Vehicle type (Base: Car and others)										
SUV	--	--	--	--	--	--	0.511	4.043	0.511	4.043
*SUV*nYear2*	--	--	--	--	--	--	-0.624	-3.915	-0.624	-3.915
*SUV*nYear7*	--	--	--	--	--	--	0.487	2.493	0.487	2.493
Pickup	--	--	--	--	--	--	0.280	2.023	0.280	2.023
*Pickup *nYear2*	--	--	--	--	--	--	-0.295	-1.734	-0.295	-1.734
Vehicle model year (Base: Model 2006-2021)										
Model < 2006	0.044	3.646	--	--			--	--	--	--
Point of impact (Base: Front impact)										
Left impact	--	--	-0.081	-3.153	-0.081	-3.153	-0.123	-5.762	-0.123	-5.762
Rear impact	--	--	--	--	--	--	-0.105	-3.793	--	--
Right impact	--	--	-0.045	-2.230	-0.045	-2.230	-0.209	-8.036	-0.126	-4.372

Variables	Location Type Model (Base: Intersection)		Intersection Severity Model				Segment Severity Model			
			Pedestrian		Bicycle		Pedestrian		Bicycle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
*Right impact*nYear6*	--	--	--	--	--	--	0.386	3.395	0.386	3.395
Roadway Characteristics										
Road class (Base: Urban roads)										
Rural roads	0.165	4.545	0.368	3.952	0.368	3.952	0.192	4.856	0.192	4.856
*Rural roads*nYear2*	--	--	-0.368	-3.183	-0.368	-3.183	--	--	--	--
*Rural roads*nYear3*	-0.146	-2.559	--	--	--	--	-0.237	-3.849	-0.237	-3.849
Road system identifier (Base: Local roads and others)										
State roads	--	--	--	--	--	--	0.061	3.246	--	--
US roads	--	--	--	--	--	--	1.033	6.570	1.033	6.570
*US roads*nYear2*	--	--	--	--	--	--	-1.206	-6.220	-1.206	-6.220
Parking lots	--	--	--	--	-0.194	-1.723	-0.061	-3.783	-0.061	-3.783
Shoulder type (Base: Other types)										
Curb shoulder	-0.338	-9.125	--	--	--	--	--	--	--	--
*Curb shoulder*nYear3*	0.472	7.220	--	--	--	--	--	--	--	--
*Curb shoulder*nYear6*	-0.187	-2.680	--	--	--	--	--	--	--	--
Speed limit (Base: SL ≤ 25 mph)										
SL 26-40	--	--	--	--	--	--	0.504	5.018	0.504	5.018
*SL 26-40*nYear2*	--	--	--	--	--	--	-0.554	-4.523	-0.554	-4.523
SL ≥ 41	0.043	3.195	0.416	3.552	0.416	3.552	0.098	5.518	0.098	5.518
*SL ≥ 41*nYear2*	--	--	-0.459	-3.174	-0.459	-3.174	--	--	--	--
Threshold between NII-II	--	--	--	--	--	--	-0.036	-3.890	-0.036	-3.890
Number of lanes (Base: Lane ≤ 2)										
Lane 3	-0.626	-5.038	--	--	--	--	--	--	--	--
*Lane 3*nYear3*	0.786	4.065	--	--	--	--	--	--	--	--
Lane 4	-0.064	-4.732	0.067	3.801	0.067	3.801	0.059	3.151	--	--
Lane ≥ 5	-0.031	-1.802	0.089	4.079	0.089	4.079	0.052	2.459	--	--
Traffic control device (Base: No control device)										
Traffic signs	--	--	-0.043	-2.811	-0.043	-2.811	-0.073	-2.624	-0.073	-2.624
Traffic signals	--	--	-0.035	-2.216	-0.035	-2.216	--	--	--	--
Threshold between NII-II	--	--	0.036	3.380	0.036	3.380	--	--	--	--
Threshold between II-FI	--	--	0.243	4.820	0.243	4.820	--	--	--	--
Weather and Environmental Characteristics										
Weather condition (Base: Clear)										

Variables	Location Type Model (Base: Intersection)		Intersection Severity Model				Segment Severity Model			
			Pedestrian		Bicycle		Pedestrian		Bicycle	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Rainy	--	--	--	--	--	--	0.065	2.046	--	--
Cloudy	0.035	2.556	--	--	--	--	0.041	2.589	0.041	2.589
Light condition (Base: Daylight)										
Dawn and dusk	0.041	2.016	--	--	--	--	--	--	--	--
Dark lighted	0.040	3.267	0.098	5.911	0.098	5.911	--	--	--	--
Dark not lighted	0.646	6.943	0.765	3.745	0.765	3.745	--	--	0.110	3.477
*Dark not lighted*nYear2*	--	--	-0.733	-2.916	-0.733	-2.916	--	--	--	--
*Dark not lighted*nYear3*	-1.098	-3.583	--	--	--	--	--	--	--	--
*Dark not lighted*nYear4*	0.435	1.674	--	--	--	--	--	--	--	--
Time of the day (Off-peak and peak evening)										
Late night (00:00-6:30)	--	--	--	--	--	--	0.749	5.580	0.749	5.580
*Late night*nYear2*	--	--	--	--	--	--	-0.784	-4.728	-0.784	-4.728
Peak morning (6:30:9:00)	-0.100	-7.011	--	--	--	--	--	--	--	--
Off-peak morning (9:00-12:00)	--	--	--	--	0.073	2.892	--	--	--	--
Late evening (18:30-24:00)	--	--	--	--	--	--	0.083	5.621	--	--
Socio-demographic Characteristics										
Proportion of public transportation means	0.217	2.172	--	--	--	--	--	--	--	--
Log-likelihood	-6,531.80		-5,969.33				-7,713.35			
BIC	13,284.65		12,190.50				15,806.24			
Number of parameters	24		30				44			
Total log-likelihood: -20,214.50; Total BIC: 41,331.61; Total number of parameters: 98										

Note: "*" Represents the effect of the variable for the year 2015 (nYear1*Age <20); "--" Represents the variables are not significant at 90% confidence level; NI=No injury, PI=Possible injury, NII=Non-incapacitating injury, II=Incapacitating injury, FI=Fatal injury.