



Exploring factors contributing to injury severity at freeway merging and diverging locations in Ohio



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ABSTRACT

Identifying factors that affect crash injury severity and understanding how these factors affect injury severity is critical in planning and implementing highway safety improvement programs. Factors such as driver-related, traffic-related, environment-related and geometric design-related were considered when developing statistical models to predict the effects of these factors on the severity of injuries sustained from motor vehicle crashes at merging and diverging locations. Police-reported crash data at selected freeway merging and diverging areas in the state of Ohio were used for the development of the models. A generalized ordinal logit model also known as partial proportional odds model was applied to identify significant factors increasing the likelihood of one of the five KABCO scale of injury severity: no injuries, possible/invisible injuries, non-incapacitating injuries, incapacitating injuries, or fatal injuries. The results of this study show that semi-truck related crashes, higher number of lanes on freeways, higher number of lanes on ramps, speeding related crashes, and alcohol related crashes tend to increase the likelihood of sustaining severe injuries at freeway merging locations. In addition, females and older persons are more likely to sustain severe injuries especially at freeway merge locations. Alcohol related crashes, speeding related crashes, angle-type collisions, and lane-ramp configuration type D significantly increase the likelihood of severe injury crashes at diverging areas. Poor lighting condition tends to increase non-incapacitating injuries at diverging areas only. Moreover, adverse weather condition increases the likelihood of no-injury and fatal injuries at merging areas only and adverse road conditions tend to increase a range of injury severity levels from possible/invisible injuries to incapacitating injuries at merging areas only.

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1. Introduction

Freeway merging and diverging areas are locations subject to a higher proportion of competition for space by vehicles compared to other sections along the freeway. At merging areas vehicles coming from entrance ramps joining the freeway are competing for space with traffic already flowing along the mainline freeway lanes as the merging vehicles try to find gaps in the traffic stream. At

diverging locations vehicles leaving the freeway are competing for space while decelerating to reach the speed limit of the off-ramps as they try to change lanes to make it to the off-ramps. Owing to this high intensity of competition for space, freeway merge and diverge areas may be prone to a relatively larger number of crashes compared to other sections along the freeway. These crashes could result into different levels of injury severities which may range from minor property damages to more serious injuries such as incapacitation or fatalities.

The most common classification of the levels of injury severity is the one that uses the KABCO crash injury scale, that is, fatal injury (K), incapacitating injury (A), non-incapacitating injury (B), possible/invisible injury (C), and no injury (O). The levels of severities of injury sustained from crashes may be attributed to various factors that are possible causes of these crashes. A study of crash data at freeway entrance and exit ramp locations to identify the possible factors that are likely to cause crashes and their contribution to

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injury severity is beneficial to transportation engineers for a better design, operation and management of freeways. The purpose of this paper is to study the contribution of these factors by considering the injury severity of the most severely injured individual in a crash as the dependent variable by developing separate models for crashes occurring at freeway merge and diverge areas.

Various methodological approaches have been applied in previous efforts related to the analysis of injury severity data. Modeling approaches that apply statistical or probabilistic methods and artificial neural networks (ANNs) have been applied. Two major classifications of statistical modeling approaches (ordered and unordered) have been noted in previous injury severity studies. Ordered categorical models have been the most commonly applied methods of analysis (see e.g., Abdel-Aty, 2003; Abdel-Aty and Keller, 2005; Gray et al., 2008; Kockelman and Kweon, 2002; O'Donnell and Connor, 1996; Wang et al., 2009; Xie et al., 2009; Yamamoto and Shankar, 2004; Zajac and Ivan, 2003). A common drawback of the conventional ordered methods of analysis is that these models tend to constrain the effects of the coefficient β across injury outcome levels (Eluru et al., 2008; Wang and Abdel-Aty, 2008; Eustace et al., 2011; Savolainen et al., 2011). In addition to ordered categorical models, unordered categorical models have also been extensively applied in the analysis of injury severity (see e.g., Carson and Mannering, 2001; Eustace et al., 2011; Khorashadi et al., 2005; Shankar and Mannering, 1996; Ulfarsson and Mannering, 2004). The problem with this set of modeling methods is that they ignore the ordinal nature of injury severity data. Artificial neural networks (ANNs) have rarely been used to predict injury severity (see e.g., Abdel-Aty and Abdelwahab, 2004).

O'Donnell and Connor (1996) used the ordered logit and ordered probit models to determine the effect of variations of crash and road user related attributes on the probability of sustaining different levels of injuries. They used ordered multiple choice logit and probit models to estimate parameters using attributes such as gender, speed, blood alcohol level, seat belt use, seating position, type of collision, type of vehicle and vehicle make. Shankar et al. (1996) studied the effects of a number of variables such as environmental conditions, highway design, crash types, vehicle attributes and driver characteristics on injury severity using nested logit models. They conclude that a nested logit model which accounts for shared un-observables between property damage and possible injury accidents provided the best structural fit for the observed distribution of accident severities and commented that the nested logit model formulation to be a promising approach to evaluate the impact that ITS or other safety-related countermeasures may have on accident severities. Chang and Mannering (1999) studied the effects of large trucks on injury severity by developing a nested logit model. They developed two separate models for truck-involved and non-truck-involved crashes. Their models also considered the effects of geometric characteristics, driver characteristics, temporal characteristics, traffic characteristics and environmental characteristics.

Ulfarsson and Mannering (2004) conducted a research to develop statistical models that examined the differences between male and female driver-injury severity in passenger cars, pickup trucks, sport-utility vehicles (SUV) and minivans. They state that ordered models restrict the effect of the variables across outcomes. According to their argument, in the case of ordinal analysis, explanatory variables are constrained to increase or decrease the outcome probabilities across the range, from low to high, of severity categories. They argue such a restriction is inappropriate because they believe there is no compelling theoretical evidence indicating that variables cannot increase the probability of mid-level severities and reduce the probability of no injury and fatal/disabling injury. To support their argument they provided an example of an airbag deployment, which may cause minor abrasions (elevating some severities from no injury to possible or evident injury)

while simultaneously reducing the likelihood of an incapacitating or disabling/fatal injury.

Abdel-Aty and Abdelwahab (2004) used artificial neural networks (ANN) to predict injury severity of drivers and they compared the prediction performance of artificial neural networks with that of ordered probit (OP) models in modeling driver injury severity. In their study, they used a set of crash data to calibrate and test the performance of each modeling approach. They also conclude that neural networks are good prediction tools. Islam and Mannering (2006) studied the differences in injury severity between male and female drivers across three age groups in crashes involving single passenger cars. They modeled injury severity as an unordered multilevel response variable having three outcomes: no injury, injury and fatality. Like Ulfarsson and Mannering (2004), they also argued that ordinal analysis of injury severity data constrains outcome levels to either increase or decrease; consequently, they chose the multinomial logit model for analysis. Milton et al. (2008) conducted a study that sought to better understand the distribution of injury severity of crashes on highway segments. They modeled the effect of both random-parameters such as average daily traffic per lane, average truck traffic, truck percentage, and interchanges per mile as well as the effects of fixed-parameters such as number of horizontal curves, and number of grade breaks per mile. They used a mixed logit model, also known as random parameters logit model, to estimate the effects of these variables on injury severity of crashes.

Xie et al. (2009) compared a Bayesian inference method to the traditional models that use the maximum likelihood estimation (MLE) method for parameter estimation in injury severity modeling of traffic crashes. They suggest that compared to the traditional models that use MLE method, the Bayesian inference method provides a flexible framework that can incorporate the analysts' prior knowledge of the data such that model fitting is not completely dependent on the data. They introduced the application of a Bayesian ordered probit (BOP) model to analyze drivers' injury severity for both large and small sample sizes.

A number of researchers have attempted to search for better fitting models but making sure keeping the ordinal nature of injury severity. Wang and Abdel-Aty (2008) used the partial proportional odds models and the conventional ordered probability models in investigating left-turn crash injury severity by conflicting pattern. They conclude that partial proportional models consistently outperform the ordered probability models. Wang et al. (2009) compared injury severity at freeway diverge areas by different design types. They used partial proportional odds and ordered probit models in modeling the effects of four different types of ramp-lane arrangements on injury severity in addition to other variables such as geometric, environmental, traffic, and behavioral factors. From the results of their study they recommend the use of the partial proportional odds models for injury severity analysis. Other notable studies include the efforts by Eluru et al. (2008) mixed generalized ordered response model in examining the injury severity to pedestrians and bicyclist who get involved in traffic crashes using the 2004 General Estimates System (GES) database. Their method is essentially similar to generalized partial proportional odds models that seek to relax the β parameters where the parallel line's assumption is violated. Their method was an extension of an earlier study by Srinivasan (2002) who formulated an ordered mixed logit model to study the correlated injury thresholds associated with various severity levels by using the 1996 GES database. Other efforts that were formulated by other researchers to overcome the same limitation and having a similar design to that of generalized partial proportional odds model include the sequential binary probit/logit models of Saccomanno et al. (1996), Dissanayake and Lu (2002a,b), and Yamamoto et al. (2008). All these studies were able to relax the parallel lines assumption of

ordered probability models but keeping the ordered nature of injury severity. More recently, Savolainen et al. (2011) present a thorough review and assessment of commonly used statistical methodologies in the analyses of motor vehicle injury severity.

A literature search found a few studies that modeled injury severity at freeway diverge areas (Wang et al., 2009, 2011; Yang et al., 2011). No similar previous studies were found for merging areas. Wang et al. (2009) who used a partial proportional odds model found contributing factors related to crash injury severity at freeway diverge areas that included ADT on mainline, length of deceleration/ramp lanes, curve and grade, light and weather conditions, alcohol/drug and heavy vehicle involvement, lane number on mainline, surface condition, land type, and crash type. A study by Wang et al. (2011) utilized an ordered probit model in assessing factors affecting injury severity of truck-related crashes at freeway diverge areas. Their study found that deceleration lane length, number of mainline lanes, median/shoulder width, curve and grade, speed limit, ADT on mainline and ramp, and truck percentage were significant contributing factors. Yang et al. (2011) developed an ordered probit model by investigating factors contributing to injury severity at freeways' diverge areas. Factors found significant included the mainline lane number, length of ramp, difference of speed limits between mainline and ramp, light condition, weather condition, land type, alcohol/drug involvement, road surface condition, shoulder width, and crash types of rear-end and sideswipe. All reviewed studies that examined injury severity factors at freeway diverge areas utilized data from Florida.

In summary, a number of studies that encompass a wide range of methodological as well as empirical issues have been conducted. Issues relating to methods of analysis or modeling approaches such as ordered probit/logit, nested logit, ANNs, mixed logit model, BOP, sequential binary probit/logit, and partial proportional odds models etc. that considered various types of predictors have been discussed. Ordinal nature of severity data, and data characteristics such as fixed and random parameters have also been a topic of discussion by a number of researchers. Each of the two conventional mostly used models discussed above has a serious limitation or setback when analyzing injury severity data. Therefore, effort in this paper was dedicated to exploring the contribution factors on injury severity at freeway merge and diverge areas using the generalized ordinal logit model, a method which has been recognized as capable of overcoming limitations of traditional ordered models.

2. Methodology

Crash injury severity is categorized into five levels in increasing severity; coded as 1=no injury, 2=possible injury, 3=non-incapacitating injury, 4=incapacitating injury and 5=fatal injury. Let us define $j=1$ as the lowest value of injury severity variable, i.e., no injury. Based on the extant literature, this paper attempts to model injury severity using the generalized ordinal logit model, a procedure found to be a more flexible modeling approach (Williams, 2006; Wang and Abdel-Aty, 2008; Wang et al., 2009). This approach is capable to circumvent the limitations with both the conventional ordinal logit/probit and the unordered methods (Savolainen et al., 2011). The generalized ordered logit regression is a flexible modeling approach because it is capable of relaxing the parallel-line assumption in the ordered logit model by allowing the variability of the regression parameter β across outcome levels, while simultaneously maintaining the ordinal nature of the response variable. This regression method is also known as the partial proportional odds model. The generalized ordered logit model can be expressed as shown in Equation 1:

$$P(Y \leq y_j | x) = \frac{\exp(\eta_j - x^T \beta_j)}{1 + \exp(\eta_j - x^T \beta_j)} \quad (1)$$

where β_j =a vector of unknown regression coefficients; x =a vector of observed explanatory variables; x^T =a transpose vector of observed explanatory variables; η_j =unknown threshold or intercept parameters, satisfying the condition $\eta_1 \leq \eta_2 \leq \dots \leq \eta_k$; j =comparison groups, $j=1, 2, \dots, k-1$; y_j =outcome in comparison group j ; Y =multinomial response variable with k outcomes; k =the number of outcome levels (categories) of injury severity (in this case = 5); $P(Y \leq y_j)$ =cumulative probability of the event ($Y \leq y_j$).

The model presented by Eq. (1) can also be written in terms of cumulative distribution function as shown in Eq. (2) (Williams, 2006). The model presentation in Eq. (1) is preferred because it facilitates comparisons among the various logit models for easier parameter interpretation (Williams, 2006). Some of the commonly known models are in fact special cases of the generalized ordered logit model presented by Eq. (1). When $k=2$, the model becomes the logistic regression model; when $k>2$, the model becomes equivalent to a series of binary logistics regressions where categories of the dependent variable are combined; and if the β 's are the same for all values of j , it becomes the traditional ordered logit model.

$$P(Y \leq y_j) = 1 - g(X^T \beta_j) = F(X^T \beta_j) \quad (2)$$

From Eq. (1), the probabilities that Y (injury severity) will take on each of the values 1, 2, 3, or 4 (i.e., the individual outcome groups) can be written using cumulative probability distribution as depicted in Eqs. (3)–(5):

$$P(Y = y_1 | x) = F(\eta_1 - x^T \beta_1) \quad (3)$$

$$P(Y = y_j | x) = F(\eta_j - x^T \beta_j) - F(\eta_{j-1} - x^T \beta_{j-1}), \quad j = 2, 3, 4 \quad (4)$$

$$P(Y = y_5 | x) = 1 - F(\eta_4 - x^T \beta_4) \quad (5)$$

As noted earlier, for the ordered logit model the regression parameter β does not depend on the outcome comparison group j , hence restricting β to be the same across all outcome categories (same slope, i.e., parallel lines) regardless of the possibility of variations (Williams, 2006; Eluru et al., 2008). In the generalized ordered logit model, however, some of the regression parameters, β_j , may be the same across outcome levels while others may vary depending on the violation of the parallel line assumption. A major setback with parallel-lines models is that their assumptions are often violated (Williams, 2006).

The results from this procedure are interpreted in a similar way as the results of a binary logistic regression (Williams, 2006). For a variable of five outcomes, this can be achieved by grouping the five outcome levels into four comparison groups. Consequently, this results into four sets of outcome groups for each model that was developed. Since $k=5$, then for $j=1$ outcome level 1 is compared with outcome levels 2, 3, 4, and 5; for $j=2$ the comparison is between outcome levels 1 and 2 vs. 3, 4, and 5; for $j=3$, it is outcome levels 1, 2, and 3 vs. outcome levels 4 and 5; and for $j=4$, it is outcome levels 1, 2, 3, and 4 vs. outcome level 5. A positive parameter estimate (regression coefficient) indicates that higher values on the predictor variable increase the likelihood of an injury being in the higher injury severity levels than the current one. Likewise, a negative parameter estimate indicates that higher values on the predictor variable increase the likelihood of an injury being in the current or lower injury severity levels; that is, it decreases the likelihood of being in higher injury groups. In other words, it increases the likelihood of being in the current or lower injury groups. For the purpose of demonstration let us take the variable: gender (coded as male=0 and female=1). For instance, if the explanatory variable gender has a positive regression coefficient in the outcome group $j=2$ (contrasting no-injury and possible injuries vs. non-incapacitating, incapacitating and fatal injuries), this indicates that female drivers are likely to sustain higher injury levels than just no-injury or possible/invisible injury.

3. Data collection and preparation

The Highway Capacity Manual (HCM) defines the influence area of merging ramp as the section of the freeway 1500-ft downstream of the painted nose of the merging gore; similarly, the influence area of diverging ramp is defined as the section of a freeway 1500-ft upstream of the painted nose of the diverging gore (TRB, 2010). The effect of traffic turbulence created due to merging vehicles may, however, propagate backward upstream of the painted nose of the merging gore. Likewise, the effect of diverging activities at freeway-ramp connection may propagate downstream of the painted nose of the diverge gore. This phenomenon of the propagation of traffic turbulence created in the vicinity of merging and diverging ramps beyond the influence areas of the definition of the HCM, was confirmed by a study of frequency differences conducted in successive sections of 0.05 mile long upstream and downstream of freeway-ramp connection areas by Janson et al. (1998). From their frequency difference tests, Janson et al. (1998) found that truck crash frequency per 0.05 miles section stopped changing significantly beyond 0.25 miles (1320 ft) upstream of both merging and diverging ramps and beyond 0.2 miles (1056 ft) and 0.15 miles (792 ft) downstream of diverging ramps and merging ramps respectively. Following the works of Janson et al. (1998), Wang et al. (2009) defined the diverging ramp influence area as a 2500-ft long section which is made of two sub-sections: a 1500-ft section located upstream of the painted nose of the diverging gore and a 1000-ft long section located downstream of the painted nose. This definition was the one adopted in this study for crash data collection used to build models of diverging and merging areas.

Police-reported crash data for years 2006–2009 obtained from the Ohio Department of Public Safety (ODPS) database was the source of crash-related, behavioral, and environmental variables. ODPS maintains a crash database for all police-reported crashes that occur on public roads in the state of Ohio. Variables such as weather condition, roadway/pavement condition, light condition, road contour, driver's age and gender, collision type, etc., were extracted from the downloadable files. The effects of factors such as weather, roadway/pavement and light conditions were categorized into binary effects. For instance, in defining the effects of weather, 'fog,' 'smog,' 'rain,' 'snow,' 'sleet,' 'hail,' 'severe winds,' 'blowing sand and soil,' etc. were classified as adverse conditions and 'clear' weather as good. Similarly, 'wet,' 'snowy,' 'icy,' 'slushy,' 'standing and moving water,' etc., were classified as adverse roadway conditions whereas 'dry' pavement condition was classified as good. 'Dusk,' 'dark' lighting conditions at both lighted and not-lighted sections and 'glare' were categorized as adverse lighting conditions. The levels of the variable 'road contour' were directly adopted as reported in the ODPS crash database. This variable estimates the roadway vertical and horizontal profiles at the crash scene. Finding the exact location on the roadway facilities where crashes occurred was emphasized in the data collection and preparation process in order to accurately match environmental, traffic and driver related attributes of crashes with their geometric attributes on the roadways. This was accomplished by the use of Geographic Information Systems (GIS) and Google Earth software, which enabled the task of linking each crash and its associated attributes accurately to corresponding roadway geometric information such as ramp-lane configuration, the ramp location (whether the ramp is located on the right side or left side of the mainline freeway-lanes), number of mainline lanes, number of ramp lanes, ramp type (whether the ramp is diverging or merging type), etc.

The lane-ramp configuration types refer to the arrangement of freeway lanes with entrance or exit ramps at freeway-ramp junctions in merging and diverging areas. Ramp-freeway junction areas are locations of competing traffic demands for space which result in intensive lane changing maneuvers. The intensity of these

maneuvers may be further intensified or calmed depending on the type of lane-ramp configuration, which dictates the type and number of weaving movements to accomplish when entering to or exiting from the freeway mainline lanes. Therefore, it is worthwhile to study the effects of these various ramp-lane configuration types. As a result the lane-ramp configuration was treated as one of the primary variables of interest. For this purpose, 80 diverging and 71 merging ramp sites, which make a total of 151 ramp locations on Interstate system and other freeways in the state of Ohio were identified and selected using Google Earth maps. Out of the 71 merging ramp locations studied, seven different types of lane-ramp configurations were identified. A total of 1489 crash records were collected and grouped according to the most severely injured individual in each crash incidence at these 71 locations. Similarly, six different types of lane-ramp configurations were identified from the 80 diverging ramp sites selected with a total of 2357 crash records (also grouped as explained above). The types of lane-ramp configurations found in the study area are depicted in Fig. 1.

Traffic volume data used in this study was obtained from the Ohio Department of Transportation (ODOT). ODOT prepares traffic count information and maps for all counties in the state. Traffic flow maps with annual average daily traffic (AADT) information is part of the information provided. Where AADT data was not available for all years considered, interpolation between the available years was done to obtain data for the missing years. The descriptions of variables for merging and diverging areas are shown in Table 1.

4. Results

The effects of the factors listed in Table 1 were analyzed using the generalized ordinal logit regression which uses a maximum likelihood estimation method. Two separate models for merging and diverging areas were developed using datasets in Table 1. Since two separate analyses were performed, one for merging areas and another for diverging areas, their results are also presented accordingly. The *gologit2* procedure in the STATA software release 11 was used to produce the parameter estimates. For variables that were found to be significant at a 0.05 significance level were used to run the model again and those that were still significant at 0.05 again were considered eligible for inclusion in predicting injury severity at merge and diverge areas and these variables are presented in Table 2.

4.1. Merging areas model

AADT is found to be significant in the fourth set of estimates (4th panel) as shown in Table 2 and has a negative coefficient indicating its tendency to decrease fatal injuries. It is intuitive that increasing traffic volume decreases the probability of sustaining fatal injuries because higher volumes of traffic force drivers to reduce their travel speeds, which reduces high impact collisions and rollover crashes that contribute to more fatal injuries. Adverse weather condition is found significant in the first and fourth set of estimates in Table 2 with a negative coefficient in the first panel indicating that adverse weather conditions increase the likelihood of no-injury crashes. This finding confirms the expectation because during adverse weather conditions drivers tend to be more cautious, which may help to decrease the likelihood of severe injuries. However, in the fourth panel it again shows that adverse weather conditions also increase greatly (positive large parameter estimate) the likelihood of fatal injuries.

Adverse roadway condition has a positive coefficient in the first and a negative in the fourth panel. This indicates that adverse roadway conditions such as wet pavement, snow or ice are likely to increase the likelihood of injuries such as possible injury,

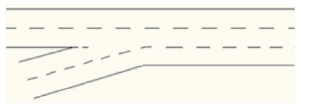

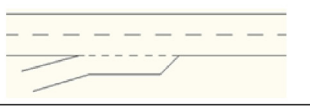
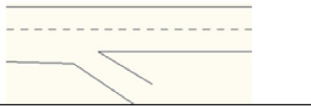

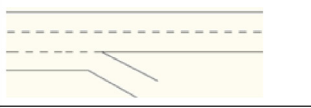



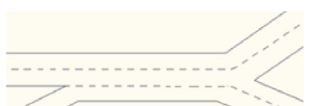

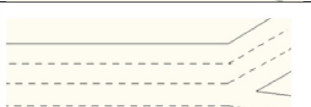

Type	Entrance ramp configuration	Exit ramp configuration
A		
B		
C		
D		
E		
F		
G		

Fig. 1. Types of lane-ramp configurations found in the study area.

non-incapacitating injury and incapacitating injury compared to no-injury whilst decreasing the likelihood of fatal injuries at the same time. Age is found to be significant in the second, third and fourth panels as shown in Table 2. It has small positive coefficients in the second and third sets of estimates indicating its modest tendency to increase injuries higher than possible/invisible injuries. However, in the fourth set of estimates, it has a negative coefficient indicating that as the age of a person involved in a crash increases the chance of sustaining fatal injuries decreases and thus it mainly increases the incapacitating injuries. This may sound counterintuitive; however, considering the fact that age in this model is used as continuous measure and the age range of the majority of the commuter population (who drive on freeways), which is mostly between 25 and 64, this finding rather makes sense.

Gender is found significant in three of the four sets of estimates with positive coefficients in all the three cases indicating that female drivers/occupants are more likely to sustain severe injuries compared to males when involved in traffic crashes. The physiological difference between males and females can be used to explain this finding. Alcohol related variable is significant with positive coefficients where the highest value occurs in the fourth panel indicating its tendency to increase the likelihood of sustaining more severe injuries and particularly fatal injuries. Speeding related variable is also significant in the three highest outcome levels with positive coefficients in all the three cases. This indicates that people involved in a crash related with a speeding vehicle are likely to sustain severe injury levels especially fatal injuries. A crash involving a semi-truck at merging areas is significant with positive

coefficients indicating that crashes involving a semi-truck are more likely to increase severe injuries and more notably fatal injuries.

Number of mainline lanes is found to be significant only in the fourth panel with a positive coefficient indicating that higher number of mainline lanes is more likely to increase the probability of sustaining a fatal injury. The number of lanes on ramps was also found to be significant only in the fourth panel with a positive coefficient indicating that higher numbers of lanes on ramps are more likely to increase fatal injuries. Collision type for merging areas is modeled as a four-category class variable. The 'not a collision' category (type 1) was used as the reference level. Rear end collisions (type 2) and same direction sideswipe collisions (type 3) are found to increase the likelihood of no-injury and possible injury crashes only while angle collisions (type 4) were found to increase fatal injuries. This makes sense because for angle collisions, it is likely that merging vehicles that are accelerating to catch up with freeway speeds are colliding with through vehicles on mainline lanes that are traveling at relatively high freeway speeds.

4.2. Diverging areas model

AADT is significant in the third and fourth panels (with negative parameter estimates) as shown in Table 2 indicating that increasing volume of traffic will have modest increase (due to small coefficient values) in the likelihood of incapacitating and lower injury levels. This result is almost similar to that of merging areas, which shows that higher traffic volumes decrease the likelihood of fatal injuries but increase incapacitating injuries. Adverse light

Table 1

Description of variables for merging and diverging areas.

Variable	Description	Frequency merging	Frequency diverging
Adverse weather condition	1 – yes	409	596
	0 – no	1025	1761
Adverse road condition	1 – yes	489	724
	0 – no	945	1633
Adverse light condition	1 – yes	384	647
	0 – no	1050	1710
Lane-ramp configuration type	1 – type A	61	662
	2 – type B	248	742
	3 – type C	361	584
	4 – type D	157	231
	5 – type E	164	101
	6 – type F	105	37
	7 – type G	338	–
Number of mainline lanes	2 lanes on freeway	623	278
	3 lanes on freeway	591	816
	4 lanes on freeway	275	1205
	5 lanes on freeway	–	58
Number of ramp lanes	1 lane on ramp	915	1787
	2 and 3 lanes on ramp	519	570
Ramp location	0 – right	1264	2122
	1 – left	225	235
Road contour	1 – straight and level	899	1610
	2 – straight and grade	260	326
	3 – curve and level	67	121
	4 – curve and grade	–	300
Collision type	1 – not a collision	448	615
	2 – rear end	623	1122
	3 – side-swipe same direction	185	295
	4 – angle	178	229
Speeding related	0 – no	1249	2073
	1 – yes	185	284
Semi-truck related	0 – no	1269	2115
	1 – yes	165	242
Traffic volume (AADT)	Directional AADT	–	–
Age	Drivers' age	–	–
Gender	0 – male	842	1470
	1 – female	592	887
Injury severity	1 – no injuries	1152	1912
	2 – possible/invisible injuries	95	181
	3 – non-incapacitating injury	124	163
	4 – incapacitating injury	31	52
	5 – fatal injury	32	49
Senior related (65-years and older)	0 – no	1346	2178
	1 – yes	88	179
Alcohol related	0 – no	1391	2258
	1 – yes	43	99

condition is significant only in the second panel with positive coefficient indicating that adverse lighting conditions such as dark and glare on roadways increase the likelihood of sustaining non-incapacitating injuries but not likely higher levels of injuries such as incapacitating and fatal injuries. This finding indicates that good lighting is important at exiting ramps.

Gender is found significant in the first and second set of estimates with positive coefficients in both cases indicating that females are more likely to sustain severe injuries compared to males. Alcohol related crashes have a very strong effect on injury severity of crashes. This variable has positive coefficients in all four estimates with the largest coefficient in the fourth panel, which indicates that alcohol related crashes increase more the likelihood of sustaining fatal injuries. Speeding related variable is significant in the second and third panels with positive coefficients and the larger value in the third panel. This indicates that speeding related crashes

increase the likelihood of sustaining severe injuries especially incapacitating injuries. Semi-truck related crashes are significant in the second panel only with a positive coefficient indicating that semi-truck related crashes increase the likelihood of sustaining non-incapacitating injuries.

The parameter estimate for the number of ramp lanes is found to be significant only in second panel with a positive coefficient indicating that higher number of ramp lanes increases the likelihood of sustaining non-incapacitating injuries at diverging areas. The lane-ramp configuration type at diverging areas is a multilevel class variable that attempts to estimate the effect of six different types of configurations. The results show that configuration types B and F increase the likelihood of sustaining only no-injury and possible/invisible injuries. Ramp configuration type B is likely to experience rear end type of crashes due to lack of separate deceleration lane for exiting traffic. On the other hand, type D tends

Table 2
Results of significant factors for merging and diverging areas.

Injury factor	Merging areas model			Diverging areas model		
	Coeff.	Std. error	$P > t $	Coeff.	Std. error	$P > t $
j = 1 (no-injury vs. possible, non-incapacitating, incapacitating and fatal)						
Adverse weather condition	−0.313	0.177	0.007			
Adverse road condition	0.368	0.108	0.001			
Gender	0.342	0.130	0.008	0.592	0.103	0.000
Collision type 2	−0.731	0.137	0.000	−0.775	0.119	0.000
Collision type 3	−0.562	0.142	0.000	−0.728	0.177	0.000
Alcohol related				1.387	0.225	0.000
Constant	−1.287	0.116	0.000	−1.449	0.097	0.000
j = 2 (no-injury and possible vs. non-incapacitating, incapacitating and fatal)						
Adverse light condition				0.180	0.090	0.046
Age	0.018	0.005	0.001			
Gender	0.403	0.157	0.010	0.322	0.116	0.006
Alcohol related	0.405	0.187	0.031	0.628	0.236	0.000
Speeding related				0.530	0.177	0.003
Semi-trailer related	0.329	0.113	0.004	0.499	0.200	0.013
Collision type 2	−0.417	0.150	0.006	−0.922	0.149	0.000
Collision type 3				−0.945	0.212	0.000
No. of ramp lanes				0.333	0.108	0.002
Lane-ramp configuration type B				−0.265	0.106	0.013
Lane-ramp configuration type F				−0.747	0.291	0.010
Constant	−2.731	0.256	0.000	−2.383	0.183	0.000
j = 3 (no-injury, possible and non-incapacitating vs. incapacitating and fatal)						
AADT				−0.003	0.003	0.450
Age	0.028	0.009	0.001			
Alcohol related	1.455	0.375	0.000	2.567	0.280	0.000
Speeding related	0.728	0.301	0.016	0.840	0.240	0.000
Collision type 2				−1.186	0.238	0.000
Constant	−4.737	0.421	0.000	−2.982	0.434	0.000
j = 4 (no-injury, possible, non-incapacitating and incapacitating vs. fatal)						
AADT	−0.148	0.027	0.000	−0.034	0.008	0.000
Adverse weather condition	2.625	0.920	0.004			
Adverse road condition	−1.777	0.847	0.036			
Age	0.058	0.024	0.014			
Gender	4.472	1.051	0.000			
Alcohol related	6.769	1.043	0.000	2.973	0.413	0.000
Speeding related	5.086	1.068	0.000			
Semi-trailer related	3.307	0.836	0.000			
No. of mainline lanes	4.160	1.056	0.000			
No. of ramp lanes	5.264	1.012	0.000			
Lane-ramp configuration type D				2.730	0.855	0.001
Collision type 4	−0.841	0.805	0.296	1.615	0.424	0.000
Constant	−14.579	2.522	0.000	−0.247	0.774	0.075
Model goodness-of-fit statistics						
Number of observations	1434			2357		
Likelihood ratio (LR) chi-square	146.69			260.46		
Prob > chi-square	0.0000			0.0000		
Log likelihood	−949.5904			−1531.3546		
Pseudo R^2	0.1030			0.0929		

to increase the likelihood of fatal injuries. Looking closely to the configuration type D in Fig. 1, we see the potential of weaving problems that may contribute to their worsened safety operations. At diverging areas rear end collisions (type 2) and same direction sideswipe collisions (type 3) increase the likelihood of no-injury, possible/invisible and non-incapacitating injury crashes only. However, angle collisions (type 4) increase the likelihood of sustaining fatal injuries.

Comparing with similar previous studies of diverging models, there are notable agreements of significant contributing factors and some exceptions. For instance, light condition (Wang et al., 2009; Yang et al., 2011), alcohol involvement (Wang et al., 2009, 2011; Yang et al., 2011), heavy truck involvement (Wang et al., 2009), and crash type (Wang et al., 2009; Yang et al., 2011). The number of lanes on ramps and speeding involvement appeared significant in our study but not in the reviewed previous studies. Weather condition was not significant in our diverging model,

but it was significant in some studies (Wang et al., 2009; Yang et al., 2011), mainline number of lanes were significant in Wang et al. (2009, 2011) and Yang et al. (2011) studies, curve and grade were significant in Wang et al. (2009, 2011). Although shoulder width was found significant in all studies (Wang et al., 2009, 2011; Yang et al., 2011), however, we could not test it in our study because this variable was not available in our dataset.

5. Conclusions

This study covered factors related to driver characteristics, geometric design elements, environment and traffic. Other factors such as collision types were also considered. The current study has identified that the higher number of lanes on the freeways and ramps, speeding-related, alcohol-related, and semi-truck-related crashes are factors that increase the probability of sustaining

severe injuries, specifically, incapacitating and fatal injuries at merging areas. On the other hand, only alcohol-related, lane-ramp configuration type D, angle collisions (type 4) and speeding-related increase the likelihood of sustaining fatal and incapacitating injuries at diverging areas. In addition, the study has also found that higher traffic volumes tend to mainly increase lower levels of injury severity and specifically decreasing the likelihood of sustaining fatal injuries. Crashes involving a semi-truck and a passenger car vehicle could be severe due to the large differences in the weights of the two vehicles colliding. It is also intuitively apparent that the reduction of truck traffic volumes on freeways would also reduce the number of truck-involving crashes thereby reducing the likelihood of sustaining severe injuries. It is recommended that a further study considering truck volumes and weights of vehicles in collision be conducted to create a better understanding.

Crashes involving angle collisions at diverging areas have an elevated likelihood of causing fatal injuries whereas rear-end and side-swipe in the same direction collisions mainly increase no injury and possible severity injuries at merging areas. While at diverging areas rear-end collisions also cause no injury and possible injuries only, side-swipe same direction collisions tend to increase a combination of no-injury, possible injury and non-incapacitating injuries. Therefore, it was expected that rear-end and side-swipe in the same direction type of crashes generally result into lower levels of injury severity. Likewise, this study also confirms known results that females in traffic crashes have a higher likelihood of sustaining major injuries when compared to males in the same situations. Another similar conclusion that is drawn in the present study is that older people have an elevated likelihood of sustaining more injuries in traffic crashes when compared to younger persons.

A few interesting conclusions were made in the present study. First, while the ramp configuration types did not have any influence to the injury severity for the merging areas, however, they have effect to injury severity of diverging areas. Though configuration types B and F mainly increase minor injury severity levels, type D increases fatal injuries. It is suggested that exit ramps with lane configurations that increase chances of weaving maneuvers such as types D be discouraged for new constructions or be redesigned for existing ones whenever possible in order to minimize their safety impacts. Likewise, ramps that lack deceleration lanes for existing traffic, i.e., where exiting vehicles are forced to decelerate in the mainline shared lanes, such as type B configuration need to be discouraged as well. While adverse weather conditions tend to increase no-injury and fatal injuries at merging areas, they do not have significant effect to the diverging areas. On the other hand, adverse light conditions have no significant effect to the merging areas but they tend to increase minor (non-incapacitating) injuries at diverging areas. This shows that lighting is more important at exit ramps and it is suggested that roadway agencies need to make sure that all freeway diverging areas have adequate lighting. It was observed that adverse road condition has a likelihood of increasing possible/invisible injuries, non-incapacitating and incapacitating injuries at merging areas whereas it has no significant effect to the diverging areas. This may be due to accelerating nature of merging vehicle as they attempt to catch up with mainline through traffic while exiting traffic simply slow down to diverge from traffic stream.

The study presented in this paper provides an empirical knowledge on the effect of several factors affecting vehicle occupants' injury severity at freeway's merging and diverging areas, which are very critical locations in the freeway networks. The development of such probabilistic models helps gauge the performance of the systems thereby providing traffic safety professionals with information needed for efficient

planning of improvement programs and strengthening enforcement programs.

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