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Mixed logit analysis of bicyclist injury severity resulting from motor vehicle crashes at intersection and non-intersection locations

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ABSTRACT

Standard multinomial logit (MNL) and mixed logit (MXL) models are developed to estimate the degree of influence that bicyclist, driver, motor vehicle, geometric, environmental, and crash type characteristics have on bicyclist injury severity, classified as property damage only, possible, nonincapacitating or severe (i.e., incapacitating or fatal) injury. This study is based on 10,029 bicycleinvolved crashes that occurred in the State of Ohio from 2002 to 2008. Results of likelihood ratio tests reveal that some of the factors affecting bicyclist injury severity at intersection and non-intersection locations are substantively different and using a common model to jointly estimate impacts on severity at both types of locations may result in biased or inconsistent estimates. Consequently, separate models are developed to independently assess the impacts of various factors on the degree of bicyclist injury severity resulting from crashes at intersection and non-intersection locations.

Several covariates are found to have similar impacts on injury severity at both intersection and non-intersection locations. Conversely, six variables were found to significantly influence injury severity at intersection locations but not non-intersection locations while four variables influenced bicyclist injury severity only at non-intersection locations. In crashes occurring at intersection locations, the likelihood of severe bicyclist injury increases by 14.8 percent if the bicyclist is not wearing a helmet, 82.2 percent if the motorist is under the influence of alcohol, 141.3 percent if the crash-involved motor vehicle is a van, 40.6 percent if the motor vehicle strikes the side of the bicycle, and 182.6 percent if the crash occurs on a horizontal curve with a grade. Results from non-intersection locations show the likelihood of severe injuries increases by 374.5 percent if the bicyclist is under the influence of drugs, 150.1 percent if the motorist is under the influence of alcohol, 53.5 percent if the motor vehicle strikes the side of the bicycle and 99.9 percent if the crash-involved motor vehicle is a heavy-duty truck.

1. Introduction

As vehicle congestion continues to increase across the United States, non-motorized travel alternatives such as bicycles are becoming a more viable alternative for many travelers. Unfortunately, while such modes may provide advantages in terms of reductions in congestion and environmental impacts, statistics reveal that bicyclists in the United States are twelve times more likely to be killed in a crash than motor vehicle drivers (Pucher and Dijkstra, 2003). In comparison to other developed countries, bicyclists in the US are twice as likely to be fatally injured in comparison to German bicyclists and three times more likely than Dutch bicyclists (Pucher and Dijkstra, 2003). In light of these facts, there is a clear need to investigate the causes of bicycle/motor vehicle crashes and to identify what factors affect the level of injury severity sustained by crash-involved bicyclists. As bicycle use continues to increase in the United States, research in this area has the potential to influence future design and safety initiates, thereby decreasing the frequency and severity of such crashes.

There are a number of recent studies which have identified areas of opportunity for positively impacting bicycle safety in the United States. These studies encompass a variety of topics, including the impacts of bicyclist demographics, land use characteristics, geometric design standards and policies, and other variables on bicycle crashes.

Wessels investigated crash causal factors based upon the age of the crash involved bicyclist and determined that those less than

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15 years of age caused approximately half of all bicycle crashes in Washington State from 1988 to 1993 (Wessels, 1996). Motorist age, gender, and alcohol consumption, the presence of a median, and the disparity between the speed of the crash-involved motor vehicle and the speed limit are all shown to impact the likelihood of a crash occurring.

Rural and urban areas are characterized by subtle differences in roadway design policies and standards which may impact the frequency and severity of crashes between bicycles and motor vehicles. Amsden and Huber (2008) explored the differences between bicycle crashes in urban and rural locations while controlling for the impacts of speed limits and geometric design elements. Intuitively, bicycle crashes tend to be more concentrated in urban streets and at intersections where motor vehicle and bicycle volumes tend to be higher and there are more frequent opportunities for traffic conflicts between these road users. However, when adjusting for their distance travelled, bicyclists are twice as likely to be involved in a crash on rural roadways (Amsden and Huber, 2008). Council and Carter (2007) also evaluated differences between rural and urban areas and determined that rural locations exhibit a higher proportion of fatal crashes in comparison to urban areas. Crashes that involved alcohol, higher motor vehicle speeds, those which occurred at mid-block locations or along road segments where shoulders were narrower, also showed a higher propensity to result in fatal injuries. Conversely, Jensen (2007) shows both crash frequency and bicyclist injury to increase by 10 percent in urban areas as compared to rural locations.

Intersections, including roundabouts, have been shown to be particularly problematic areas for crashes between bicycles and motor vehicles. Garber and Srinivasan (1991) found that higher vehicular turning volumes significantly increased the frequency of bicycle-involved crashes. One potential explanation for this increase is that drivers typically concentrate either in the direction they are turning or in the direction of oncoming traffic and may not be cognizant of nearby bicyclists (Garber and Srinivasan, 1991). Gill (2007) investigated crashes at 34 intersections and found that the prevalent types of crashes and the prevailing causal factors of bicycle- and pedestrian-involved crashes are quite similar. They found that driveways within close proximity of the intersection increase the frequency of bicycle-involved crashes. Harkey and Carter (2006) conducted an observational study of motorist, pedestrian, and bicyclist interaction at roundabouts and identified several aspects of roundabout design that could be addressed in order to optimize safety for all groups of road users. The results from this study showed that roundabouts do not appear to create significant conflict or collision problems for bicyclists or pedestrians.

In addition to the previously described studies which evaluated the influence of various factors on the frequency of bicycle crashes at particular locations, another important research emphasis is to identify those factors that affect the level of injury severity sustained by crash-involved bicyclists. In order to ascertain the effects of such factors, several studies have involved the development of various types of discrete outcome models. Klop and Khattak (1999) investigated variables influencing bicyclist injury severity on two-way undivided roadways using an ordered probit model. The model results showed a positive and statistically significant correlation between injury severity and several variables, including increases in vertical grades, the presence of horizontal curves along vertical grades, higher speeds, and adverse environmental conditions, including darkness and fog. Kim et al. (2007) developed a multinomial logit (MNL) model to determine significant influences on bicyclist injury severity using North Carolina data from 1997 to 2000. Four injury severity levels were considered using the KABCO scale, with the no injury (O) and possible injury (C) levels being combined into a single category. Numerous variables were found to increase the likelihood of fatal injuries, including the involvement of large trucks, high motor vehicle speeds at impact, alcohol use by drivers, older crash-involved bicyclists (55 years and above), inclement lighting and weather conditions, and head-on collisions. Eluru et al. (2008) developed a mixed generalized ordered response model to determine significant variables influencing relevant pedestrian and bicyclist injury severity outcomes. The results from this study conclude that non-motorists' (pedestrian or bicyclist) age-level most influences the injury severity outcome, along with the roadway speed limit, geometric location of the crashes and time-of-day. Crashes occurring at signalized intersections were typically less severe than at other roadway locations and the effects of unobserved variables were found to result in inconsistent parameter estimates under a standard (i.e., non-mixed) ordered response structure.

The objective of this study is to develop discrete outcome models in order to identify the impacts of numerous factors on the level of injury severity sustained by crash-involved bicyclists at a sample of both intersection and non-intersection locations. Separate multinomial logit (MNL) injury severity models are initially developed for each type of location and the results are compared with those of a single, joint model. A likelihood ratio test confirms the effects of relevant factors are not uniform among crashes occurring at intersections and non-intersection locations and that separate injury severity models are appropriate. The two location-specific MNL models serve as the basis for subsequent mixed logit (MXL) models that are developed through an empirical procedure which involved testing various model formulations, simulation frameworks, and underlying probability distributions for various model parameters. Finally, those variables found to significantly impact bicyclist injury severity are identified and the results from the traditional MNL formulation are compared to those of the more flexible MXL model, which is shown to provide superior fit.

2. Data

Data from Ohio Department of Public Safety crash report forms are used to provide detailed information regarding bicycle-involved crashes from throughout the State of Ohio. The information provided includes data on the crash-involved bicyclists and drivers, vehicle characteristics, crash geometry, roadway geometry, and environmental conditions associated with each crash using the most recent crash data available from 2002 to 2008. The final data set contains details from 10,029 crashes between bicycles and motor vehicles. The distribution of bicyclist injury severity among this data set is comprised of 1583 property damage only crashes (PDO), 2731 possible injuries (POSS), 4485 non-incapacitating injuries (NON), 1162 incapacitating injuries, and 68 bicyclist fatalities. Due to the relatively small number of bicyclist fatalities, incapacitating and fatal injuries are aggregated into a single severe (SEV) injury outcome category. Table 1 provides detailed summary statistics related to the crash-involved bicyclists, drivers, and vehicles while Table 2 presents data related to the type of crash and environmental conditions. A few points are noteworthy when examining the aggregate data. First, approximately 80 percent of crash-involved bicyclists are male and this is consistent among both intersection and non-intersection crashes. This is likely reflective of the gender representation among the bicyclist population, though there is no available estimate of Ohio bicyclist demographics. Helmet use is also relatively consistent among the two types of locations as 31.5 percent of crash-involved bicyclists were wearing helmets in the intersection-related crashes and 30.8 percent were helmeted in the non-intersections sample. The

Table 1
Descriptive statistics related to crash-involved bicyclists, drivers, and vehicles.

Variable name	Full data set	Intersection data set	Non-intersection data set
Number of observations	10,029	5935	4094
Bicyclist characteristics			
Female	2005 (20.0%)	1219 (20.5%)	786 (19.4%)
Wearing a helmet	3132 (31.2%)	1871 (31.5%)	1261 (30.8%)
Not wearing a helmet	6897 (68.8%)	4064 (68.5%)	2833 (69.2%)
Under age 10	2108 (21.0%)	1046 (17.6%)	1062 (25.9%)
Age 10–19	4509 (45.0%)	2795 (47.1%)	1714 (41.9%)
Age 20–29	904 (9.0%)	571 (9.6%)	333 (8.1%)
Age 30–39	787 (7.8%)	485 (8.2%)	302 (7.4%)
Age 40 and above	1677 (16.7%)	1008 (17.0%)	669 (16.3%)
Unknown age	44 (0.4%)	30 (0.5%)	14 (0.3%)
Alcohol use by bicyclist	187 (1.9%)	105 (1.8%)	82 (2.0%)
Drug use by bicyclist	11 (0.1%)	5 (0.01%)	6 (0.1%)
No injury/property damage only	1583 (15.8%)	937 (15.8%)	646 (15.8%)
Possible injury	2731 (27.2%)	1689 (28.5%)	1042 (25.5%)
Non-incapacitating injury	4485 (44.7%)	2643 (44.5%)	1842 (45.0%)
Severe injury	1230 (12.3%)	666 (11.2%)	564 (13.8%)
Driver characteristics			
Under age 25	2230 (22.2%)	1281 (21.6%)	949 (23.2%)
Age 25–34	1886 (18.8%)	1115 (18.8%)	771 (18.8%)
Age 35–44	1870 (18.6%)	1086 (18.3%)	784 (19.1%)
Age 45–54	1865 (18.6%)	1116 (18.8%)	749 (18.3%)
Age 55 and above	2178 (21.7%)	1337 (22.5%)	841 (20.5%)
Driver is uninsured	277 (2.8%)	146 (2.5%)	131 (3.2%)
Driver at fault	8572 (85.5%)	5022 (84.6%)	3553 (86.8%)
Alcohol use	96 (1%)	45 (0.8%)	51 (1.3%)
Drug use	3 (0.0%)	2 (0.0%)	1 (0.0%)
Impact speed of less than 5 mph	3271 (32.6%)	2203 (37.1%)	1068 (26.1%)
Impact speed of 5–14 mph	2138 (21.3%)	1334 (22.5%)	804 (19.6%)
Impact speed of 15–24 mph	2099 (20.9%)	1157 (19.5%)	942 (23.0%)
Impact speed of 25–34 mph	939 (9.4%)	445 (7.5%)	494 (12.1%)
Impact speed of more than 34 mph	383 (3.8%)	101 (1.7%)	282 (6.9%)
Unknown impact speed	1199 (12.0%)	695 (11.7%)	504 (12.3%)
Vehicle type			
Passenger car	6225 (62.1%)	3699 (62.3%)	2526 (61.7%)
Sport utility vehicle	1160 (11.6%)	725 (12.2%)	435 (10.6%)
Pickup truck	1162 (11.6%)	683 (11.5%)	479 (11.7%)
Mini van	805 (8.0%)	491 (8.3%)	314 (7.7%)
Van	229 (2.3%)	124 (2.1%)	105 (2.6%)
Semi truck	122 (1.2%)	69 (1.1%)	53 (1.3%)
Other vehicle	326 (3.3%)	144 (2.4%)	182 (4.4%)

Notes: This table displays frequencies of crashes, crash-involved drivers, and/or crash-involved bicyclists based upon selected variables of interest (percentage in parentheses).

distribution of bicyclist injury severity is similar among the two location types and so are the data related to type of crash-involved motor vehicle, time of year, and lighting condition at the time of the crash.

There are some characteristics which varied substantially among the two types of crash locations, as well. The age distributions are relatively similar among the intersection and non-intersection locations, except for the two youngest age groups. Children under age 10 comprised 25.9 percent of the sample at non-intersection locations versus 17.6 at intersections while bicyclists ages 10–19 constituted 41.9 percent and 47.1 percent of these samples, respectively. These statistics may be reflective of the riding behaviors of these particular age groups (e.g., younger children may ride in locations where there are fewer busy intersections where safety is potentially an issue) or of risk-taking behavior (e.g., older children may take greater risks when riding). As expected, impact speeds tended to be lower at intersection locations where drivers are frequently required to slow down. The crash types also varied substantially among the two types of locations and it should be noted that Ohio policy designates that driveway-related crashes be coded as non-intersection-related. For analysis purposes, the crash type geometry was looked at in greater detail by examining the configuration of the crash-involved bicycle and motor vehicle relative to one another (e.g., bicycle colliding into side of motor vehicle, motor vehicle rear-ending bicyclist, etc.).

3. Statistical methodology

The statistical methodology includes the development of multinomial logit (MNL) models and, subsequently, mixed logit (MXL) models. First, the full data set of all bicyclist-involved crashes is used to develop a base MNL model. After developing this base model, the data set was separated into two groups, one containing data for those crashes occurring at intersection locations and the other containing data for those crashes occurring at non-intersection locations. Separate MNL models were then developed for each data set and a likelihood ratio (LR) test was conducted to determine whether the parameters impacting injury severity were significantly different between the intersection and non-intersection locations. The results of the LR test showed the separate, location-specific models to provide superior fit to the joint model which included all bicycle crashes. These intersection and non-intersection models are then used as a basis for estimating the intersection and non-intersection MXL models.

3.1. Multinomial logit model

The MNL framework is used to model the degree of injury severity sustained by a crash involved bicyclist as:

$$S_{in} = \beta_i \boldsymbol{X}_{in} + \varepsilon_{in} \quad (1)$$

Table 2
Descriptive statistics for crash-related and environmental factors.

Variable name	Run data set	Intersection data set	Non-intersection data set
Number of observations	10,029	5935	4094
Crash type			
Non-collision	4275 (42.6%)	2540 (42.8%)	1735 (42.4%)
Rear-end	246 (2.5%)	59 (1.0%)	187 (4.6%)
Head-on	263 (2.6%)	144 (2.4%)	119 (2.9%)
Rear-to-rear	6 (0.06%)	4 (0.07%)	2 (0.05%)
Backing	69 (0.7%)	19 (0.3%)	50 (1.2%)
Angle	4494 (44.8%)	2925 (49.3%)	1569 (38.3%)
Sideswipe, same direction	353 (2.5%)	78 (1.3%)	275 (6.7%)
Sideswipe, opposite direction	135 (1.4%)	61 (1.0%)	74 (1.8%)
Unknown	188 (1.9%)	105 (1.8%)	83 (2.0%)
Roadway characteristics			
Roadway curve with grade	142 (1.4%)	66 (1.1%)	76 (1.9%)
Dry roadway pavement	9066 (90.4%)	5321 (89.7%)	3745 (91.5%)
Driveway related	1204 (12.0%)	n/a	1204 (29.4%)
Time of year			
Spring	2434 (24.3%)	1418 (23.9%)	1016 (24.8%)
Summer	4562 (45.5%)	2685 (45.2%)	1877 (45.9%)
Fall	2491 (24.8%)	1514 (25.5%)	977 (23.9%)
Winter	542 (5.4%)	542 (9.1%)	224 (5.5%)
Lighting condition			
Daylight	8254 (82.3%)	4839 (81.5%)	3415 (83.4%)
Dawn or dusk	449 (4.5%)	268 (4.5%)	181 (4.4%)
Dark-lighted	920 (9.2%)	640 (10.8%)	280 (6.8%)
Dark-unlighted	248 (2.5%)	93 (1.6%)	155 (3.8%)
Other	20 (0.2%)	14 (0.2%)	6 (0.02%)
Unknown	138 (1.4%)	81 (1.4%)	57 (1.4%)

Notes: This table displays frequencies of crashes, crash-involved drivers, and/or crash-involved bicyclists based upon selected variables of interest (percentage in parentheses).

where S_{in} is a linear function that determines injury severity outcome i for bicyclist n, β_i is the vector of coefficient estimates, $\boldsymbol{X}_{in}$ is the vector of characteristics (driver, vehicle, and environmental attributes) that impact bicyclist injury severity, and ε_{in} is an independently and identically distributed generalized extreme value (i.e., Gumbel type 1) error term. Each crash-involved bicyclist has the same set of potential injury severity outcomes and the probability of a crash resulting in any particular outcome may be found from Eq. (2):

$$P_n(i) = \frac{\exp(\beta_i \boldsymbol{X}_{in})}{\sum_{\forall I}(\beta_i \boldsymbol{X}_{in})} \tag{2}$$

where $P_n(i)$ is the probability that bicyclist n will sustain injuries of severity level i, where I is the full set of possible injury severity outcomes.

3.2. Likelihood ratio (LR) test

Upon development of the MNL model of injury severity for all bicyclist-involved crashes in the State of Ohio, the likelihood ratio test is used to determine whether those factors affecting the degree of bicyclist injury have similar impacts in crashes occurring at both intersection and non-intersection locations. The likelihood ratio test statistic follows the chi-square distribution and is presented in Eq. (3) as:

$$X^2 = 2[LL(\beta_R) - LL(\beta_U)] \tag{3}$$

where $LL(\beta_R)$ is the log-likelihood value at convergence for the restricted model (including both intersection and non-intersection crashes with parameters constrained such that effects are homogeneous between groups) and $LL(\beta_U)$ is the sum of the log-likelihood value at convergence for the unrestricted models (where parameters are free to vary among the separate intersection and non-intersection models). The resulting X^2 test statistic has degrees of freedom equal to the difference in parameters between the restricted and unrestricted models. Test results show that at a 95-percent confidence level, the location-specific models separated into intersection and non-intersection crash locations provide a superior fit in comparison to the unrestricted (i.e., joint) model of all bicyclist-involved crashes. Additional information regarding the use of likelihood ratio tests may be found in Puhan et al. (2005) and Steurer et al. (2002).

3.3. Mixed logit model

The MNL model has several potentially serious limitations which inhibit its applicability under particular conditions (Jones and Hensher, 2007). The MXL model addresses these limitations by: (1) allowing for a complete and total relaxation of the independent and identically distributed (IID) condition, (2) avoiding the violation of the independence from irrelevant alternatives (IIA) condition, and (3) allowing for heterogeneity in parameter effects. In fact, it has been shown that the MXL model may be specified to approximate any discrete outcome model (Hensher and Greene, 2003). To begin constructing an MXL model, Eq. (4) is defined as:

$$S_{in} = \beta_i \boldsymbol{X}_{in} + [\eta_{in} + \varepsilon_{in}], \tag{4}$$

where S_{in} is the value of the function which determines the injury severity outcome i for crash-involved bicyclist n, β_i is the vector of coefficient estimates, $\boldsymbol{X}_{in}$ is the vector of non-stochastic variables which affect injury severity, η_{in} is the random term with zero mean, and ε_{in} is the error term that is independent and identically distributed, and does not depend on underlying parameters or data (Hensher and Greene, 2003).

The MXL model is a generalization of the MNL structure which allows the parameter vector β_i to vary across individuals. The outcome-specific constants and each elements of β_i may be either fixed or randomly distributed over all parameters with fixed means, allowing for heterogeneity within the observed crash data set. A mixing distribution is introduced to the model formulation, resulting in injury severity probabilities as follows (Train, 2003):

$$P_{in} = \int \frac{\exp(\beta_i \boldsymbol{X}_{in})}{\sum_I \exp(\beta_i \boldsymbol{X}_{in})} f\left(\beta \middle| \varphi\right) d\beta \tag{5}$$

where $f(\beta|\varphi)$ is a density function of β and φ is a vector of parameters which describe the density function, with all other terms as previously defined (Milton et al., 2008). The injury severity outcome probability is then simply a mixture of logits (Hensher and Greene, 2003). The β distribution may allow for individual-level variations of the effects of X on the resultant injury severity. The distribution is also flexible in that β may also be fixed and when all parameters are fixed, the model reduces the standard MNL formulation. In instances where β is allowed to vary, the model is open form and the probability of a bicyclist sustaining a particular level of injury severity may be calculated through integration.

There are five specific empirical specifications for the MXL model development process: (1) the selection and distribution of the random parameters, (2) specification of the type and number of simulation points, (3) investigation of the existence of heterogeneity among model parameters, (4) adjustments for correlation among outcomes, and (5) adjustment for correlation between model parameters (Hensher and Greene, 2003). Fig. 1 provides a complete overview of the MXL model development process.

The research literature details two general methods which may be used to determine whether a mixing distribution is appropriate for specific variables within an MXL model. A popular and frequently referenced test, established by McFadden and Train (2000), is the Lagrange Multiplier Test. A second method, utilized by Milton et al. (2008) and Gkritza and Mannering (2008), is to simply compare when the estimated standard error for each random parameter is significantly different from zero. If the standard error is not found to be significantly different from zero, it is assumed fixed across all observations as per the MNL model.

Numerous distributional forms have been examined for model parameters in past research, including normal, lognormal, uniform, triangular, dome, Erlang, Weibull, exponential, and nonstochastic distributions. The prevailing findings from the literature conclude that the normal distribution generally establishes the best fit for injury severity data (Milton et al., 2008; Gkritza and Mannering, 2008). As a part of this research, the normal, lognormal, uniform, triangular, and dome distributions are tested as potential mixing distributions. Consistent with past research, the normal distribution is found to provide the best estimation results (Milton et al., 2008; Gkritza and Mannering, 2008).

The number of simulations required is strictly dependent upon the complexity of the model. More simulation points are required as the number of randomized variables increase. Past research has investigated the performance of various random draw routes, including Halton, random, and shuffled draws (Bhat, 2003; Hensher et al., 1999). Bhat (2003) and Hensher et al. (1999) concluded that Halton draws of a specific number will produce results as accurate as ten times that number in random draws. Based upon past research, simulations were run using 500–1000 Halton draws to establish the lowest log-likelihood value at convergence for the final models (Council and Carter, 2007; Milton et al., 2008; Bhat, 2003; Train, 1999). This approach was used to develop the final intersection and non-intersection MXL models shown in Tables 3 and 4, respectively.

3.4. Impacts of model parameters

In order to comparatively assess the impacts of each model parameter, elasticities are calculated to measure the magnitude of impact of individual parameters on the likelihood of the four injury-severity-outcomes. For continuous variables, such as bicyclist age,

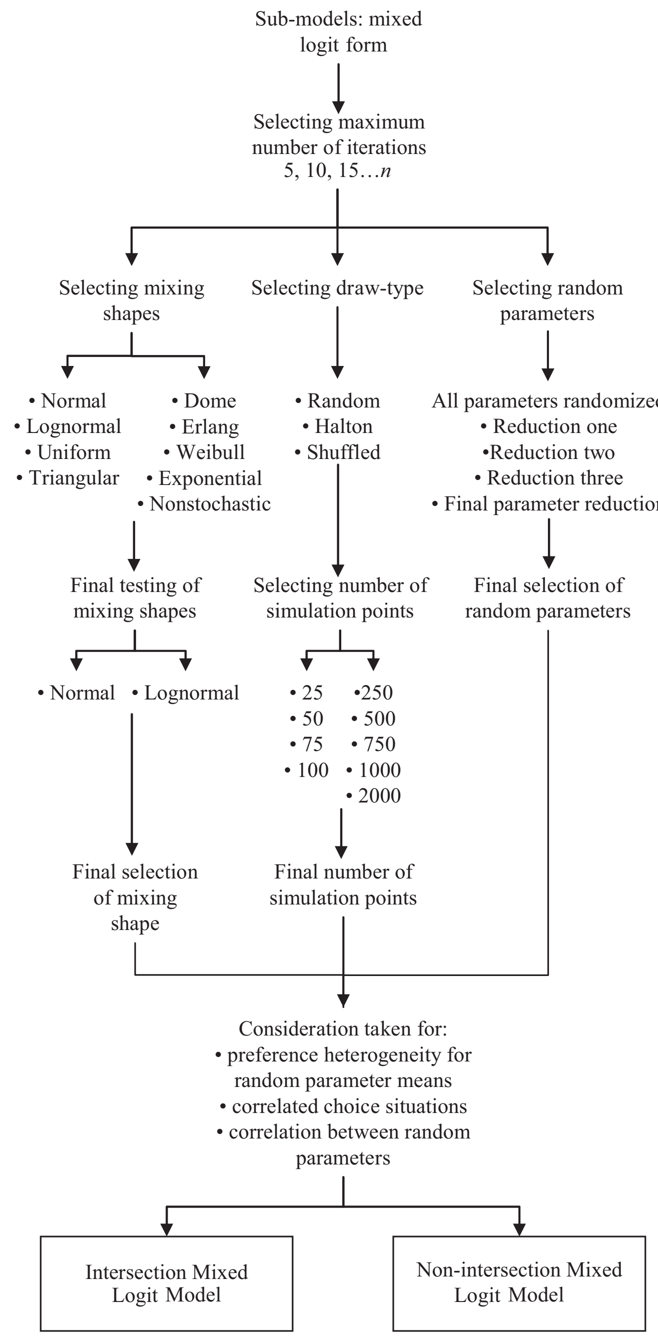

Fig. 1. Mixed logit model development process.

the elasticity corresponding to each variable is computed using the following formula:

$$E^{P_n(i)}_{\boldsymbol{X}_{in}} = \left[1 - \sum_{I=I_n} P(i)\right] \beta_i \boldsymbol{X}_{in}, \tag{6}$$

where I_n is the subset of injury-severity levels that include variable $\boldsymbol{X}_{in}$ in the severity function and β_i is the estimated coefficient that is associated with $\boldsymbol{X}_{in}$. As described by Eq. (6), an elastic change of 1 percent will correspond to an approximate 1 percent change in the injury-severity-outcome probability.

The calculation of elasticities for indicator variables using Eq. (6) is inappropriate as such variables take values of only zero or one, rendering a one percent change in a particular variable meaningless. In order to appropriately quantify the effects of such

Table 3
Parameter estimates for intersection-specific mixed logit model.

Variable name	Injury severity	Coeff.	S.E.	*t*-Ratio	*p*-Value
Alternative specific constant					
Property damage only	PDO	2.609	0.195	13.361	0.000
Possible injury	Poss	3.001	0.188	15.970	0.000
Non-incapacitating injury	Non	2.799	0.152	18.398	0.000
Bicyclist characteristics					
Female	Poss, Non	0.469	0.108	4.361	0.000
Female	Sev	0.393	0.148	2.658	0.008
Age[a]	Sev	0.018 (0.0001)	0.003 (0.011)	6.790	0.000
No helmet	Poss, Non	0.289	0.083	3.478	0.001
No helmet	Sev	0.394	0.121	3.249	0.001
Driver characteristics					
No insurance	Poss, Non	0.877	0.372	2.361	0.018
No insurance	Sev	1.161	0.424	2.739	0.006
Impact speed	Non	0.019	0.003	5.865	0.000
Impact speed	Sev	0.064	0.004	14.593	0.000
Driver error[a]	Non, Sev	0.223 (0.096)	0.081 (0.587)	2.754	0.006
Alcohol	Sev	0.705	0.384	1.832	0.067
Vehicle type					
Pickup truck[a]	Sev	0.219 (0.024)	0.103 (0.728)	2.119	0.034
Van[a]	Sev	1.060 (0.031)	0.245 (1.512)	4.325	0.000
Crash geometry					
Bicycle front, motor vehicle rear	PDO	0.518	0.191	2.711	0.007
Motor vehicle front, bicycle rear	PDO	0.666	0.158	4.225	0.000
Motor vehicle front, bicycle rear	Poss	0.412	0.135	3.057	0.002
Motor vehicle front, bicycle side[a]	Non	0.248 (0.036)	0.068 (0.575)	3.659	0.000
Motor vehicle front, bicycle side[a]	Sev	0.517 (0.009)	0.103 (0.430)	5.027	0.000
Roadway geometry					
Dry roadway pavement[a]	Non, Sev	0.216 (0.074)	0.094 (1.088)	2.308	0.021
Roadway curve with grade	Non	0.928	0.378	2.455	0.014
Roadway curve with grade	Sev	1.843	0.418	4.415	0.000
Model statistics					
Log-likelihood		−6289.2			
Restricted log-likelihood		−7217.1			
Chi-squared		1855.6			

Notes: Parentheses indicate standard errors of random parameter estimates.
[a] Denotes normally distributed random parameters, MXL models uses a maximum of 50 iterations, and 1000 simulation points.

binary indicator variables, pseudo-elasticities should be calculated as shown in Eq. (7), where all variables are as previously defined (Shankar and Mannering, 1995).

$$E_{\boldsymbol{X}_{in}}^{P_n(i)} = \frac{\exp\left[\Delta(\beta_i \boldsymbol{X}_{in})\right] \sum_{\forall I} \exp(\beta_i \boldsymbol{X}_{in})}{\exp\left[\Delta(\beta_i \boldsymbol{X}_{in})\right] \sum_{I=I_n} \exp(\beta_i \boldsymbol{X}_{in}) + \sum_{I \neq I_n} \exp(\beta_i \boldsymbol{X}_{in})} - 1 \tag{7}$$

These pseudo-elasticity values are effectively equal to the average change in the likelihood of a particular severity level if the conditions corresponding to the variable of interest are met. For example, the results from this study show that when the crash-involved bicyclist is female (i.e., the female variable is changed from 0 to 1), the likelihood of severe injury increases by 42.9 percent. The calculated elasticity (and pseudo-elasticity) values for all parameters are shown in Table 5. The following section discusses the effects of these parameters in detail.

4. Results and discussion

4.1. Bicyclist characteristics

Helmet-use is a popular and highly sought after remedy to improve bicyclist safety. However, only 21 states have some form of helmet law and none of these laws cover bicyclists over the age of 17 (IIHS, 2010). The study results show that not wearing a helmet in intersection-related crash increases the likelihood of possible and non-incapacitating by 3.4 percent and severe injury by 34.8 percent. The results from the intersection model are similar to numerous past studies (O'Callaghan and Nausbaum, 2006; Everett et al., 1996). Helmet use is also found to reduce the degree of injury severity resulting from non-intersection crashes, though this finding was not statistically significant. This may be reflective of the types of crashes that occur at non-intersection locations, which generally are less severe such as sideswipe and rear-end collisions. Ohio does not have any form of statewide helmet law currently, though some municipalities have implemented local legislation. While no statewide estimate of helmet use is currently available, police-reported crash data indicates that less than 32 percent of crash-involved bicyclists wear helmets. Interestingly, this figure is still above the national estimate of overall use which ranges from 20 to 25 percent (NHTSA, 2008). As helmet use has been shown to be 85–88-percent effective in mitigating head and brain injuries and nearly 70 percent of bicyclist fatalities involve head injuries, increasing helmet use is an important emphasis area for future improvements in bicycle safety (NHTSA, 2008).

Males comprise the vast majority of crash-involved and fatally injured bicyclists as the national bicyclist fatality rate per capita was eight times higher for males than for females, and the injury rate per capita was more than four times higher for males in 2008 (NHTSA, 2009). Similar trends are exhibited in Ohio; however, it appears that these percentages may be largely due to significantly larger volumes of male bicyclists. The injury severity model results show that female bicyclists are 7.3 percent more likely to suffer possible or non-incapacitating injuries and 7.6 percent more likely to be severely injured in crashes occurring at intersection locations. The results from the non-intersection locations show that females are 6.5 percent more likely to sustain non-incapacitating injuries and 42.9 percent more likely to be severely injured. These results may be explained as the fundamental physiological differences between genders (Gill, 2007; Ulfarsson and Mannering, 2004) or differences in riding styles.

Various model specifications were tested to examine the effects of age on injury severity. This included testing age as a continuous variable, as well as through a series of discrete variables (e.g., age groups). Model results show that injury severity tends to consistently increase with age at both intersection and non-intersection locations, with older bicyclists being slightly more prone to severe injuries in intersection-related crashes. Age was also among the variables found to have heterogeneous impacts among crash-involved bicyclists. This finding is consistent with expectations as injury severity would be expected to vary among persons of the same age based upon differences in physical abilities, riding styles, and other factors.

These results are consistent with recent national trends which show the average age of fatally injured bicyclists to have increased from 32 years of age in 1998 to 41 years of age in 2008 while the percentage of fatally injured bicyclists under age 16 decreased from 30 percent to 13 percent over this same period (NHTSA, 2009).

Drug use by the crash-involved bicyclist was associated with an increase of over 370 percent in the likelihood of severe bicyclist injuries at non-intersections locations, consistent with past studies (Smink et al., 2005; Barkley et al., 2005).

4.2. Motorist characteristics

Consistent with previous studies, high-risk driver groups and risky driving behaviors were found to have substantial impacts on the level of injuries sustained by crash-involved bicyclists (Clyde et al., 1996; Hemenway, 1992). Drivers without insurance were 5.6 percent more likely to cause possible or non-incapacitating bicyclist injuries and 40.2 percent more likely to cause severe injuries. The impact of driver errors on injury severity was found to vary significantly through the MXL model and, on average, such errors increased the likelihood of non-incapacitating and severe injury at intersections by 10.5 percent at intersections and by 12.4 percent at non-intersection locations.

Alcohol use by the crash-involved driver increases the likelihood of severe bicyclist injury by 82.2 percent for intersection-related crashes, which is likely due to drivers not being able to recognize a nearby bicyclist and react appropriately. At non-intersection locations, alcohol use increases the likelihood of severe bicyclist injuries by 150.1 percent. These results are similar to past bicycle safety research that shows alcohol impairment to have substantial effects on injury severity (Kim et al., 2007).

As the speed of the crash-involved motor vehicle increases at intersection locations, there is a 0.2 percent increase in the likelihood of non-incapacitating injuries and a 0.7 percent increase in the likelihood of severe injuries for every 1 percent increase in speed. These effects were found to be heterogeneous at non-intersection locations, where each 1 mile per hour increase in motor vehicle speed resulted in an average increase of 0.3 percent in the likelihood of a non-incapacitating injuries and a 0.8 percent increase in the likelihood of severe injury.

Table 4
Parameter estimates for non-intersection mixed logit model.

Variable name	Injury severity	Coeff.	S.E.	*t*-Ratio	*p*-Value
Alternative specific constant					
Property damage only	PDO	2.494	0.307	8.130	0.000
Possible injury	Poss	3.044	0.305	9.994	0.000
Non-incapacitating Injury	Non	2.567	0.166	15.420	0.000
Bicyclist characteristics					
Female	Poss, Non	0.462	0.137	3.375	0.001
Female	Sev	0.371	0.181	2.051	0.040
Age[a]	Sev	0.011 (0.0007)	0.003 (0.0249)	3.447	0.001
Drugs[a]	Sev	2.233 (0.0004)	0.965 (1.768)	2.315	0.021
Driver characteristics					
Driver error[a]	Non, Sev	0.277 (0.655)	0.133 (0.826)	2.079	0.038
Alcohol[a]	Sev	1.164 (0.003)	0.363 (1.239)	3.206	0.001
Impact speed[a]	Non	0.018 (0.016)	0.006 (0.031)	2.816	0.005
Impact speed[a]	Sev	0.059 (0.0008)	0.007 (0.011)	9.011	0.000
Vehicle type					
Semi truck[a]	Sev	0.856	0.347	2.468	0.014
Crash geometry					
Bicycle front, motor vehicle side	PDO	0.342	0.107	3.184	0.002
Motor vehicle front, bicycle side[a]	Non	0.284 (0.042)	0.116 (0.653)	2.452	0.014
Motor vehicle front, bicycle side[a]	Sev	0.662 (0.008)	0.140 (0.344)	4.729	0.000
Roadway geometry					
Dry roadway pavement[a]	Non, Sev	0.451	0.162	2.782	0.005
Driveway related	Non, Sev	0.212	0.098	2.159	0.031
Time of year					
Summer[a]	Sev	0.268	0.105	2.547	0.011
Model statistics					
Log-likelihood		−4324.4			
Restricted log-likelihood		−4914.4			
Chi-squared		1180.1			

Notes: Parentheses indicate standard errors of random parameter estimates.
[a] Denotes normally distributed random parameters, MXL models uses a maximum of 50 iterations, and 1000 simulation points.

Table 5
Comparison of elasticities between the two mixed multinomial logit models.

Variable name	Intersection	Non-intersection
Bicyclist characteristics		
Female (Poss, Non)	7.3%	7.6%
Female (Sev)	−0.5%	−1.8%
No helmet (Poss, Non)	3.4%	
No helmet (Sev)	14.8%	
Age (Sev)	0.35%	0.2%
Drugs (Sev)		374.5%
Driver characteristics		
No insurance (Poss, Non)	5.6%	
No insurance (Sev)	40.2%	
Driver error (Non, Sev)	10.5%	12.4%
Alcohol (Sev)	82.2%	150.1%
Impact speed (Non)	0.2%	0.3%
Impact speed (Sev)	0.7%	0.8%
Vehicle type		
Pickup (Sev)	21.3%	
Van (Sev)	141.3%	
Semi truck (Sev)		99.9%
Crash geometry		
Bicycle front, motor vehicle rear (PDO)	53.1%	
Bicycle front, motor vehicle side (PDO)		33.4%
Motor vehicle front, bicycle rear (PDO)	52.4%	
Motor vehicle front, bicycle rear (Poss)	18.2%	
Motor vehicle front, bicycle side (Non)	7.4%	5.2%
Motor vehicle front, bicycle side (Sev)	40.6%	53.5%
Roadway characteristics		
Roadway curve with grade (Non)	13.2%	
Roadway curve with grade (Sev)	182.6%	
Dry roadway pavement (Non, Sev)	10.2%	22.1%
Driveway related (Non, Sev)		8.6%
Time of year		
Summer* (Sev)		25.9%

Notes: PDO, property damage only; Poss, possible injury; Non, non-incapacitating injury; Sev, severe injury. In all cases, alpha is less than 0.05.

4.3. Vehicle type

Consistent with expectations, bicyclist collisions with large trucks are found to dramatically increase the degree of injury severity. The likelihood of a severe injury increased by 99.9 percent at intersection locations and 122.4 percent at non-intersection locations. Intuitively, the shear difference in size, mass, and force is enough to explain the influence upon the severe injury severity level. Past studies conclude that heavy-duty trucks increase the likelihood of non-incapacitating and fatal injuries for bicycle/motor vehicle crashes (Garber and Srinivasan, 1991; Kim et al., 2007).

Pickup trucks are also found to increases the likelihood of severe bicyclist injuries at intersection locations, consistent with past research in other areas that shows such vehicles to exacerbate the severity of injuries (Ulfarsson and Mannering, 2004; Roudsari et al., 2004; Lee and Mannering, 2002). Vans, another relatively large vehicle, were found to increase the probability of severe bicyclist injuries by 141.3 percent at intersection locations. Past research rationalizes that vehicle size and weight affects the safety of those involved in a crash (Chang and Mannering, 1999). Similar to the reasoning behind an increase in pickup trucks and heavy-duty trucks, the geometry and mass of the van plays a role in influencing severe injuries to bicyclists (Eluru et al., 2008).

4.4. Crash geometry

The crash geometry between the bicycle and the motor vehicle also plays a significant role in determining the severity of injury sustained by crash-involved bicyclists. Rear-end collisions where the bicyclist crashes into the back of a motor vehicle were found to reduce the likelihood of injury by 53.1 percent. Crashes where the bicyclist rides directly into the side of the motor vehicle also result in a reduction in the likelihood of injury by 33.4 percent. When a motor vehicle rear-ends a bicyclist at an intersection location, the likelihood of no injury occurring increases by 52.4 percent and the probability of a possible injury increases by 18.2 percent.

Conversely, when a motor vehicle crashes into the side of a bicycle at intersections, there is a 7.4 percent increase in the likelihood of non-incapacitating injuries and a 40.6 percent increase in the likelihood of severe injuries. At non-intersection locations, this same crash configuration results in a 5.2 percent increase in the likelihood of a non-incapacitating injury and a 53.5 percent increase in the likelihood of severe injury.

4.5. Road geometry

At intersection locations along combination horizontal and vertical curves, injury severities tend to be much more severe, which may be due to drivers and bicyclists not being cognizant of one another. At such locations, the likelihood a non-incapacitating injury is increased by 13.2 percent and the likelihood of severe injuries is increased by 182.6 percent. These findings are consistent with past research that has concluded that curved roads with grades increase injury severity in sport-utility vehicle, minivan, pickup and passenger car crashes (Ulfarsson and Mannering, 2004).

Dry roadway pavement conditions are found to increase the probability of non-incapacitating and severe injuries at intersection locations by 10.2 percent, though this effect is heterogeneous, which may be picking up on differences in driver behavior. Similar results were found at non-intersection locations where the average increase in the likelihood of non-incapacitating and severe injuries was 22.1 percent.

The presence of driveways are estimated to cause a slight increase in the likelihood of non-incapacitating or severe bicyclist injury increases of 8.6 percent. Driveway safety concerns involve safe sight distance of the motorist while entering or exiting the driveways as investigated in past research (Clifton and Kreamer-Fults, 2007; Ivan et al., 1999).

4.6. Environmental

Crashes occurring at non-intersection locations during June, July, or August were 25.9 percent more likely to result in severe bicyclist injury. The causes or patterns of seasonal effects have been investigated in past research (Shankar and Mannering, 1995). In past research of motorcycle crashes, among other summertime-related factors, motorcycle riders are more reckless during ideal riding conditions (Savolainen and Mannering, 2007). Exact parallels cannot be drawn between bicyclist and motorcyclist, but the idea that during better conditions, riders tend to display risky behavior, could be similar.

5. Conclusions

This study involves the development two mixed logit models aimed at examining those factors affecting the level of injury sustained by crash-involved bicyclists at a sample of intersection and non-intersection locations. Multinomial logit models are initially developed using a full data set comprised of all bicycle-involved crashes occurring in the State of Ohio from 2002 to 2008. The results of a likelihood ratio test show that the injury mechanisms are substantially different in crashes occurring at intersection and non-intersection locations. Based upon this result, separate MNL models are developed for crashes occurring at intersection and non-intersection locations. These models are then improved by introducing heterogeneity in parameter effects through a mixed logit model using a series of trial analyses as suggested by Hensher and Greene (2003). The variables found to significantly impact bicyclist injury severity in the MNL models are tested for heterogeneity using a variety of mixing distributions, including normal, lognormal, uniform, triangular, and dome distributions. In concert with the selection of the distribution shape random, Halton and shuffled draw types are tested. The final MXL model framework results show that normally distributed random parameters and the use of Halton draws result in optimal model fit. The finding regarding normally distributed parameters estimates is consistent with past research by Milton et al. (2008) while the selection of Halton draws, instead of random or shuffled draws, also corresponds with past research (Milton et al., 2008; Bhat, 2003; Train, 1999).

When comparing the results of the MXL models at intersection and non-intersection locations, several variables are found to significantly impact bicyclist injury severity at both types of locations. Six variables (the bicyclist not wearing a helmet, no motorist insurance, when the vehicle is pickup or van, when the front of the bicycle impacts the rear of the vehicle, a roadway curve with grade) significantly influenced bicyclist injury severity at intersection locations, but not at non-intersection locations. Conversely, four variables (bicyclist age, when the bicyclist is under the influence of drugs, when the front of the bicycle impacts the side of the vehicle, driveway related crashes) influenced bicyclist injury severity at non-intersection locations, but not intersection locations.

The potential for severe bicyclist injuries at intersection and non-intersection locations is higher when the following conditions are met: the bicyclist is female, the driver is under the influence of alcohol, the vehicle is a heavy-duty truck, the front of the motor vehicle impacts the side of the bicycle and the roadway pavement is dry. As the speed of the motor vehicle increases, so does the likelihood for a severe bicyclist injury.

For the intersection specific locations, variables increasing severe bicyclist injuries include: the bicyclist not wearing a helmet, the driver being uninsured, collisions involving pickup trucks or vans, and collisions occurring at intersection on a horizontal curves with grades. The least severe injuries tend to occur when the front of the bicycle impacts the rear of the motor vehicle or the front of the motor vehicle impacts the rear of the bicycle.

At non-intersection locations, bicyclist injuries are more severe when: the bicyclist is under the influence of drugs, the crash is driveway related, and the crash occurs during the summer: June, July, or August. Also, as the age of the bicyclist increases, so does the likelihood for a severe bicyclist injury. The crash geometry with the least severe, PDO, bicyclist injury severity occurs when the front of the bicycle impacts the side of the motor vehicle.

It appears that driver recognition of bicycles is a serious problem that increases not just the frequency of bicycle-involved crashes, but also the degree of injury severity sustained by crash-involved bicyclists. Injuries tended to be more severe when speeds were higher, as well as along horizontal and vertical curves, potential indicators of insufficient perception-reaction time on the part of the crash-involved motorist. Injuries also tended to be more severe when they involved larger vehicles, which may reflect both the greater impact forces involved in collisions with such vehicles, as well as difficulty in identifying bicyclists by drivers of these larger vehicles. Alcohol-involved crashes also significantly impacted injury severity, which is particular problematic in that these types of crashes predominantly occur at night when visibility and driver cognition are already limited. The continuation of state- and national-level programs aimed at increasing driver awareness of bicyclists may be warranted. Infrastructure-related measures such as bicycle lanes, improved lighting, and signage may also reduce some of these problems. Stringent enforcement programs also remain a key component as, in addition to alcohol use, motorists driving without insurance also tended to be involved in crashes which led to more severe bicyclist injuries.

From the standpoint of bicyclists, evidence continues to show that helmet use provides the greatest measure of protection from injury in the event of a crash. Unfortunately, less than 32 percent of crash-involved cyclists were reported to be wearing a helmet at the time of the crash. Among other factors, older bicyclists were also prone to be more severely injured in a crash, which may be due to physical limitations associated with aging or with different riding patterns as these bicyclists may be more likely to ride on higher volume and higher speed roads.

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