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Impact of roadway geometric features on crash severity on rural two-lane highways

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ABSTRACT

This study examines the impact of a wide range of roadway geometric features on the severity outcomes of crashes occurred on rural two-lane highways. We argue that crash data have a hierarchical structure which needs to be addressed in modeling procedure. Moreover, most of previous studies ignored the impact of geometric features on crash types when developing crash severity models. We hypothesis that geometric features are more likely to determine crash type, and crash type together with other occupant, environmental and vehicle characteristics determine crash severity outcome. This paper presents an application of multilevel models to successfully capture both hierarchical structure of crash data and indirect impact of geometric features on crash severity. Using data collected in Illinois from 2007 to 2009, multilevel ordered logit model is developed to quantify the impact of geometric features and environmental conditions on crash severity outcome. Analysis results revealed that there is a significant variation in severity outcomes of crashes occurred across segments which verifies the presence of hierarchical structure. Lower risk of severe crashes is found to be associated with the presence of 10-ft lane and/or narrow shoulders, lower roadside hazard rate, higher driveway density, longer barrier length, and shorter barrier offset. The developed multilevel model offers greater consistency with data generating mechanism and can be utilized to evaluate safety effects of geometric design improvement projects.

1. Introduction

Motor vehicle crashes impose enormous economic and social losses on society, vehicle manufactures, and transportation agencies. In 2010 alone, the economic losses due to motor vehicle crashes accounted for $242 billion which is equivalent to 1.6 percent of the U.S. Gross Domestic Product (GDP) (NHTSA, 2015). The death toll due to motor vehicle crashes was 35,092 people during 2015, equivalent to 96 death per day nationwide (NHTSA, 2016).

Previous studies identified a myriad of factors that may affect both the frequency and severity of motor vehicle crashes (Abdel-Aty and Radwan, 2000; Cafiso et al., 2010; Chen et al., 2016; de Ona et al., 2013; Lord et al., 2005; Siskind et al., 2011; Zegeer et al., 1981). These factors can be classified as roadway characteristics (e.g. pavement surface, roadside condition, number of lanes, lane width, shoulder width), occupant attributes (e.g. seat belt use, driver attention, driver eyesight, age, gender), vehicle characteristics (e.g. vehicle weight, vehicle height, vehicle class), crash characteristics (e.g. crash type, impact speed), and environmental conditions (e.g. weather condition, light condition, visibility).

Numerous studies examined the impact of roadway features on crash frequency (Ye et al., 2013; Yu and Abdel-Aty, 2013; Castro et al., 2012; Bella, 2013; Park et al., 2012; Zegeer et al., 1988; Lee and Mannering, 2002; Zegeer and Deacon, 1987; Vogt and Bared, 1998; Karlaftis and Golias, 2002; Shankar et al., 1995). However, very few have investigated the influence of roadway features on the crash injury severity outcome. Most of the available studies developed distinct crash severity models for different crash types but since roadway features have significant impact on crash type, these models do not completely reflect the safety effect of roadway features (Duncan et al., 1998; Krull et al., 2000; Lee and Mannering, 2002; Yamamoto and Shankar, 2004).

In the meantime, crash severity data have a hierarchical structure which needs to be addressed in modeling procedure. A hierarchy implies that lower-level observations are clustered within higher level(s). In crash data for example, occupants are clustered within vehicles in which they are located, vehicles are clustered within road segments where the crash occurred, and road segments are clustered within geographical regions. Therefore, crashes occurred on the same segments tend to share similar severity outcomes. Most of previous studies overlooked such hierarchical structure of crash data and used

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traditional regression models (Duncan et al., 1998; Eluru, 2013; Haleem and Abdel-Aty, 2010; Boodlal et al., 2015; Krull et al., 2000; Lee and Mannering, 2002; Yamamoto and Shankar, 2004; Peek-Asa et al., 2010; Ye and Lord, 2011; Yasmin and Eluru, 2013; Ye and Lord, 2014; Schneider and Savolainen, 2011; Wu et al., 2013). The problem with these models is that they assume the residuals are independent across observations. Disregarding such hierarchical structure, when present, may result in models with biased parameter estimates and biased standard errors. This might as well explain several inconsistencies among previous studies on safety effect of roadway features. For instance, upgrading roadway features such as increasing number of travel lanes, widening lanes and shoulders, reducing number of curves, and reducing roadside hazards are generally considered viable solutions to fatality and injury reductions associated with motor vehicle crashes (Hadi et al., 1995; Gross et al., 2009). Yet several studies reported that some upgrades may increase frequency and severity of motor vehicle crashes (Ivan et al., 2000; Karlaftis and Tarko, 1998; Milton and Mannering, 1998; Sawalha and Sayed, 2001; Shankar et al., 1995; Vitaliano and Held, 1991).

To address these research gaps, this study attempts to assess the impact of a wide range of roadway geometric features on the severity of crashes occurred on rural two-lane highways. The contribution of this paper is threefold. First, to address hierarchical structure of crash data, a multilevel modeling approach is developed for analyzing crash severity. Second, the setting of multilevel model is configured to successfully capture the indirect impact of geometric features. Third, this study does not limit the impact of roadway geometric features by conditioning severity models on any specific crash type. To estimate the proposed models, crash data recorded on rural two-lane highway segments in Illinois from 2007 to 2009 were used. The developed crash severity models can be utilized to evaluate safety effects of geometric design improvement projects.

2. Literature review

Several studies have investigated the influence of roadway features on the crash injury severity outcome. Lee and Mannering (2002) used a nested logit model to predict the severity of run-off roadway crashes. Data from State Route 3 in Washington State was used to develop the crash severity model. The presence of horizontal curve was found to have significant impact on crash severity. Khorashadi et al. (2005) explored the difference between urban and rural driver injuries in crashes involving large trucks. Using accident data from 1998 to 2000 in California, two multinomial logit models were developed separately for rural and urban environments. Results revealed that number of lanes, highway terrain, median barrier type and road lighting have significant impact on rural crash severity. In urban area, highway type, median type, presence of construction zone, and weather were found to significantly influence crash severity. Moreover, the presence of concrete median barriers was found to reduce the risk of severe/fatal injury by 68.7%. Duncan et al. (1998) used ordered probit model to assess the impact of occupant characteristics, roadway features, and environmental conditions on injury severity. Their study focused on rear-end crashes involving truck-passenger car collisions. Results revealed that roadway features do not have significant impact on crash severity. Krull et al. (2000) developed logit models to predict injury severity of drivers involved in single-vehicle crashes. They used three years crash data from Michigan and Illinois to evaluate the impact of rollover, while controlling for roadway, vehicle, and driver factors. The roadway features found to increase the probability of severe injury are higher speed limits and dry pavement (as opposed to slick pavement). Yamamoto and Shankar (2004) used a bivariate ordered probit model to analyze driver injury severity and most severely injured passenger's severity in collisions with fixed objects. The study used 4-year statewide crash data in Washington State. Results revealed that icy roadway surface and rain decrease the risk of more severe driver injury crashes. They also found that while collision with guardrail face decreases the probability of severe driver injury, collision with guardrail end increases the risk of severe driver injury.

Most of these studies only investigated the relationship between roadway features and injury severity for a specific crash type. Moreover, previous studies often describe the relationship between geometric features and injury severity as a direct effect. Yet it is difficult to explain the underlying reason why such direct effect would exist. For example, the presence of a median barrier influences the type of crashes − preventing head-on collisions but increasing barrier collisions. It appears more likely that roadway geometric features directly impact crash type. And crash type, together with occupant and vehicle characteristics determine crash severity. Therefore, the safety effect of roadway geometric features on crash severity is not fully captured by these studies due to the negligence of this intermediate layer. Recently, some researchers used crash severity models without focusing on specific crash types. Boodlal et al. (2015) analyzed the safety effects of lane width and shoulder width combination on rural two-lane highways. The study used 3-year crash data collected in Illinois and Minnesota. They developed two multinomial logit models to predict the probability of total and fatal-plus-injury crashes. No significant relationship was found between geometric features and crash severity. They reported that geometric features are not expected to directly affect severity outcome and it is more likely that they just impact likelihood of crash occurrence. Chen et al. (2016) used a hierarchical Bayesian model to investigate the impact of occupant characteristics, roadway features, and vehicle characteristics on driver injury severity. They used 2-year rural interstate crash data from New Mexico. They found significant relationship between the presence of curve and driver injury severity.

From a methodological standpoint, a wide range of econometric modeling approaches including binary logit/probit (Haleem and Abdel-Aty, 2010; Peek-Asa et al., 2010; Kononen et al., 2011; Santolino et al., 2012), multinomial logit (Ye and Lord, 2011; Yasmin and Eluru, 2013; Ye and Lord, 2014; Schneider and Savolainen, 2011), ordered logit/probit (Abay, 2013; Eluru, 2013; Jiang et al., 2013a,b; Mergia et al., 2013), nested logit (Abdel-Aty, 2010; Patil et al., 2012; Wu et al., 2013), bivariate/multivariate ordered probit (de Lapparent, 2008; Abay et al., 2013), copula based (Rana et al., 2010; Yasmin et al., 2014; Eluru et al., 2010), latent class (Xie et al., 2012; Eluru et al., 2012; Shaheed and Gkritza, 2014; Behnood et al., 2014; Behnood and Mannering, 2016), and mixed logit/probit (Aziz et al., 2013; Morgan and Mannering, 2011; Manner and Wünsch-Ziegler, 2013; Paleti et al., 2010) were used to analyze crash severity outcome. Most of these methods are based on the assumption that the model residuals are independent. However, very few of them are able to capture correlation across observations. Multivariate and copula-based methods are mostly used to jointly model multiple dependent variables that are inter-related with one another. For example Eluru et al. (2010) used a copula-based multivariate model to simultaneously examine injury severity experienced by drivers, front-seat passengers, and rear-seat passengers. Latent class models are mostly used when there is correlation across observations but the source of correlation is unknown to the analyst. They attempt to identify groups of observations with homogenous variable effects within each group. The model requires analyst to specify the number of groups. However, in some cases, analyst is aware (or at least partially aware) of the source of correlation and homogenous groups. For instance, it is known that hierarchical structure of data may cause some observations to share similar unobserved characteristics. Recently, studies started to use multilevel models to address this issue. Multilevel modeling approach allows modeling the hierarchical structure of data and capturing correlation at different levels of hierarchy. The application of multilevel models is appropriate when correlation exists within clusters in different levels of hierarchy; otherwise traditional models are sufficient. Jones and Jørgensen (2003) developed a multilevel binary logit model to assess the impact of occupant and vehicle characteristics on fatality risk on Norwegian public roads.

Casualties were clustered within crashes and crashes were clustered within municipalities. Their results revealed that there is a correlation among injury severity outcomes of casualties involved in the same crashes, or crashes occurred in the same municipalities. Abdel-Aty et al. (2011) used a multilevel ordered logit model to investigate the impact of occupant characteristics, roadway features, and light condition on severity outcome of fog or smoke (FS)-related crashes in Florida. To account for hierarchical structure of data, crashes were nested within road segments. Results showed that significant correlation exists among crashes occurred on the same road segments. Although this study provided valuable insight on the impact of some roadway features on crash severity, it only focused on FS-related crashes and its conclusions cannot be extended to all crashes.

3. Data

In this study, the safety effects of various geometric features are examined. The data collection was performed on rural two-lane highway segments in Illinois in 2015 (Boodlal et al., 2015). The dataset contains geometric features, traffic data, and crash data on rural roads. Geometric features associated with each segment include lane width, shoulder width, shoulder type (paved or unpaved), length of no passing zone, length of one-sided passing zone, barrier length and offset, rumble strips presence, number of driveway, curve rate, and roadside hazard rate. Roadside hazard rate is estimated based on roadside hazard rating system developed by Zegeer et al. (1981) and currently employed in the Highway Safety Manual (HSM) predictive method. The geometric features were retrieved through a combination of FHWA's Highway Safety Information System (HSIS) database, Geographic Information System (GIS) roadway database, and Google Earth/Google Street View. The data collection process includes defining homogenous study segments, collecting geometric features from HSIS roadway database, and verifying these features using Google Earth/Google Street View. Roadway segmentation was bounded by changes of number of lanes, lane width, shoulder width, shoulder type, and traffic volume. Homogenous segment therefore indicates that within that specific segment, number of lanes, lane width, shoulder width, shoulder type and traffic volume remain unchanged. Moreover, any segment does not include intersections, and is at least 250 ft away from adjacent intersections. Traffic and crash data associated with study segments were collected from HSIS database. Table 1 summarizes all the variables' descriptive statistics. To analyze crash injury severity, individual crashes were used as the unit of observation.

A total of 460 rural, two-lane highway segments were identified in the dataset. The database was restructured for severity model estimation. A total of 2082 crashes were identified between Years 2007 and 2009 in Illinois. The crash severity was represented using a five-point ordinal scale: 0 − no injury; 1 − possible injury; 2 − non-incapacitating injury; 3 − capacitating injury and 4 − fatal injury. Of the 2082 crashes, 1766 (84.8%) resulted in no injury, 39 (1.9%) involved possible injury, 155 (7.4%) involved non-incapacitating injury, 102 (4.9%) involved incapacitating injury, and 20 (1%) resulted in fatalities.

The analysis of crash type revealed that of the total crashes, 1272 (61.1%) were animal collision, 360 (17.3%) were fixed object collision, 126 (6.1%) were overturn collision, 96 (4.6%) were rear-end collision, 28 (1.3%) head-on, 4 pedestrian (0.2%) and 196 (9.4%) were other collision types.

Fig. 1 depicts the average severity outcome for each crash type. As shown in the figure, pedestrian, head-on, and overturn collisions resulted in most severe crashes, while animal collision ended up with least severe crashes.

4. Methodological approach

Crash severity models are conditioned on the fact that a crash has happened. Crash severity is usually measured as the highest level of injury sustained by any vehicle occupant. Given that the severity is an ordered-response discrete variable, an ordered logit model appears to be most appropriate to model the relationship between crash severity and roadway geometric features, occupant attributes, vehicle characteristics, and environmental conditions. Here we present two types of models: Standard Ordered Logit (SOL) and Multilevel Ordered Logit (MOL), both of which consider the ordered nature of severity outcomes.

4.1. Standard ordered logit (SOL)

The SOE model uses a continuous latent variable y_i^*, to determine the severity outcome of crash i. The latent variable y_i^* is assumed to be associated with the discrete injury severity category y_i

This latent variable is specified as:

$$y_i^* = X_i\beta + \varepsilon_{\mathrm{i}} \tag{1}$$

where X_i is a vector of explanatory variables for crash i, β is a vector of estimated coefficients for the explanatory variables, and ε_i is a random term following a logistic distribution. The dependent variable y_i is determined as:

$$y_i = \begin{cases} 0, & if\ \ y_i^* \le \mu_0 \\ 1, & if \mu_0 \ll y_i^* \le \mu_1 \\ \vdots & \quad\vdots \\ 4, & if y_i^* \gg > \mu_3 \end{cases} \tag{2}$$

where μ_0, …,μ_3 are the threshold values for different crash severity categories 0, 1, 2,…4 (no-injury, possible injury, non-incapacitating injury, incapacitating injury, and fatal injury). The probability of different severity categories can be calculated as follows (Long, 1997):

$$P(y_i = 0) = 1 - \frac{\exp(X_i\beta - \mu_0)}{1 + \exp(X_i\beta - \mu_0)} \tag{3}$$

$$P(y_i = k) = \frac{\exp(X_i\beta - \mu_{k-1})}{1 + \exp(X_i\beta - \mu_{k-1})} - \frac{\exp(X_i\beta - \mu_k)}{1 + \exp(X_i\beta - \mu_k)} \quad k = 1, 2, 3 \tag{4}$$

$$P(y_i = 4) = \frac{\exp(X_i\beta - \mu_3)}{1 + \exp(X_i\beta - \mu_3)} \tag{5}$$

4.2. Linear multilevel model

Multilevel models are particularly suited for modeling data with a hierarchical structure. Fig. 2 depicts the hierarchical nature of crash data. The crash data can consist of four different levels of information, including occupant-level characteristics, vehicle-level characteristics, crash-level characteristics, and segment-level characteristics. Occupant-level characteristics such as age, gender, and restraint use are associated with individuals involved in a crash; vehicle-level characteristics include information such as vehicle type, vehicle speed, and driver characteristics; crash-level characteristics are those such as crash type, weather condition, and light condition; segment-level characteristics describe geometric design features of various road segments. Note that the listed characteristics in Fig. 2 only represent a portion of features within each level. It is reasonable to claim that correlations exist among some observations (crashes). For instance, correlation might exist among crashes occurred on the same segment due to possible unobserved and/or unrecorded geometric features of the road segment. These unobserved and/or unrecorded geometric features might include the condition of pavement, sight distance, road signs, and cross slopes. In addition to geometric features, animal population might also be an unobserved characteristic of different road segments.

Ignoring the correlation associated with hierarchical structure of the data might be problematic, as traditional logistic regression models assume that the residuals are independent across observations. For example, suppose that there is a high animal population in the vicinity

Table 1
Descriptive statistics.

Variable	Description	Mean	Std. Dev.	Min	Max
AADT	Continuous variable: average annual daily traffic (veh/day)	3609.9	2559.17	400	15000
AADT Cat1	If AADT ≤ 5000 = 1, otherwise = 0	0.81	0.39	0	1
AADT Cat2	If 5000 ≪ AADT ≤ 10,000 = 1, otherwise = 0	0.15	0.36	0	1
AADT Cat3	If AADT ≫ > 10,000 = 1, otherwise = 0	0.04	0.19	0	1
Driveway density	Continuous variable: (number of driveways)/(segment length)	5.54	6.05	0	63.41
Shoulder width	Continuous variable (feet)	3.63	2.10	0	12
Narrow shoulder	If shoulder width ≪ 6 (ft) = 1, otherwise = 0	0.80	0.40	0	1
Inclement weather	If crash occurred at rain or snow or fog/smoke/haze or slet/hail or severe wind = 1, otherwise = 0	0.16	0.36	0	1
Adverse light	If crash occurred at dusk or dawn or darkness = 1, otherwise = 0	0.66	0.48	0	1
Lane width	Continuous variable (feet)	11.19	0.55	9.73	12.48
Lane10	If lane width is 10-ft = 1, otherwise = 0	0.11	0.31	0	1
Barrier	Continuous variable: (barrier length)/(barrier offset*total segment length)	0.01	0.02	0	0.13
RHR3	If roadside hazard rate is 3 = 1, otherwise = 0	0.01	0.12	0	1
Curve rate	Continuous variable	31.05	224.93	0	5881.2
Rumble	If rumble strips are present on the segment = 1, otherwise = 0	0.00	0.06	0	1
Dash1 center-line[a]	Continuous variable: (total length of one-sided solid center line)/(total segment length)	0.13	0.12	0	0.50
Solid center-line[b]	Continuous variable: (total length of solid center line)/(total segment length)	0.11	0.19	0	1.13
Head-on	If crash type is head-on collision = 1, otherwise = 0	0.01	0.12	0	1
Fixed object	If crash type is fixed-object collision = 1, otherwise = 0	0.17	0.38	0	1
Overturn	If crash type is overturn collision = 1, otherwise = 0	0.06	0.24	0	1
Pedestrian	If crash type is pedestrian collision = 1, otherwise = 0	0.00	0.04	0	1
Animal	If crash type is animal collision = 1, otherwise = 0	0.61	0.49	0	1
Rear-end	If crash type is rear-end collision = 1, otherwise = 0	0.05	0.21	0	1

[a] Dash 1 center-line is calculated as the ratio of length of one-sided solid centerline over the entire segment length. It represents the proportion of segment where passing is not permitted in either direction.

[b] Solid center-line is calculated as the ratio of length of solid centerline over the entire segment length. It represents the proportion of segment where passing is not permitted in both directions.

of a specific road segment. The severity of crashes occurred on this segment are correlated since most of crashes are collisions with animals which are potentially of the lowest severity outcomes. The violation of such residual independence assumption results in biased parameter estimates and biased standard errors (Bryk and Raudenbush, 1992). Multilevel modeling approaches overcome this problem by nesting correlated observations within hierarchical structures. They essentially provide a conceptual framework to assess individual, cluster, and cross-level effects.

To explain the application of multilevel models for analyzing crash severity outcomes, we first present linear multilevel models. For algebraic simplicity, suppose that a dataset has a hierarchical structure with N observations (level 1) nested within J clusters (level 2) and only one explanatory variable. The basic linear multilevel model for level 1 can be formulated as follows:

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij} \quad \text{(Level 1 model)} \tag{6}$$

where Y_{ij} is the outcome variable (e.g., crash severity) for observation i nested in cluster j, β_{0j} is the intercept, X_{ij} is the explanatory variable for observation i nested in cluster j, β_{1j} is the estimated coefficient for explanatory variable X_{ij}, and r_{ij} is the disturbance term for level 1 model which is assumed to follow a normal distribution.

Eq. (6) is similar to the formulation of traditional linear regression

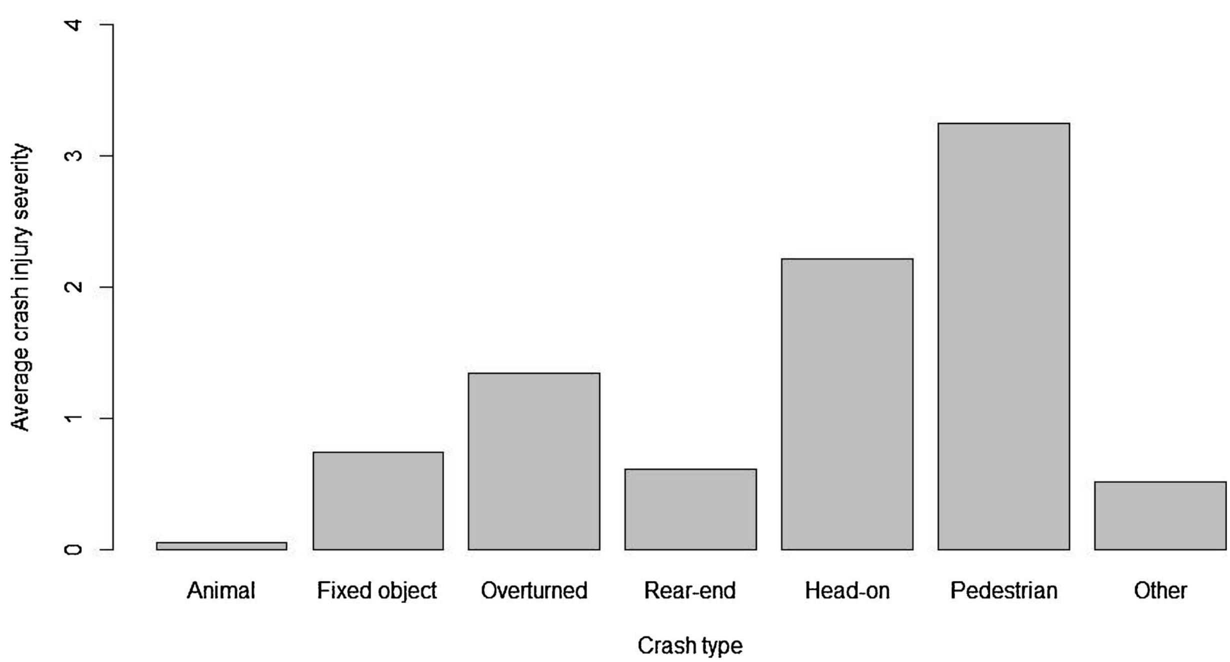

Fig. 1. Average injury severity by crash types (0 = no-injury, 1 = possible injury, 2 = non-incapacitating injury, 3 = incapacitating injury, and 4 = fatal injury).

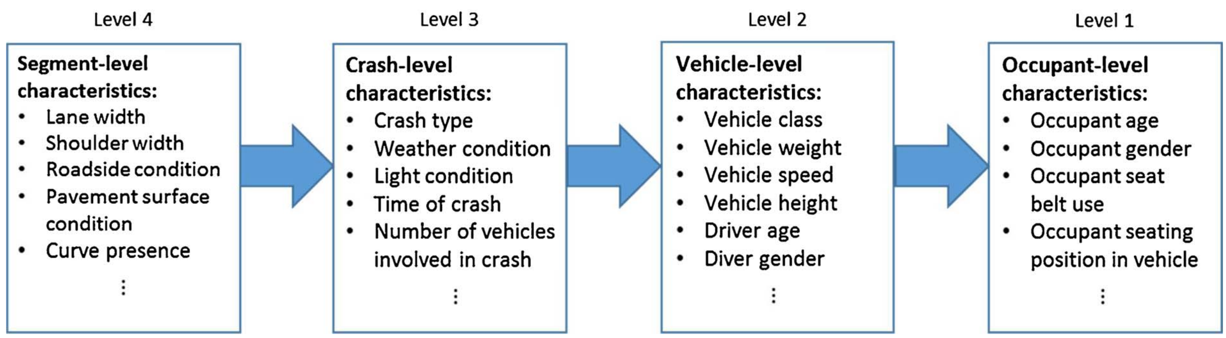

Fig. 2. Hierarchical structure of crash data: at level 1 occupants are clustered within vehicles (level 2), at level 2 vehicles are clustered within crashes (level 3), and at level 3 crashes are clustered within road segments (level 4).

Table 2
Parameter estimation of the SOL model without controlling for crash type.

Variable	Coefficient	Standard Error	z	P ≫ > z
Ln AADT	0.201	0.102	1.97	0.048
Lane10	−0.420	0.261	−1.61	0.108
Barrier	−4.966	3.545	−1.4	0.161
Driveway density	−0.025	0.012	−2.13	0.033
RHR3	0.629	0.453	1.39	0.164
Adverse light	−1.152	0.129	−8.96	0
Inclement weather	0.243	0.157	1.55	0.122
Narrow shoulder	−0.259	0.153	−1.69	0.091
μ_0	2.342	0.870		
μ_1	2.505	0.870		
μ_2	3.427	0.873		
μ_3	5.300	0.897		
Number of observations =	2044			
LR chi2(8) =	120.7			
Probability ≫ > chi2 =	0.000			
Pseudo R2 =	0.049			

models. The main difference distinguishing multilevel model is the subscript j in both intercept and explanatory variable coefficients. The subscript j allows both intercept and coefficients to vary across clusters, yet remain constant for all observations within the same cluster. Here, by assuming the intercept to vary across clusters (random effect) and coefficient of explanatory variable to be fixed across clusters (fixed effect), the level 2 model can be formulated as follows:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} L_j + u_{0j} \quad \text{(Level 2 model)} \tag{7}$$

$$\beta_{1j} = \gamma_{10} \quad \text{(Level 2 model)} \tag{8}$$

where γ_{00}, γ_{01}, and γ_{10} are coefficients which are not varying across clusters, L_j is the explanatory variable describing cluster j at level 2, and u_{0j} is the disturbance term at level 2.

4.3. Multilevel ordered logit (MOL)

The linear multilevel model described above is appropriate for modeling continuous outcome variables. Crash injury severity outcome, however, is an ordered-response discrete variable which justifies the application of MOL models. MOL models, similar to SOL models, utilize latent response variable to determine observed dependent variable. The observed dependent variable y_{ij} is related to y_{ij}^* as described in Eq. (2). The latent response variable y_{ij}^* represents the unobserved crash severity outcome for i-th crash occurred on the j-th segment. y_{ij}^* is estimated as (Bauer and Sterba, 2011):

$$y_{ij}^* = \beta_{0j} + \sum_{p=1}^{P} \beta_p X_{pij} + \varepsilon_{\mathrm{ij}} \quad \text{(Leve 1 model)} \tag{9}$$

$$\beta_{0j} = \gamma_0 + \sum_{m=1}^{M} \gamma_m X_{mj} + \mathrm{u_j} \quad \text{(Level 2 model)} \tag{10}$$

where X_{pij} and X_{mj} are crash-level (level 1) and segment-level (level 2) characteristics, respectively; β_p and γ_m are fixed effects regression coefficients for level and segment-level characteristics. β_{0j} is the random-effect intercept which is a function of segment-level characteristics. $\varepsilon_{\mathrm{ij}}$ is the disturbance term which is assumed to follow a logistic distribution. γ_0 is the intercept for the model at level 2 and $\mathrm{u_j}$ is the random effect accounting for random variation at level 2. It is assumed that $\mathrm{u_j}$ follows a normal distribution. The value of dependent variable y_{ij} and its probability can be estimated using Eqs. (2) through (5).

5. Model estimation results

We developed SOL and MOL models to examine the safety effect of roadway geometric features on crashes occurred on rural two-lane highway segments in Illinois. Several explanatory variables including geometric design feature, traffic volume, crash type, and environmental condition are used to describe the variation in crash severity. SOL models with and without crash type variables were estimated. To choose the best model, a backward procedure was employed to select significant variables. The process started with including all explanatory variables, testing variables' statistical significance, and eventually excluding insignificant variables. Tables 2 and 3 illustrate the final results of the two models (with and without crash type variable).

Table 3
Parameter estimation of the standard ordered logit model with crash type variables.

Variable	Coefficient	Standard Error	z	P ≫ > z
Ln AADT	−0.127	0.120	−1.06	0.288
Lane10	−0.284	0.287	−0.99	0.322
Barrier	−4.255	3.807	−1.12	0.264
Driveway density	−0.018	0.012	−1.50	0.133
RHR3	0.892	0.520	1.72	0.086
Adverse light	−0.176	0.152	−1.16	0.247
Inclement weather	−0.639	0.171	−3.73	0
Narrow shoulder	−0.230	0.167	−1.38	0.167
Head-on	2.823	0.420	6.73	0
Fixed object	0.625	0.212	2.95	0.003
Overturn	1.530	0.247	6.2	0
Pedestrian	4.452	1.057	4.21	0
Animal	−2.446	0.269	−9.11	0
Rear-end	0.371	0.279	1.33	0.184
μ_0	−0.287	1.028		
μ_1	−0.082	1.028		
μ_2	1.032	1.029		
μ_3	3.140	1.049		
Number of observations =	2044			
LR chi2(15) =	530.21			
Probability ≫ > chi2 =	0			
Pseudo R2 =	0.217			

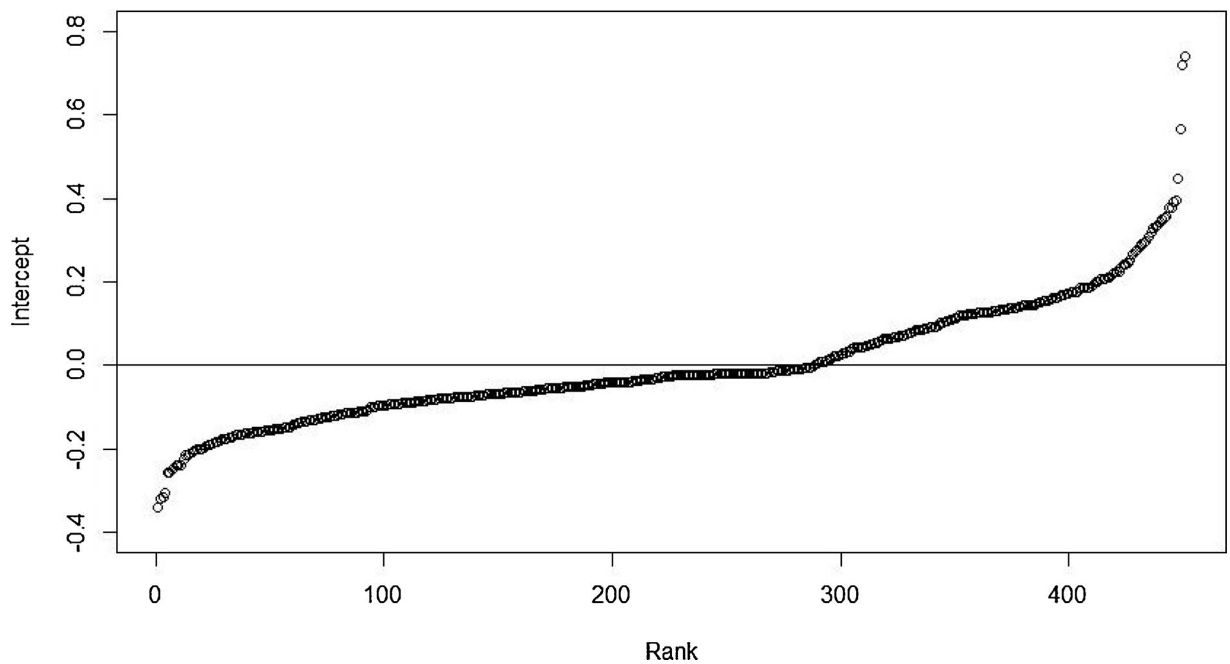

Fig. 3. Ranked estimated intercepts for different road segments from multilevel analysis.

Comparing the results of two models, it clearly shows that the model with crash type variables can better explain the variation in crash severity. The McFadden's pseudo R-squared for the model with crash type variables is significantly better than the one without. This indicates that the vast majority of variation in crash severity is explained by crash type variables. Note that by including crash type variables, the *p*-values of some explanatory variables are significantly increased. This might be interpreted as a sign of multicollinearity between crash type and geometric design variables. This finding is consistent with previous studies showing that geometric features are not expected to directly impact crash severity. While geometric features are more likely to influence the likelihood of the crash occurrence and crash type, essentially it is vehicle and occupant characteristics, together with crash type that determine crash severity outcome (Boodlal et al., 2015).

To overcome potential within-segment correlation due to unobserved characteristics and address the indirect influence of geometric features, MOL model is developed for analyzing crash severity. The model intercept (β_{0j}) is a function of geometric design features capturing the indirect impact of geometric characteristics on crash severity. Fig. 3 shows the estimated intercepts for different road segments which are ranked in order of magnitude. The result indicates that there are several road segments that are associated with extremely low or high risk of severe crashes.

To further explain the intercept variation, crash type distribution is analyzed in these segments. Fig. 4 illustrates the crash type distribution against the range of segment intercept. As the intercept increases, the proportion of less severe crash types such as animal collision decreases. On the other hand, the proportion of more severe crash types such as fixed object, overturned, and head-on collisions increases. Therefore, it can be concluded that the intercept of level 1 model (β_{0j}), in essence, reflects the impact of dominant crash types on the segment. Table 4 presents the estimation results of MOL model. The precision parameter τ shows the variability of intercept across different road segments. The significant value of τ (p-value of 0.06) justifies the use of multilevel model. The reported likelihood-ratio test suggests that there is enough variability between segments to favor a MOL model over a SOL model. As shown in Table 4, there are a few variables in the model with relatively large p-values (e.g., AADT Cat1). From statistical perspective, excluding these variables from the model would not result in a loss in model performance, but could result in a loss of useful information for future research to reference. The signs of estimated parameters associated with these variables were intuitive, and increasing sample size would result in lower p-values. We felt in this case that reporting the potentially useful information is worthwhile. On a related note, previous studies (Klop and Khattak, 1999; Duncan et al., 1998; Haleem and Gan, 2013; Lee and Mannering, 2002) have shown that these variables impact crash severity. Estimating severity models without these variables could result in some level of omitted variable bias (erroneous parameter estimates for variables in the model). We therefore try not to let statistical significance be the main driver of model specifications, as outlined by Hauer (2004).

The results show that the presence of 10-ft lane width and/or narrow shoulders reduces the injury severity of crashes. This might be because drivers do not feel safe to take faster speeds on the segments with such configurations, and consequently drive more cautiously (Shinar et al., 1980; Kolsrud, 1985; Martens et al., 1997; Godley et al., 2004). The speed reduction significantly decreases the transferred kinetic energy during a collision which results in lower risk for severe injuries. The increase in barrier length and the decrease in barrier offset are found to be associated with less severe crashes. This may be explained by the capability of the barrier to redirect an errant vehicle and provide an opportunity to the driver to regain control of the vehicle. The barrier can also dissipate the impact energy during redirection and minimize the risk to vehicle occupants. The model also indicates that higher number of driveways per mile reduces the injury severity of crashes. This might be due to the fact that drivers tend to drive at slower speed and with higher levels of alertness when encountering several driveways on a road segment.

High roadside hazard rate increases the injury severity of crashes. This finding might be explained by the high risk of overturn and fixed object crashes on these segments which are potentially among the most severe crash types. Adverse light condition is found to be associated with less severe crashes. This seems counterintuitive, however, looking into crash types, it appears that adverse light condition is strongly associated with animal collisions which are potentially of lowest crash severity. The results also show that inclement weather condition increases the injury severity of crashes, which is induced by a combination of limited vision and slippery road surface. Crashes occurred on segments with higher AADT tend to be less severe. Driving at lower

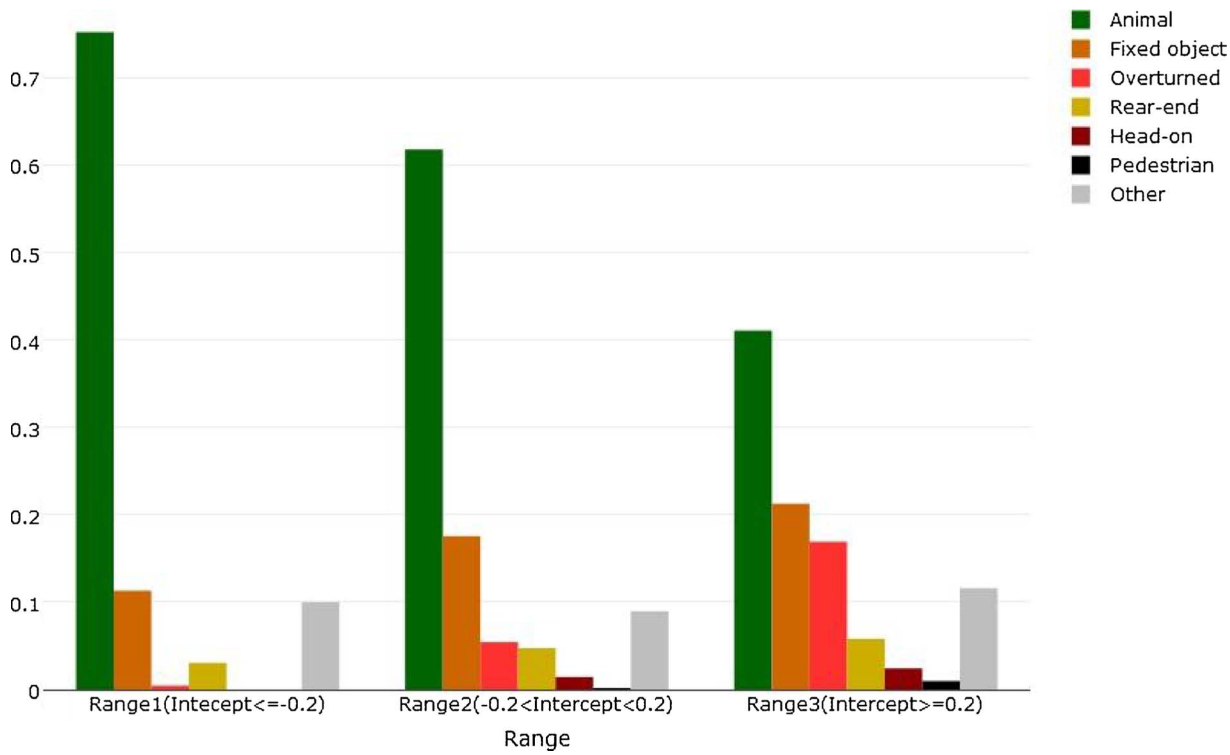

Fig. 4. Comparison of crash type distribution in road segments with different intercept ranges.

Table 4
Parameter estimation of the multilevel ordered logit model.

Variable	Coefficient	Standard Error	z	P ≫ > z
Segment-level variables (level 2)				
Lane10	−0.552	0.272	−2.03	0.042
Barrier	−5.916	3.878	−1.53	0.127
Driveway density	−0.024	0.013	−1.86	0.063
RHR3	0.561	0.518	1.08	0.279
Narrow shoulder	−0.379	0.166	−2.29	0.022
AADT Cat1	0.213	0.390	0.55	0.585
AADT Cat2	0.478	0.416	1.15	0.25
Crash-level variables (level 1)				
Inclement weather	0.215	0.164	1.31	0.19
Adverse light	−1.159	0.132	−8.75	0
μ_0	0.917	0.400	2.29	0.022
μ_1	1.085	0.401	2.71	0.007
μ_2	2.027	0.408	4.97	0
μ_3	3.915	0.457	8.57	0
τ	0.218	0.143		
LR test vs. standard ordered logit model: chibar2(01) =	3.2			
Probability ≫ > = chibar2 =	0.037			

speed with higher levels of alertness might explain such lower injury severity of crashes occurred on segments with higher AADT.

Table 5 shows the marginal effect of each explanatory variable on each severity outcome. Marginal effect indicates how probabilities of various severity outcomes change with a unit change in the explanatory variable while holding all other variables at their means. For instance, a unit increase in driveway density above the mean value of 5.54 is associated with an increased probability of no injury crash (0.0027). This increased probability of no injury crashes is resulted from the decreased probabilities of possible injury (−0.0003), non-incapacitating injury (−0.0013), incapacitating injury (−0.0009), and fatal injury crashes (−0.0002).

6. Conclusion

This study used statistical models to analyze the impact of geometric design features, environmental conditions, and traffic characteristics on crash injury severity. Crash severity models were estimated using data from crashes occurred on rural two-lane highway segments in Illinois from years 2007–2009. Multilevel modeling techniques were employed to address the hierarchical structure of crash data and to model the indirect impact of geometric features on the severity outcome. We hypothesized that upper level model includes segment-characteristics while the lower level includes crash characteristics.

The results of the model verify that hierarchical structure resided within the data, where correlation exists between severity outcomes of crashes occurred on the same road segments. This presence of within-segment correlation justified the use of multilevel models for analyzing crash injury severity. Examination of random effect shows that there is significant variation in the probability associated with severity of crashes across different segments. Our finding revealed that there is a strong association between some geometric features and crash severity outcome. However, the transferability of model results to other states likely depends on the similarity of crash type distributions in those states. Similar to traditional crash severity models, multilevel models are not immune to underreporting issues. The different magnitudes of underreporting for different severity levels and across different crash reporting jurisdictions can lead to biased estimations. While several studies have investigated the effect of underreporting crash data on traditional crash severity models (Ye and Lord, 2011; Yamamoto et al., 2008; Yasmin and Eluru, 2013; Abay, 2015), in the future, there is a need to investigate the impact of underreporting crash data on multilevel models (likely using a simulated dataset) and compare it with commonly used models.

In addition to the variables included in the models, other variables might also influence crash severity outcomes. Occupant characteristics including occupant age, sex, and restraint use, and vehicle characteristics such as vehicle mass, speed, and braking characteristics can significantly impact severity outcome. Including these variables into the

Table 5
Marginal effects in injury severity.

Variable	Marginal effects				
	No injury	Possible injury	Non-incapacitating injury	Incapacitating injury	Fatal injury
Lane10	0.0624	−0.0071	−0.0297	−0.0213	−0.0043
Barrier	0.6691	−0.0757	−0.3184	−0.2287	−0.0462
Driveway density	0.0027	−0.0003	−0.0013	−0.0009	−0.0002
RHR3	−0.0634	0.0072	0.0302	0.0217	0.0044
Narrow shoulder	0.0429	−0.0049	−0.0204	−0.0147	−0.0030
AADT Cat1	−0.0241	0.0027	0.0115	0.0082	0.0017
AADT Cat2	−0.0541	0.0061	0.0257	0.0185	0.0037
Inclement weather	−0.0240	0.0027	0.0116	0.0083	0.0017
Adverse light	0.1311	−0.0148	−0.0624	−0.0448	−0.0091

model may improve the predication accuracy. Moreover, the impact of various definitions of clusters (e.g., clustering observations that occurred within the same spatiotemporal window) needs to be investigated in the future.

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