Original Article

Advanced multilevel analysis of crash counts by severity type on multilane arterial segments with multiple intersections

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Abstract This paper employs advanced multilevel modeling to predict crash counts on multilane arterial segments with numerous intersections, providing actionable insights into traffic safety. Using crash data from Ohio (2016–2017), two-level (univariate) and three-level (multivariate) models are constructed to analyze fatal and injury (FI) crashes and property damage-only (PDO) crashes both separately and jointly. The multivariate model demonstrates superior predictive performance, reducing root mean square error from 11.017 to 5.615 and explaining 92% of the variance in out-of-sample 2017 data. Key findings reveal significant heterogeneity across state routes and strong correlations between FI and PDO crash counts. The analysis identifies eight critical factors influencing FI crashes and five for PDO crashes. For example, adding a lane in a multilane arterial segment increases FI crashes by an average of 1.546 crashes, while divided segments decrease FI and PDO crashes by 3 and 9 crashes, respectively. Additionally, each additional signalized intersection raises FI and PDO crashes counts by 0.992 and 3.840 crashes, respectively.

Keywords: (Multilevel modeling, multivariate analysis, heterogeneity, sign control, signal control, intersection density

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1 INTRODUCTION

Globally, road crashes are a leading cause of death, with approximately 1.9 million lives lost each year [1]. Although the annual rate is gradually declining, these numbers still represent a significant loss of life, particularly among those aged 5 to 29 years [2], making road safety a priority worldwide. Efforts to enhance road safety are multifaceted, focusing on reducing the incidence and severity of crashes through diligent infrastructure maintenance. However, crashes generally stem from errors associated with three critical elements, namely roads, vehicles, and drivers, which are complex and highly dependent on the context. Thus, crashes can occur even on roads that are maintained to the highest standards. To better understand and prevent these incidents, researchers are developing predictive models to identify locations with higher-than-expected numbers of crashes [3]. These models, which are informed by variables that describe road segments or crash characteristics [4–7], help policymakers formulate strategies to systematically decrease the number of crashes and mitigate their severities.

Road networks are typically divided into intersections and homogeneous segments [3], with specialized predictive models created for each type. These models are used to predict crash counts and then compared with actual crash data. Segments that are associated with a larger number of observed crashes than predicted are identified as hotspots, indicating the need for further investigation. Thus, ensuring the accuracy of these predictive models is crucial. A major challenge in analyzing road crash data is the heterogeneity of observations, wherein the number or severity of crashes may vary owing to factors that are not directly observed or measured, such as endogeneity, risk compensation, and spatial or temporal correlations [8,9]. In other words, omitting important factors from a model can result in the heterogeneity of observations and skewed model parameters and predictions.

1.1 Segment-level prediction models

Numerous studies have focused on developing predictive models for road segments across different classes, including highways, arterials, and collectors. In these models, average annual daily traffic (AADT) and segment length consistently play crucial roles and are often managed using logarithmic scaling. However, the selection of other predictors varies depending on the specific road segment class. In a comprehensive study examining factors related to crashes on major urban arterial roads, several key insights emerged [10]. First, the logarithm of AADT and the length of the segment were identified as significant predictors of crash counts. Specifically, higher AADT and longer road segments were correlated with increased crash rates. Second, side access density, referring to the presence of driveways, intersections, and access points along the road, was associated with more frequent crashes. In contrast, the presence of medians (central dividers) acted as a mitigating factor, reducing the frequency of crashes. While examining factors that influence crashes on minor arterial and collector roads, it was shown that minor arterial roads were associated with a higher rate of crashes than collector roads [11]. Separate predictive models were developed based on total crashes, fatal and injury (FI) crashes, and property damage–only (PDO) crashes for each type of road class, and a consistent trend was observed: An increase in driveway density was associated with higher crash rates in all models. Several studies have linked the number of conflict points with crashes [12,13], and intersections, which create multiple conflict points, often contribute to increased crashes [14]. Consequently, segments with many intersections tend to exhibit more crashes than segments without intersections. These findings underscore the importance of considering road design and traffic flow when developing predictive models for arterial and collector roads.

In a recent study, researchers developed a predictive model for signalized intersections along urban arterial roads, revealing that traffic signal operations significantly impact crash counts at these intersections [15]. Additionally, higher intersection density may exacerbate crash risks, emphasizing the need for thoughtful planning and management. In another study, 21 separate models were developed to analyze crash types and severity levels, specifically for interstate roads, highlighting the significant impact of AADT, road curvature, and medians on the occurrence of crashes [16]. However, it is important to note that these separate models were developed for the same segments, suggesting a potential correlation between crash types. Various studies conducted on highways have consistently shown that AADT, segment length, curved segments, and the number of lanes significantly impact crash counts [17,18], consistent with previous work focused on unobserved heterogeneity and omitted variables [19]. Additionally, the latter study revealed that the impacts of heavy truck proportion, road curvature, and grade vary significantly across observations. Overall, these studies emphasize the need for nuanced approaches to road safety management.

1.2 Multilevel modeling in traffic safety

Crash data typically possess hierarchical or multilevel structures. For example, crashes that occur on a specific road in a particular county are more likely to share similarities than crashes that occur on different roads or in different counties. Although these similarities are often not captured by explanatory variables, multilevel models are well suited to account for the dependencies between observations. Huang and Abdel-Aty [20] proposed a five-level hierarchy to represent multilevel structures in road crash data. The framework included the following levels: geographic region, traffic site, traffic crash, driver–vehicle unit, and occupant, in conjunction with the spatiotemporal level. Different sub-groups were emphasized within these levels based on their specific research goals. Notably, the involvement of and emphasis on different sub-groups depended on the corresponding research purposes. Furthermore, the approach relied on the heterogeneity examination of the crash data to inform the selection of the relevant levels. To address heterogeneity and spatiotemporal correlation, the authors recommended the use of multilevel models that explicitly specify the multilevel structure and produce reliable parameter estimates. However, the structure of multilevel models depends on the type of data (aggregate or disaggregate) being analyzed.

Although multilevel models appear to offer clear benefits for aggregate data, their application to disaggregate data should be considered more carefully [21]. One study modeled single-vehicle and multi-vehicle crashes on interstates using both the Bayesian bivariate Poisson–log-normal model and a hierarchical Poisson model [22], demonstrating that the Bayesian bivariate Poisson–log-normal model significantly outperformed the hierarchical Poisson model. Specifically, the hierarchical Poisson model may not handle overdispersion effectively. In another study, crashes at intersections and segments along 20 corridors were mutually modeled using multilevel Poisson–log-normal joint models [23]. The corridors were segmented into sub-corridors based on similarities in traffic volumes and roadway characteristics, and four models were constructed: a multilevel Poisson–log-normal joint model using corridors as a higher level with random effects, a multilevel Poisson–log-normal joint model using sub-corridors as a higher level with random effects, a multilevel Poisson–log-normal joint model using corridors as a higher level with random parameters, and a multilevel Poisson–log-normal joint model using sub-corridors as a higher level with random parameters. The model using sub-corridors as a higher level and random parameters outperformed the other models. Key findings from the study include the significant impact of intersection density along the corridor and sub-corridors, as well as the county where the corridor is located, on the crash counts at the intersections or segments, suggesting that there are heterogeneous effects across corridors and counties. Moreover, a study by Almutairi [24] proposed a multilevel model that accounts for correlations along county routes and over time, confirming the presence of heterogeneous effects across different county routes. Multilevel modeling is generally an effective tool for managing dependencies between observations, and it has a wide range of applications.

1.3 Key contributions of the present research

The present study provides the following contributions: 1) modeling crash counts in segments with a large number of intersections and studying the impact of intersection numbers on crash counts per segment. Prior studies focused on the intersection effect at an aggregate level, whereas the present study focuses on the intersection effect at a disaggregate level, an area that has been scarcely investigated; and 2) modeling two distinct dependent variables, namely, FI crashes and PDO crashes, while accounting for heterogeneity across state routes. Prior studies utilized multivariate models to account for the correlation between FI and PDO crashes, whereas this study employs a three-level model to account for both the correlation between FI and PDO crashes and the heterogeneity across county routes. This article describes a valuable approach for simultaneously modeling these two distinct types of crashes using multilevel modeling. Additionally, this research reveals the factors that contribute to crash counts in segments with a large number of intersections, thus improving our understanding of road safety. This work not only advances the field of multilevel modeling in road safety but also provides practical insights that can lead to improved road safety measures.

2. Methodology

Crash counts in segments are typically overdispersed, implying that the variance is greater than the mean [25]. Thus, the negative binomial model is better suited for crash counts and is used more prevalently in modeling crash counts [5]. A standard negative binomial density function is presented in Equation (1).

$$f(y_i; k, \mu_i) = \frac{\Gamma(y_i + k)}{\Gamma(\mathrm{k}) \times y_i!} \times \left(\frac{k}{\mu_i + k}\right)^k \times \left(\frac{\mu_i}{\mu_i + k}\right)^{y_i} \qquad (1)$$

Above, $\Gamma(.)$ represents a gamma function. The relationship between the variance (σ^2) and the mean (μ) is expressed by the equation $\sigma^2 = \mu + \frac{\mu^2}{k}$, indicating that the variance increases quadratically with the mean. If the dispersion parameter k approaches infinity, the mean and variance become equal; the negative binomial model is then simplified to a Poisson model [4]. In this context, y_i represents the number of crashes in segment i. The present study models FI and PDO crash counts using both a two-level model and a three-level model.

2.1 Two-level negative binomial models

The two-level negative binomial model is applied separately for both FI crashes and PDO crashes. The formula is represented by Equation (2):

$$y_{ij} = e^{(\beta_{0j} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + \cdots + \beta_{pj}X_{pij} + \varepsilon_{ij})} \qquad (2)$$

In this equation, the response variable, y_{ij}, represents the crash count in segment i in route j. The intercept, β_{0j}, is allowed to vary across different routes, as shown in Equation (3):

$$\beta_{0j} = \beta_0 + \mu_{0j} \qquad (3)$$

Here, β_0 is the overall intercept, and the random parameter, μ_{0j}, is introduced to capture the heterogeneity across different routes. This parameter is normally distributed with a mean of 0 and a variance of σ_{u_0}. The parameters $\beta_{1j}, \beta_{2j}, \ldots, \beta_{pj}$ are fixed coefficients for independent variables denoted by X. The last term in Equation (2), ε_{ij}, is a random parameter at the lowest level and is gamma-distributed, with a mean of 1 and a variance of 1/k.

However, modeling FI and PDO crashes separately neglects any correlation between them. To address this, the next section proposes an approach using a three-level negative binomial model to model FI and PDO crash counts together.

2.2 Multivariate multilevel negative binomial model

A multilevel model typically analyzes one dependent variable, but it can be used to analyze more than one response variable by placing these response variables on a separate level, namely the lowest level. In this study, the two response variables are FI and PDO crash counts. The formula is expressed using Equation (4):

$$\begin{aligned} y_{ijk} &= e^{(\beta_{0jk} + \beta_{1jk}X_{1ijk} + \beta_{2jk}X_{2ijk} + \cdots + \beta_{pjk}X_{pijk}) \times d_{1jk}} \\ &\times e^{(\gamma_{0jk} + \gamma_{1jk}X_{1ijk} + \gamma_{2jk}X_{2ijk} + \cdots + \gamma_{pjk}X_{pijk}) \times d_{2jk}} \times e^{\varepsilon_{ijk}} \end{aligned} \qquad (4)$$

Here, the response variable, y_{ijk}, is measure i of segment j in route k. The dummy variables, d_{1jk} and d_{2jk}, are indicators corresponding to FI and PDO crash counts, respectively. The assumption is that the intercepts of both the FI and PDO crash counts are nested in segments, and these segments are nested in routes (Figure 1). The formulas are shown in Equations (5) and (6):

$$\begin{aligned} \beta_{0jk} &= \beta_{0k} + \mu_{0jk} \\ \gamma_{0jk} &= \gamma_{0k} + \upsilon_{0jk} \end{aligned} \qquad (5)$$

$$\begin{aligned} \beta_{0k} &= \beta_0 + \mu_{0k} \\ \gamma_{0k} &= \gamma_0 + \upsilon_{0k} \end{aligned} \qquad (6)$$

The coefficients $\beta_0$and γ_0 are the overall intercepts for FI and PDO crash counts, respectively. The last terms in Equations (5) and (6) are the deviations, and they have multivariate normal distributions with means of 0. These deviations are allowed to be correlated with each other, as shown in Equations (7) and (8).

At level 2:

$$\begin{pmatrix} \mu_{0j} \\ \upsilon_{0j} \end{pmatrix} \sim \mathrm{N}\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{\mu_{0j}} & \sigma_{\mu_{0j}\upsilon_{0j}} \\ \sigma_{\mu_{0j}\upsilon_{0j}} & \sigma^2_{\upsilon_{0j}} \end{pmatrix}\right] \qquad (7)$$

At level 3:

$$\begin{pmatrix} \mu_{0k} \\ \upsilon_{0k} \end{pmatrix} \sim \mathrm{N}\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{\mu_{0k}} & \sigma_{\mu_{0k}\upsilon_{0k}} \\ \sigma_{\mu_{0k}\upsilon_{0k}} & \sigma^2_{\upsilon_{0k}} \end{pmatrix}\right] \qquad (8)$$

Hence, the deviations at level 2 are assumed to be independent across the segments (j), and similarly, the deviations at level 3 are assumed to be independent across the routes (k). Deviations at all levels are also assumed to be mutually independent. Finally, all model estimations were performed using the glmmTMB R package, which employs maximum likelihood estimation and Laplace approximation to integrate over random parameters [26].

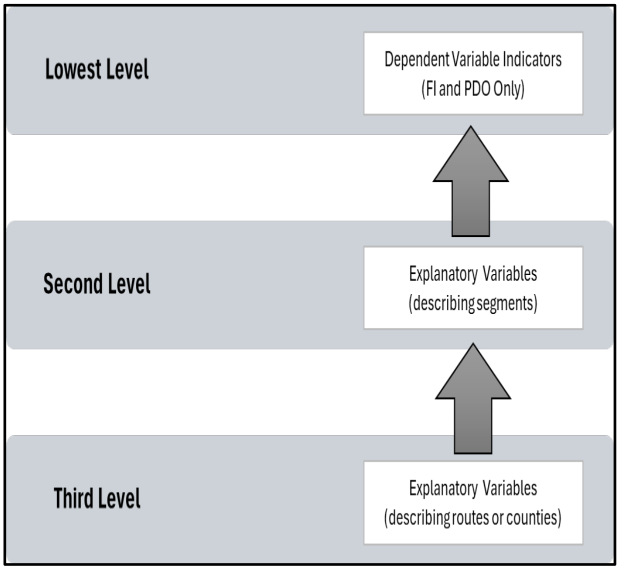

Figure 1: Illustration of the multivariate multilevel model structure.

2.3 Assessing model performance and comparing model predictions

In Sections 2.1 and 2.2, two univariate models and one multivariate model are introduced for modeling FI and PDO crash counts separately and together, respectively. In these models, a bottom-up approach is used to test and construct each model using sequential likelihood ratio tests. The test statistic for the likelihood ratio is computed using the difference in deviance between the two competing models. In this context, “deviance” is defined as −2 times the logarithm of the likelihood, where the likelihood is the value of the likelihood function at its convergence point. This value follows a chi-squared distribution, with the degrees of freedom being the difference in the number of parameters estimated in the two competing models. Akaike’s information criterion (AIC) and Schwarz’s Bayesian information criterion (BIC) use deviance but impose a penalty for each estimated parameter. Thus, the test statistic for comparing or assessing the performance of the univariate models with the multivariate model is expressed using Equation (9):

$$\chi^2 = (deviance_{Model\ FI} + deviance_{Model\ PDO}) - deviance_{Model\ M} \quad (9)$$

The first two terms are deviances for the univariate models of the FI and PDO crash counts, respectively. The last term is the deviance for the multivariate model. The degree of freedom is the difference in the estimated parameters between both univariate models and the multivariate model. For AIC and BIC, the formulas are expressed using Equations (10) and (11):

$$AIC = deviance + 2 \times q, \quad (10)$$

$$BIC = deviance + q \times \ln(N) \quad (11)$$

Here, the deviance is the sum of the deviances for both univariate models or the deviance for the multivariate model, q is the number of estimated parameters, and N is the total number of observations. Similarly, the predictions are evaluated using root mean square errors (RMSEs) for in-sample and out-of-sample data, the univariate models, and the multivariate model.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n_1}(OV_i - PV_i)^2 + \sum_{i=1}^{n_2}(OV_i - PV_i)^2}{n_1 + n_2}} \quad (12)$$

Here, OV and PV are the observed and predicted values, and n_1 and n_2 are the total observations for FI and PDO crash counts, respectively. Moreover, the graphs for the predicted values versus the observed values, along with their regression lines, have been obtained for in-sample and out-of-sample data to assess the prediction performance of the models.

3. Data wrangling and descriptive statistics

The data utilized in this study were collected between 2016 and 2017 for the state of Ohio. The data from 2016 were used to train the models, and the data from 2017 were employed to assess the predictive performance of the models. Three Excel files from the Highway Safety Information System were received regarding segments, crash data, and intersections. The “segments” file contained homogeneous segments located on state routes. The target population in this research comprised multilane arterial segments with at least five intersections located in each segment. Consequently, the count of intersections per segment was determined by identifying those that fall within the range of mileposts from the starting point to the ending point along a specific route. Similarly, the numbers of sign-controlled and signal-controlled intersections were determined, and based on the crash data, the numbers of total, FI, and PDO crash counts were computed.

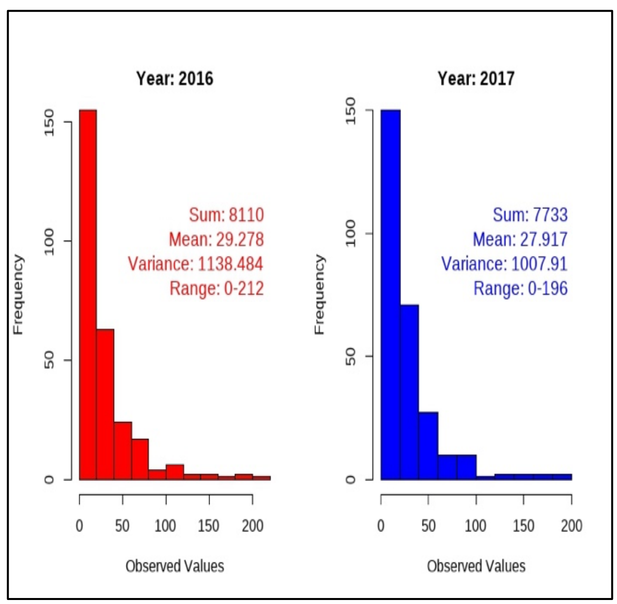

Figure 2: Total crashes for 2016 and 2017 in Ohio.

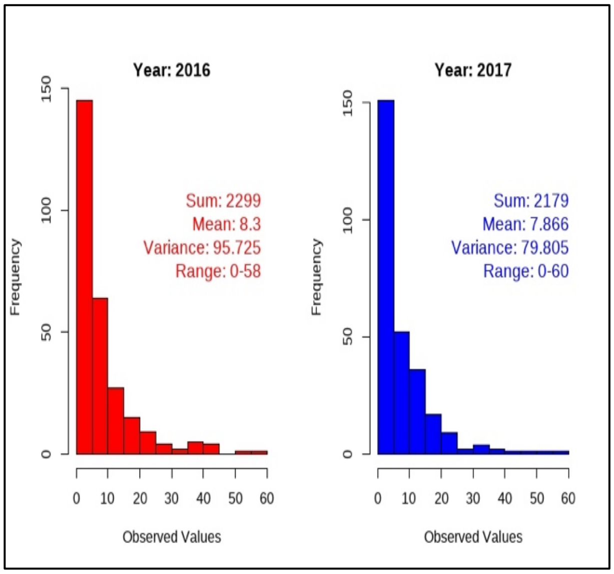

Figure 3: Fatal and injury crashes for 2016 and 2017 in Ohio.

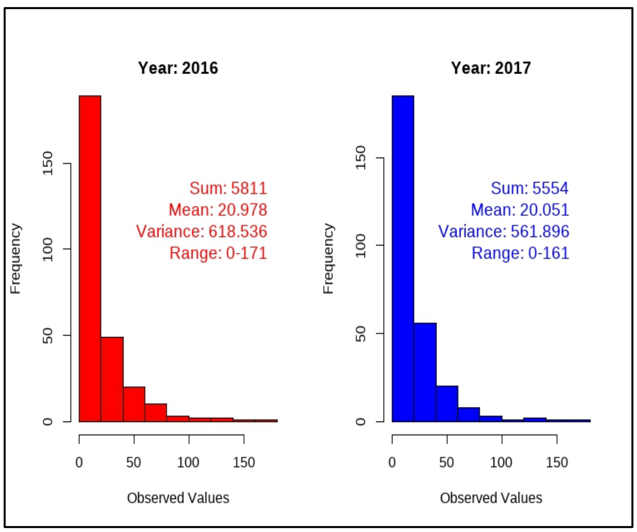

Figure 4: Property damage-only crashes for 2016 and 2017 in Ohio.

Figure 2 through Figure 4 display histograms illustrating the distributions of total, FI, and PDO crashes for 2016 and 2017. Accompanying these histograms are the corresponding descriptive statistics. The distributions depicted by the histograms demonstrate a consistent pattern across both years, as evidenced by the comparative analysis of their descriptive measures. This consistency underscores the stability of the observed crash patterns over the two years. There are 277 segments for each year, encompassing 2,239 intersections: 1,619 are sign-controlled, and 620 are signal-controlled. The dataset designed for multivariate analysis was structured by stacking the univariate dataset twice, resulting in one dependent variable that represents the crash counts, accompanied by two indicators: one for FI crashes and another for PDO crashes.

Table **1** presents the descriptive statistics of the explanatory variables. There are two grouping variables: The first variable pertains to segments, with two observations (one for FI crashes and one for PDO crashes), and the second variable groups segments that are located on the same routes (refer to Figure 1). The county population data were obtained from the United States Census Bureau website (data.census.gov) and merged with the dataset by county name. The total shoulder width represents the combined width of both the inner and outer sides of the road segments, measured in feet.

Table 1: Statistics of the explanatory variables

Variable	Mean	Range	SD
Ln (AADT)	9.605	7.863 – 11.097	0.464
Ln (segment length) (miles)	−0.328	−2.040 – 1.477	0.639
Number of lanes	4.054	3 – 6	0.320
Intersection density (intersections/mile)	11.620	1.359 – 38.462	5. 265
Divided road indicator	0.119	0 – 1	0.325
Number of signalized intersections	2.238	0 – 14	2.033
Principal road indicator (1 if principal, 0 if minor)	0.722	0 – 1	0.449
Ln (county population)	12.652	10.243 – 14.058	1.123
Total shoulder width (feet)	2.67	0 – 26	6.610
Number of sign-controlled intersections	5.845	0 – 23	3.279
Area indicator (1 if the segment is located in a rural area, 0 in an urban area)	0.058	0 – 1	0.234
International roughness index, IRI (1 if the IRI reading is greater than 95 and less than or equal to 170, otherwise 0)	0.386	0 – 1	0.488
International roughness index, IRI (1 if the IRI reading is greater than 170, otherwise 0)	0.469	0 – 1	0.500

4. Results and discussion

This study models FI and PDO crashes on multilane arterial segments with a large number of intersections, which are typically associated with higher crash rates, as confirmed in Figure 2 through Figure 4. Notably, overdispersion is evident, with variances significantly exceeding the means, suggesting that the negative binomial model is a better fit for these data, according to the work reported by Mannering et al. [25]. As outlined in the methodology, two univariate models for FI and PDO crashes and a multivariate model were constructed. Initially, intercept-only models for FI and PDO crashes yielded deviances of 1,757 and 2,253, respectively, with a combined sum of 4,010, which was similar to the deviance produced by the multivariate intercept-only model. Adjustments to the intercepts, as detailed in Sections 2.1 and 2.2, led to deviance reductions of 42 for the univariate models and 357.2 for the multivariate model. Explanatory variables from

Table **1** were sequentially introduced, assessed, and selected using the likelihood ratio test; significant variables were retained, and non-significant ones were excluded. The final models, detailed in Tables 2 and 3, contain eight significant variables for FI crashes and five significant variables for PDO crashes.

Table 2: Results of the univariate model estimations for FI and PDO crashes

Model	**FI**			**PDO**		
Fixed parameter	*Estimate*	*Std. error*	*Z-stat*	*Estimate*	*Std. error*	*Z-stat*
Intercept	−13.572	1.202	−11.288	−8.400	1.045	−8.039
Ln (AADT)	1.201	0.111	10.806	0.978	0.099	9.853
Ln (segment length)	0.839	0.113	7.449	0.532	0.075	7.075
Number of lanes	0.275	0.119	2.315	-	-	-
Intersection density (intersections/mile)	0.028	0.013	2.186	-	-	-
Divided road indicator	−0.410	0.145	−2.822	−0.422	0.142	−2.967
Number of signalized intersections	0.101	0.025	4.027	0.187	0.025	7.517
Principal road indicator	−0.348	0.103	−3.370	-	-	-
Ln (county population)	0.208	0.045	4.612	0.113	0.047	2.425
Random parameter						
Standard deviation of the intercept (negative sign percentages)	0.222 (~100%)	0.057	3.91	0.348 (~100%)	0.056	6.248
Goodness-of-fit measure						
Deviance	1466			1969.7		
Degrees of freedom	11			8		
AIC	1488.0			1985.7		
BIC	1527.9			2014.7		

FI, fatal and injury; PDO, property damage only; AADT, average annual daily traffic; AIC, Akaike's information criterion; BIC, Bayesian information criterion

Table 2 indicates that the intercepts for both univariate models—FI and PDO—significantly vary across state routes and are normally distributed, with a mean of 0. The standard deviations are 0.222 for the FI model and 0.348 for the PDO model. **Error! Not a valid bookmark self-reference.** shows that both intercepts for FI and PDO crashes exhibit significant variations across segments within routes and across routes, as determined using Equations (7) and (8). This indicates that the deviations of the intercepts at the second and third levels are significant, with means of 0, and the four standard deviation values are listed in **Error! Not a valid bookmark self-reference.**. Moreover, there is a significant correlation between the random parameters for FI and PDO at both levels, suggesting that segments prone to FI crashes are also likely to be associated with PDO crashes. These findings are consistent with the research conducted by [23,24], who identified significant variations across corridors and state routes. Table 4 presents a comparison between the two univariate models and the multivariate model, as specified in Section 2.3. The multivariate model significantly outperformed the univariate models in terms of three fitness measures, namely deviance, AIC, and BIC, showing a strong reduction of 143 in deviance.

Table 3: Results of the multivariate model estimations for FI and PDO crashes

Model	FI			PDO		
Fixed parameter	*Estimate*	*Std. error*	*Z-stat*	*Estimate*	*Std. error*	*Z-stat*
Intercept	−12.875	1.099	−11.720	−8.512	1.072	−7.941
Ln (AADT)	1.128	0.105	10.767	0.994	0.101	9.799
Ln (segment length)	0.827	0.096	8.595	0.571	0.077	7.435
Number of lanes	0.187	0.075	2.512	-	-	-
Intersection density (intersections/mile)	0.021	0.009	2.416	-	-	-
Divided road indicator	−0.436	0.141	−3.088	−0.517	0.143	−3.608
Number of signalized intersections	0.120	0.023	5.209	0.183	0.023	7.819
Principal road indicator	−0.228	0.074	−3.065	-	-	-
Ln (county population)	0.223	0.044	5.089	0.103	0.048	2.143
Random parameter						
Standard deviation of intercept at the second level (negative sign percentages)	0.457 (~100%)	0.043	10.542	0.506 (~100%)	0.038	13.264
Correlation	0.95					
Standard deviation of intercept at the second level (negative sign percentages)	0.249 (~100%)	0.057	4.335	0.373 (~100%)	0.057	6.535
Correlation	0.85					
Goodness-of-fit measure						
Deviance	3292.7					
Degrees of freedom	22					
AIC	3336.7					
BIC	3431.6					

FI, fatal and injury; PDO, property damage only; AADT, average annual daily traffic; AIC, Akaike's information criterion; BIC, Bayesian information criterion

Table 4: Comparison of the univariate models and the multivariate model

Model	**Univariate models (Error! Not a valid result for table.)**	**Multivariate model (Error! Not a valid result for table.)**
Goodness-of-fit measure		
Deviance	3435.7	3292.7
AIC	3473.7	3336.7
BIC	3555.7	3431.6
Degrees of freedom	19	22
Likelihood ratio test		
Difference in degrees of freedom	3	
Chi-squared statistics	143	
P-value	< 0.0001	
Forecasting accuracy		
RMSE (in-sample, 2016)	10.949	2.119
RMSE (out-of-sample, 2017)	11.017	5.615

AIC, Akaike's information criterion; BIC, Bayesian information criterion; RMSE, Root mean square error

The univariate models and the multivariate model predictions were evaluated using in-sample and out-of-sample data, as explained in Section 2.3. The 2016 data were used to train the models, whereas the 2017 data were used to test the models and assess their predictions. As shown in

Table 4, the RMSE of the in-sample data is lower than that of the out-of-sample data, which is logical because the models were trained using in-sample data. However, the multivariate model demonstrated superior predictive performance compared with the univariate models, as evidenced by a significant improvement in RMSE.

Additionally, the predicted values were plotted versus the observed values, as shown in Figure 5 and Figure 6, using both in-sample and out-of-sample data for the univariate and multivariate models. A regression line was fitted for each dataset, and the R-squared values were computed. Consistent results were observed for the in-sample and out-of-sample data in the univariate and multivariate models. The regression lines are close to the 45° line, demonstrating the similarity between the predicted and observed values. However, the red lines (2016 in-sample data) are closer to the 45° line than the blue lines (2017 out-of-sample data), which is logical because the models were trained on the in-sample data. Furthermore, the regression lines for the multivariate model are closer to the 45° line than those for the univariate models. The R-squared values indicate how much variation in the observed values is explained by the predicted values. For example, the predicted values from the multivariate model explained ~92% of the variation in the observed values for the out-of-sample data from 2017, as shown in Figure 6. These results highlight the superior performance of the multivariate model over the univariate models.

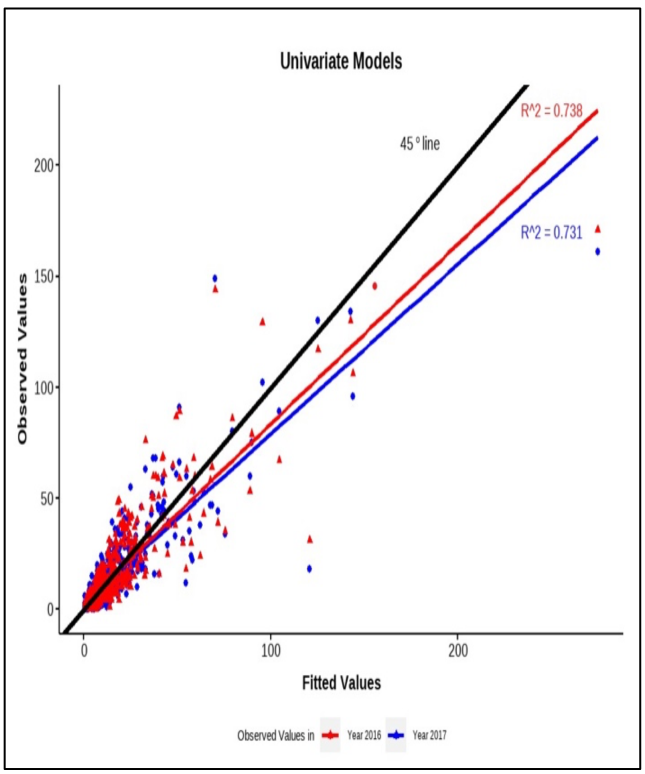

Figure 5: Predicted values versus observed values based on the univariate models.

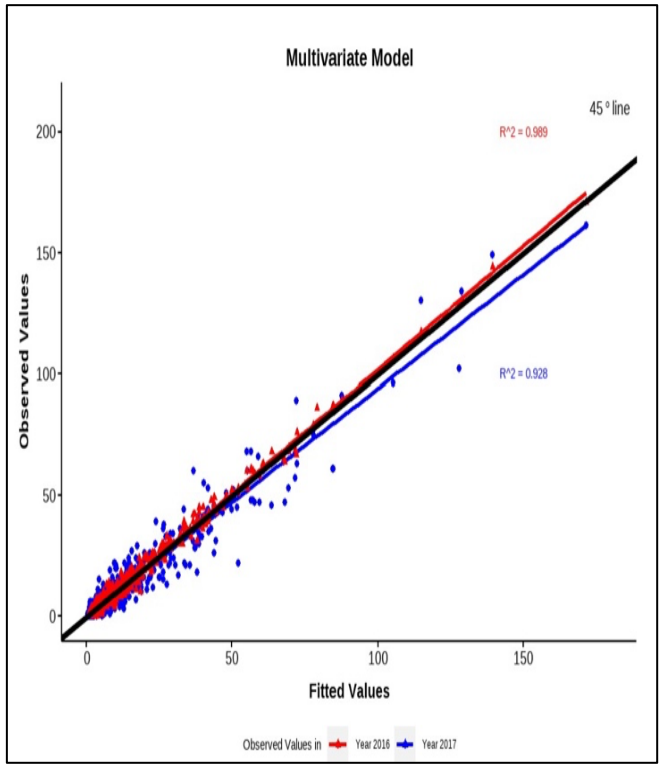

Figure 6: Predicted values versus observed values based on the multivariate model.

There are eight significant contributing variables for FI crashes and five for PDO crashes, as presented in

. The results reveal that higher AADT and longer segment lengths increase the number of both FI and PDO crashes, as observed in previous studies [4,5,10,24]. The number of lanes was found to significantly contribute to FI crashes but not to PDO crashes. This finding suggests that an increase in the number of lanes tends to cause more FI crashes than PDO crashes on multilane arterial segments with numerous intersections. Notably, an increase in intersection density (i.e., intersections per mile) tends to significantly increase FI crashes but not PDO crashes. This finding is consistent with previous studies [10,11] showing a similar impact on total crashes. An increase in these factors leads to an increase in conflict points, resulting in more severe crashes. For a continuous pattern with fewer conflict points, divided segments tend to have fewer FI and PDO crashes than undivided segments, as indicated by the negative sign for the divided road indicator coefficient and confirmed by a previous study [10]. More signalized intersections per segment, however, lead to more FI and PDO crashes, although a higher number of sign-controlled intersections exerts no significant effect on FI or PDO crashes; the only factor that matters for FI crashes is the intersection density. Principal multilane arterial segments tend to have fewer FI crashes than minor multilane arterial segments, but this does not significantly affect PDO crashes. This result contradicts the observations reported by [11], who found that higher segment classes were associated with more crashes than lower segment classes. A possible reason for this discrepancy is the higher accessibility of minor multilane arterial segments than of principal multilane arterial segments, leading to more conflict points for the former than the latter. Moreover, in the present study, the natural logarithm of the county population was found to be a significant contributing factor to both FI and PDO crashes.

Table 5: Average marginal effects

Variables	Univariate models		Multivariate model	
	FI	PDO	FI	PDO
Ln (AADT)	10.064	20.90	9.320	20.834
Ln (segment length)	7.026	11.36	6.835	11.962
Number of lanes	2.300	-	1.546	-
Intersection density	0.232	-	0.176	-
Divided road indicator	−2.968	−7.74	−3.088	−9.049
Number of signalized intersections	0.849	4	0.992	3.840
Arterial type indicator	−3.230	-	−2.009	-
Ln (county population)	1.740	2.42	1.842	2.154

Table 5 lists the average marginal effects for the univariate models and the multivariate model. The values shown in this table represent the average increases or decreases in crashes for each unit increase in that variable. This table provides several useful interpretations. For instance, an additional lane in multilane arterial segments with large numbers of intersections is expected to increase FI crash counts by 1.546 crashes. Additionally, divided segments are expected to decrease FI and PDO crash counts by approximately 3 and 9 crashes, respectively, and an additional signalized intersection per segment is expected to increase FI and PDO crash counts by 0.992 and 3.840 crashes, respectively. Ultimately, the findings in this study may be instrumental for safety analysts and decision-makers, providing valuable insights into the factors that contribute to FI and PDO crashes on multilane arterial segments with numerous intersections.

5. Conclusions

This study demonstrates the effectiveness of multivariate multilevel models in predicting fatal and injury (FI) crashes and property damage-only (PDO) crashes on multilane arterial segments with numerous intersections. The results highlight the model's superiority in performance and its ability to provide actionable insights for improving road safety.

- The multivariate three-level model significantly outperformed the univariate two-level models, reducing the root mean square error (RMSE) from 11.017 to 5.615 and explaining 92% of the variance in the out-of-sample 2017 data.
- Eight significant variables were identified for FI crashes, including the natural logarithms of AADT and segment length, number of lanes, intersection density, divided road indicator, number of signalized intersections, arterial type indicator, and natural logarithm of county population.
- Divided roadways were found to reduce FI crashes by approximately 3 crashes and PDO crashes by 9 crashes per segment.
- An additional lane increased FI crash counts by 1.546, while signalized intersections raised FI and PDO crashes by 0.992 and 3.840 crashes per segment, respectively.
- Strong correlations between FI and PDO crashes and significant variations across state routes were observed, further emphasizing the complexity of crash dynamics.

The findings provide a robust foundation for implementing targeted interventions to reduce crashes and improve road safety. Future research should explore additional variables, such as economic indicators or weather patterns, to enhance predictive accuracy and deepen the understanding of factors contributing to crash occurrences. This research reinforces the value of multilevel modeling in traffic safety analysis and offers a strong framework for guiding future studies and decision-making.

6. References

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