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Modeling Vehicle Collision Injury Severity Involving Distracted Driving: Assessing the Effects of Land Use and Built Environment

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Abstract

This paper presents the findings of the vehicle occupant injury severity model, particularly focusing on the collisions involving distracted driving. The study develops a latent segmentation-based logit model for analyzing crash injury severity utilizing police-reported collision data from 2007 to 2011 in Nova Scotia, Canada. A segment allocation model is estimated to capture latent heterogeneity based on individual victims' and drivers' profiles, and collision attributes including vehicle type, vehicle trajectory, collision object, and collision type. The segment allocation model results suggest the existence of high-risk and low-risk injury severity segments. This study extensively tests the effects of built environment characteristics. The model results suggest that rain, curved road, freeway, and mid-block collisions aggravate vehicle occupant injury severity; whereas, higher land use mix, longer length of sidewalk, and higher population density mitigate injury severity. Significant heterogeneity is found across the high- and low-risk segments. For instance, straight road alignment is found to yield higher injury severity in the high-risk segment and lower severity in the low-risk segment. Moreover, the model unveils the interplay between built environment and distraction type. Driver distraction by communication device increases injury severity at a curved road intersection. Additionally, distraction because of inattentiveness increases injury severity. The findings of this study assist road safety engineers and planners to identify effective countermeasures and awareness programs for reducing the crash injury severity or consequences for vehicle occupants.

Injuries and fatalities in roadway collisions involving distracted driving are increasingly presenting road safety-related concerns and challenges. The National Highway Traffic Safety Association (NHTSA) reported that 16% of the total fatalities and 21% of the total injuries in the United States in 2008 involved distracted drivers (*1*). Fatalities from distracted driving increased by 28% in 2008 compared with 2005 (*2*). Distracted driving includes inattention to driving and performing non-driving activities during driving, such as texting, talking over the phone, use of in-vehicle technologies, eating, drinking, applying makeup, and so forth (*3–5*). Most of the previous studies related to distracted driving have examined crash occurrence and crash types (*6, 7*). Although injury severity is one of the crucial dimensions in transportation safety literature, limited studies have focused on the injury severity of crashes involving distracted driving. Among the few, Liu and Donmez investigated the relationship between distracted driving and injury severity; however, they only considered collisions concerning police drivers (*8*). Further effort is required to understand the interplay between distracted driving and injury severity of road users.

This study investigates vehicle occupants' injury severity in collisions involving distracted driving. The study utilizes 2007 to 2011 police-reported collision data from the Nova Scotia Collision Record Database (NSCRD). A latent segmentation-based ordered logit (LSOL) model is developed that addresses the ordered nature of the reported injury severity levels and captures heterogeneity or variation based on the characteristics of the involved parties and collisions. The LSOL model endogenously

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allocates victims into discrete latent segments based on the individual victims' and drivers' characteristics, and collision attributes. One of the key features of this study is to extensively examine the effects of built environment, including land use, neighborhood characteristics, road design, road configuration, and environmental factors. This study examines some fundamental hypotheses with regard to the effects of built environment on injury severity, such as how injury severity varies by distraction type, collision type, and individual victim and driver characteristics. Such findings provide insights toward understanding the factors affecting injury severity of crashes involving distracted driving, as well as assist in targeting and prioritizing effective road safety countermeasures and awareness programs for the road users.

Literature Review

Distracted driving is a major road safety concern as it is a significant contributing factor to roadway collisions (*10*). Driver's distraction can be cognitive or noncognitive. Cognitive distraction refers to inattention or loss of focus on the road while driving, such as daydreaming (*11*). Non-cognitive distraction can include performing non-driving activities while driving, such as use of communication devices (*3*), in-vehicle technologies (*4*), and eating or drinking (*5*). As drivers are distracted, the risk of collision (*11*), as well as severity of injury (*8*), increases. As a result, several policies are adopted to reduce distracted driving, which mainly focus on prohibiting the use of cell phones. For example, the NHTSA recommended restricting cell phone use during driving (*12*). In Canada, many provinces such as Quebec, Nova Scotia, and Newfoundland and Labrador have banned the use of handheld cellular phones while driving. In the case of reducing other distraction types, such as drowsiness, strategies include limited number of passengers, and graduated driver's licensing provisions (*12*). However, more efforts are required to develop effective awareness programs that address specific distraction types among certain high-risk populations (*12*). Donmez et al. argued that policy interventions are required to provide feedback to inattentive drivers, which might encourage the drivers to improve their performance (*13*).

Most distracted driving studies have concentrated on the relationship between distraction factors and occurrence of crash (*6*) and crash types (*7*). Limited studies have investigated the interplay between driver's distraction and injury severity. However, most of these studies have focused on a specific segment of population (*8, 14*). For instance, Neyens and Boyle developed an ordered logit model to investigate the effects of distraction on injury severity of teenage drivers and their passengers (*14*). Liu and Donmez developed an ordered logit model to investigate the crash injury severity of distracted police drivers (*8*). Further research is required to examine the effects of driver's distraction on injury severity.

Crash injury severity is one of the major areas of research in the road safety literature. A wide array of modeling methods is employed to analyze injury severity levels, ranging from ordered modeling techniques, such as ordered logit (*15*), ordered probit (*16*) and random coefficients heteroscedastic ordered logit (*17*) models, to unordered modeling approaches, such as multinomial logit (*18*), mixed multinomial logit (*19*), and latent class logit (*20*) models. One of the major advantages of the traditional ordered approach is to capture the ordinal nature of the reported injury severity levels. On the other hand, the disadvantage is the monotonic assumption that the effect of an exogenous factor does not vary across individuals or crashes. Although unordered models relax such restrictive assumptions, these models ignore the inherent ordinality of the injury severity. To address the ordinal nature as well as the heterogeneity, traditional ordered models are extended to random parameter ordered logit (*21*) and latent class ordered logit (*22*) models.

In the injury severity research paradigm, most of the previous studies have found that injury severity is influenced by sociodemographic characteristics of the road users, time of day, roadway design, and vehicular characteristics, among others (*22–24*). For example, Wang and Kockelman developed a heteroscedastic ordered logit model to examine the influence of vehicle type, roadway design, environment, and characteristics of drivers and passengers on the injury severity of vehicle occupants (*23*). They argued that older and female vehicle occupants are more injury prone and are more often the fatal victims. They also revealed that occupants of heavier vehicles are less vulnerable to injury. However, heavier vehicles were found to pose the risk of severe injury to the vehicle occupants of the collision partner. Eluru et al. developed a latent class ordered logit model to investigate the factors influencing driver injury severity at highway and railway crossings (*22*). The model allows the effects of the exogenous parameters to vary by probabilistically assigning drivers into different latent segments based on highway–railway crossing characteristics. The results suggest the existence of a high-risk and a low-risk segment. They also concluded that driver age, time of day, and weather condition are key determinants of drivers' injury severity. Yasmin et al. developed a latent segmentation-based generalized ordered logit model to examine the effects of a comprehensive set of variables on drivers' injury severity level (*25*). They varied injury severity level across drivers by assigning the levels into different segments based on crash characteristics. They revealed that older drivers of age 65 and above and collisions in higher speed zones are associated with severe injury for the drivers. The study also argued that driving a large vehicle (e.g., panel van), unpaved road, and the presence of passengers reduce injury severity.

Recently, few studies have focused on the role of land use and built environment of crash locations on injury severity levels. For example, Kim et al. developed a hierarchical ordered model in which built environment characteristics are examined at the municipality level (*26*). The hierarchical model has two levels, which include crash characteristics at the lower level and municipality characteristics at the upper level. The results of the lower level suggest that drunk drivers, heavy vehicles, darkness, and fog increase injury severity. The upper-level results reveal that severity increases in the municipalities with low population density and a high proportion of older adults. Prato et al. developed a linearized spatial logit model with an emphasis on built environment and spatial correlation across crashes during injury severity estimation (*27*). They found that industrial, shopping, and residential areas are associated with a lower injury severity. On the other hand, several studies found that an urban environment with a higher proportion of commercial areas and mixed land uses increases injury severity (*28, 29*). Nevertheless, further research is required to investigate the effects of land use and built environment, which are important variables in identifying countermeasures to reduce injury severity, particularly of those collisions that involve distracted driving.

Key Features of the Current Study

The contributions of this study to the road safety literature are threefold: 1) investigating the crash injury severity of vehicle occupants when collisions involve distracted driving; 2) developing an LSOL model to address the ordinal nature of injury severity and capture latent heterogeneity by allocating victims into discrete latent segments; and 3) examining the influence of the built environment of the collision location. This study focuses on the injury severity of vehicle occupants. The severity of injury experienced by an individual might vary by the characteristics of the road user, vehicle involved, and type of collision. Such heterogeneity is accommodated within the model formulation by endogenously allocating individual victims into discrete segments based on the victim and driver profile, and collision characteristics. The interplay between injury severity and built environment is comprehensively examined, including the effects of land use, neighborhood characteristics, roadway design and configuration, and collision location. A wide array of hypotheses is tested to explore the relationships. These include how the impact of the built environment varies in different segments by the characteristics of the victims and collision types, and whether the effect of the built environment varies by distraction types or not, among other factors.

Data

Data Sources

The primary data source for this study is the NSCRD collected from the Service Nova Scotia and Municipal Relations. The database includes all police-reported collisions that occurred between 2007 and 2011 in the province of Nova Scotia, Canada. The database contains details with regard to the time, location, and characteristic of the individuals (e.g., age, gender, road user type) involved in the collision. Further information includes vehicle type, road classification and design characteristics, weather condition, lighting condition, driver condition, and crash configuration. In addition, land use, and location information of major activity points and transportation services are collected from the Desktop Mapping Technologies Inc. (DMTI). Neighborhood characteristics at the dissemination area (DA) level are collected from the 2011 Canadian Census.

Data Description and Preparation

The NSCRD data include distraction type information of drivers in the following categories: distracted by communication device; distracted by entertainment device; distracted by vehicle display; distracted because of inattention; and others. Following data processing, 8,864 collisions involving 11,247 individuals are identified to have a distracted driver. Among these individuals, around 10,502 individuals are vehicle occupants (auto driver and auto passenger). The NSCRD provides injury severity of each individual in the following five-point ordinal scales: 1) no injury; 2) minor injury; 3) moderate injury; 4) major injury; and 5) fatal injury. The distribution of injury severity levels among the vehicle occupants is as follows: 81.0% no injury; 7.9% minor injury; 9.7% moderate injury; 1.2% major injury; and 0.2% fatal injury.

Built environment variables are generated to capture the context of the collision area. For instance, a 250-m road network-based buffer from each collision location is generated using the Network Analyst tool in the ArcMap program by Esri. A buffer of 250 m is used to avoid correlations between the micro-level built environment attributes within this buffer and the macro-level location characteristics of crashes such as urban or rural areas. The frequency of activity points and transportation services is computed within this 250-m buffer. Further, the length of sidewalk and transit line is calculated within this buffer. In addition, distance of collision locations from the closest regional center is determined using the Network Analyst tool in ArcMap. Finally, land use information is utilized to determine the land use mix index at the DA level. Details of the land use mix index calculation can be found in Bhat and Gossen (*30*). The index value ranges from 0 to 1, where a value of 0 refers to perfect homogeneity and 1 indicates perfect heterogeneity.

Modeling Approach

This paper develops an LSOL model to investigate the injury severity of vehicle occupants when collisions involve distracted driving. One of the major purposes for developing an LSOL modeling framework is to relax the homogeneity assumption of standard ordered logit models by assigning individual victims into discrete latent segments. Assume that individual j assigned to segment s sustains injury severity level i. Here, i is in an ordinal scale and can take values of 0 (no injury), 1 (minor injury), 2 (moderate injury), 3 (major injury), and 4 (fatal injury). The continuous latent propensity function can be written as:

$$Y_{js}^* = \beta_s Z_j + \varepsilon_{is} \tag{1}$$

where

Y_{js}^* = the latent propensity,

Z_j = the environmental and built environment characteristics of the collision location,

β_s = the coefficient parameter to be estimated, and

ε_{is} = the random error term assumed to follow an identical and independent standard logit distribution.

Latent propensity Y_{js}^* corresponds to the actual injury severity Y_j through a threshold parameter μ in the following form:

$$Y_j = i \text{ if } \mu_{i-1,s} < Y_j^* < \mu_{is}$$

where $\mu_{0s} = -\infty$ and $\mu_{is} = \infty$. The probability of individual j sustaining injury severity i can be written as:

$$P_j(i|s) = \Lambda(\mu_{is} - \beta_s Z_j) - \Lambda(\mu_{i-1,s} - \beta_s Z_j) \tag{2}$$

where $\Lambda(.)$ is the standard logistic cumulative distribution function.

Now, the allocation of individual j into discrete latent segment s is probabilistically determined by formulating a latent segment allocation model within the LSOL framework. The segment allocation model is defined using the observed attributes of the involved parties and collisions. The model follows a standard multinomial logit form. The utility function of the segment allocation component can be written as:

$$U_{js}^* = \gamma_s X_j + \varphi_{is} \tag{3}$$

where

X_j = the observed attributes that determine the allocation of individuals into segment s,

γ_s = the coefficient parameter to be estimated, and

φ_{is} = the random error term. φ_{is} is assumed to be identically and independently distributed with Type 1 extreme value.

The probability of individual j assigned to segment s can be written in the following logit form:

$$P_{js} = \frac{e^{\gamma_s X_j}}{\sum_{s=1}^{S} e^{\gamma_s X_j}} \tag{4}$$

The unconditional probability function can be expressed as:

$$P_j(i) = \sum_{s=1}^{S} (P_j(i)|s)(P_{js}) \tag{5}$$

The log likelihood function is given below:

$$LL = \sum_{n=1}^{N} \ln \sum_{s=1}^{S} (P_j(i)|s)(P_{js}) \tag{6}$$

where N is the total number of observations. The model estimates segment specific parameters β_s for s segments, and segment membership parameter γ_s for *s-1* segments. In addition, a traditional ordered logit model is developed for comparison purposes. The goodness of fit of the models is evaluated on the basis of McFadden's pseudo-R^2 and Bayesian Information Criteria (BIC) measures.

Variables Considered

The model considers a wide array of variables, including the profile of involved individuals, collision characteristics, distraction types, environmental factors, and built environment attributes. The injury severity component of the LSOL model is estimated based on a wide range of environmental factors and built environment characteristics of the collision location. Environmental factors include time of day, weather, and light conditions. The effect of built environment is considered in two broad categories: roadway design and configuration, and land use and neighborhood characteristics. Road design and configuration refers to the alignment of roads, speed limits, road types, collision locations, and others. Land use and neighborhood variables are derived at the 250-m buffer level from the collision location. These variables include density of transit stations, schools, health services, park areas, food stores, groceries, restaurants, shopping centers, etc. The length of sidewalk and transit line within the buffer is considered as well. A variable representing distance to the closest regional center is tested in the model. In addition, neighborhood attributes at the DA level are considered, which include, but are not limited to, population density, dwelling density, commute mode share, percentages of different land uses, and land use mix index. To evaluate the effects of distraction,

Table 1. Summary Statistics of Explanatory Variables Retained in the Model

Variables	Mean/proportion	SD
Person profile		
Male	55.45%	na
Age above 75 years	5.79%	na
Driver under influence of alcohol	7.2%	na
Driver distraction type		
Inattentive	94.69%	na
Communication device	1.34%	na
Collision characteristics		
Vehicle type—car	68.95%	na
Vehicle type—sport utility vehicle	7.44%	na
Vehicle going straight	52.84%	na
Vehicle negotiating a curve	5.74%	na
Vehicle hit non-moving object	26.92%	na
Head-on collision	1.12%	na
Environmental factors		
Weather—rain	8.85%	na
Weather—snow	2.28%	na
Time of day—evening and overnight	20.88%	na
Built environment		
Roadway design and configuration		
Road alignment curved	1.74%	na
Road alignment straight	77.74%	na
Road type—arterial	6.06%	na
Road type—freeway	12.84%	na
Collision location— nonintersection	48.51%	na
Collision location—intersection with parking lot	9.92%	na
Land use and neighborhood		
Land use mix index	0.21	0.11
Length of sidewalk within 250-m buffer	5.02 km	7.44 km
Density of school within 250-m buffer	3.44 per km^2	8.14 per km^2
Population density	795.63 person/km^2	1,743.06 person/km^2
Population commuting by car in the dissemination area	77.76%	na

Note: SD = standard deviation; na = not applicable.

different distraction types, such as inattentiveness, use of a communication device, and use of vehicle display, among others, are interacted with the environmental factors and built environment attributes.

The latent segmentation component is defined using person profile and collision characteristics. Person profile includes individual victims' and drivers' characteristics, such as age, gender, use of alcohol and drugs. Note that individual victims' characteristics include drivers' attributes. Collision characteristics include vehicle trajectory (e.g., going straight, negotiating curve, changing lanes), collision object (e.g., non-moving object, moving object, stationary object), collision type (e.g., head on, rear end, sideswipe), and vehicle type (e.g., car, sport utility vehicle [SUV], van, panel/cargo van). The summary statistics of the variables retained in the final model are presented in Table 1.

Model Results

The latent segment allocation component of the LSOL model captures heterogeneity by assigning individual victims into discrete latent segments s. The model is estimated for a specific number of segments. The number of segments is determined on the basis of BIC measures because of the hierarchical nature of the LSOL model structure. To identify the most fitting number of segments, the model is estimated for increasing values of s (e.g., s = 2,3, ...). The model is tested for an additional segment until the inclusion of a segment does not improve the model fit. The model results suggest a BIC value of 12,924.61 and 13,108.44 for models with two and three segments, respectively. As a lower BIC value for the two-segment model indicates a better fit, the final LSOL model assumes two segments. For comparison purposes, a traditional ordered logit model is developed as well. The results suggest that the LSOL model outperforms the ordered logit model with a higher McFadden pseudo-R^2 value of 0.11 than that of the ordered logit model (0.04). Therefore, the LSOL model with two segments is considered as the final vehicle occupant injury severity level model for further discussion.

Table 2. Parameter Estimation Results of the Model

Variables	Segment 1 coefficient (*t*-stat)	Segment 2 coefficient (*t*-stat)
Latent segment allocation component		
Constant	2.003 (13.31)	na
Person profile		
Male	0.609 (7.58)	na
Age above 75 years	–0.175 (1.10)	na
Driver under influence of alcohol	–1.269 (7.25)	na
Collision characteristics		
Vehicle type—car	–0.464 (4.67)	na
Vehicle type—sport utility vehicle	–0.427 (2.56)	na
Vehicle going straight	–0.693 (8.14)	na
Vehicle negotiating a curve	–1.022 (5.90)	na
Vehicle hit non-moving object	–1.466 (14.56)	na
Head-on collision	–2.247 (4.85)	na
Injury severity component		
Environmental factors		
Weather—rain	0.870 (4.21)	na
Weather—snow	na	–0.255 (1.66)
Time of day—evening and overnight	0.207 (1.12)	–0.232 (3.66)
Built environment		
Roadway design and configuration		
Road alignment curved	0.443 (0.70)	0.539 (3.57)
Road alignment curved × communication device	1.417 (2.61)	na
Road alignment straight	–0.384 (0.60)	0.257 (1.80)
Road type—arterial	0.896 (3.86)	0.061 (0.60)
Road type—freeway	0.429 (2.08)	0.254 (3.55)
Collision location—nonintersection	1.149 (2.60)	0.227 (3.75)
Collision location—intersection with parking lot × inattentive	1.210 (2.45)	na
Land use and neighborhood		
Land use mix index	–2.401 (2.41)	na
Length of sidewalk within 250-m buffer (km)	–0.057 (1.56)	–0.014 (2.63)
Density of school within 250-m buffer (per km^2)	na	–7.884 (2.18)
Population density (person/km^2)	–2.488 (1.54)	–0.037 (1.73)
Population commuting by car in the dissemination area (%)	–2.803 (3.48)	–0.043 (–0.30)
Threshold parameters		
Threshold 1	0 (–)	0 (–)
Threshold 2	0.328 (4.41)	0.666 (13.0)
Threshold 3	1.294 (6.83)	2.04 (21.13)
Threshold 4	2.254 (2.56)	2.80 (22.86)
Goodness-of-fit measures		
Log likelihood at convergence	–6,249.339	
Log likelihood at constant	–6,989.675	
Number of observations	10,502	
McFadden's pseudo-R^2	0.106	
Bayesian information criteria	12,924.61	

Note: × = variable interaction; na = not applicable.

Model Results of the Latent Segment Allocation Component

The latent segment allocation model identifies Segment 1 as the low injury severity risk segment and Segment 2 as the high-risk segment. The model is estimated based on person profile and collision characteristics (see Table 2). Person profile refers to the victims' and drivers' age, gender, and influence of alcohol and drugs. The collision characteristics include vehicle type, vehicle trajectory, collision object, and collision type. The model assumes Segment 2 as the reference segment. The model results suggest a positive relationship for male victims in Segment 1, which indicates a higher likelihood for males to be included in this segment. The negative coefficient of males 75 years or older reveals that older victims have a lower likelihood to be assigned to Segment 1. This implies that older victims are more likely to be assigned to Segment 2. Older victims tend to be more severely injured in a collision than their younger counterparts. Drivers under the influence of alcohol are less likely to belong to Segment 1. Collisions involving sober drivers are more likely to result in lower injury severity (*31*). Consequently, Segment 1 has a higher propensity to include lower risk collisions. Among the collision characteristics, the negative signs for the variables representing vehicle types (e.g., SUV), vehicles going straight, vehicles negotiating a curve, vehicles hitting a stationary object, and head-on collisions reveal a lower risk of severe injury in Segment 1. For example, in the case of vehicles going straight, a negative sign for Segment 1 means that collisions involving such a vehicle trajectory are more likely to be included in Segment 2. Vehicles going straight ahead are likely to be at a higher speed and might cause severe injury, which further confirms the higher risk of injury in Segment 2. Therefore, Segment 1 can be identified to include vehicle occupants involved in collisions with lower injury severity risk. In contrast, Segment 2 can be identified to include vehicle occupants with higher injury severity risk.

Discussion of Parameter Estimation Results

The model results are presented in Table 2. The results suggest that adverse weather such as rain increases the probability of higher injury severity. This is a deviation from earlier findings by Eluru and Bhat, who argued that rain might decrease crash injury severity as drivers are more cautious during rain (*32*). As this study analyzes collisions involving distracted driving, the adverse weather condition coupled with distracted driving might increase the severity of injury. Snowy weather is found to have a negative impact. Snowy conditions might influence the driver to drive slowly, which results in less severe injury. Collisions occurring in evening and overnight show a higher probability for severe injury in Segment 1. Lower traffic at night encourages drivers to drive faster, and reduced visibility because of darkness might increase the likelihood of higher injury severity. On the other hand, the same variable shows a negative relationship in Segment 2.

Among the road design and configuration attributes, collisions in curved sections of the roads are found to increase injury severity. The effect of curved roads is found to be higher for the high-risk collisions in Segment 2 than for low-risk Segment 1. The manner of collisions (e.g., vehicle negotiating a curve) along with vehicle types (e.g., larger vehicles like SUVs) might contribute to the higher level of injury in Segment 2. The impact of curved road sections for the low-risk segment significantly increases injury severity if the driver is distracted by a communication device. Collisions in straight roads are associated with a higher risk of injury in Segment 2. The characteristics of Segment 2 that include impaired drivers under the influence of alcohol coupled with higher speed of vehicles on straight roads increase the severity of injury. On the other hand, straight road sections show a lower probability for severe injury in low-risk Segment 1. The low-risk manner of collision along with a sober driver might contribute to the lower injury level for Segment 1. Variables representing collisions in the arterials and freeways reveal a higher likelihood for severe injury. This aligns with the findings of Yasmin and Eluru, as the higher speed of vehicles in these mid to high speed road segments might aggravate injury severity (*31*). Collisions in the mid-block sections of roads also show a positive relationship. Where parking lot intersections interact with distraction type inattentiveness, a positive relationship is found.

In the case of the land use and neighborhood characteristics, collisions occurring in the higher mix land use areas decrease the probability for severe injury. Higher mix land use areas facilitate improved and safer transport infrastructure, reducing the injury severity level. A variable representing the length of sidewalk within a 250-m buffer from the collision location is found to reduce injury severity. Higher density of schools within the proximity of collision locations shows a negative relationship in the high-risk segment. This implies that collision locations within 250 m of schools have a lower likelihood to yield severe injury. Lower speed limits in school zones might contribute to the lower probability of injury severity. A higher population density decreases the probability of injury severity in both the segments. The negative effect is substantially higher in the low-risk Segment 1 compared with the high-risk Segment 2. The low-risk characteristics of the crashes and drivers explain the relatively lower level of crash injury severity in Segment 1.

Marginal Effects

The marginal effects of determinants of the vehicle occupant injury severity model are presented in Table 3. The marginal effects refer to the magnitude of impact of the determinants on the probability of injury severity levels. The results suggest that collisions occurring in the evening and overnight have a substantial positive impact for fatal injury. Rain, freeway, curved road, and mid-block road section have a significant positive impact on moderate injury. However, higher mixed land use, longer length of sidewalk, and higher population density show a substantial positive impact on no injury, implying a reduction of injury severity. The segmentation variables are found to have considerable magnitude of influence on the injury severity level. For example, head-on collision

Table 3. Marginal Effects

Variables	No injury	Minor injury	Moderate injury	Major injury	Fatal injury
Person profile					
Male	.067	–.024	–.037	–.004	–.0007
Age above 75 years	–.031	.011	.017	.002	0.0003
Driver under influence of alcohol	–.146	.045	.084	.013	.002
Collision characteristics					
Vehicle type—car	–.026	.009	.014	.001	.0002
Vehicle type—sport utility vehicle	–0.018	0.006	0.010	0.001	0.0002
Vehicle going straight	–.057	.021	.031	.003	.0006
Vehicle negotiating a curve	–.093	.030	.053	.007	.001
Vehicle hit non-moving object	–.145	.048	.082	.011	.002
Head-on collision	–.320	.073	.191	.044	.011
Environmental factors					
Weather—rain	–.025	.009	.014	.001	.0002
Weather—snow	.039	–.015	–.021	–.002	–.0003
Time of day—evening and overnight	–.012	–.018	–.002	–.0003	.033
Built environment					
Roadway design and configuration					
Road alignment curved	–0.024	0.008	0.013	0.001	0.0002
Road alignment curved × communication device	0.046	–0.018	–0.025	–0.002	–0.001
Road alignment straight	.046	–.016	–.025	–.003	–.0005
Road type—arterial	–.054	.018	.031	.004	.0007
Road type—freeway	–.060	.020	.033	.004	.0007
Collision location—nonintersection	–.042	.015	.023	.002	.0004
Collision location—intersection with parking lot × inattentive	0.0007	–0.001	–0.0004	–.0001	–.0001
Land use and neighborhood					
Land use mix index	.188	–.069	–.104	–.012	–.001
Length of sidewalk within 250-m buffer (km)	.004	–.001	–.002	–.0003	–.0001
Density of school within 250-m buffer (per km^2)	2.476	–.914	–1.372	–.164	–.025
Population density (person/km^2)	.017	–.006	–.009	–.001	–.0001
Population commuting by car in the dissemination area (%)	.276	–.102	–.153	–.0183	–.002

Note: × = variable interaction.

has a significant positive impact on major and fatal injury. Driver under the influence of alcohol, vehicle hitting stationary object, negotiating curve, and age of the victim significantly increase the probability for severe injury.

Conclusions

This study presents the findings of modeling vehicle occupants' injury severity in collisions involving distracted driving. The study utilizes 2007 to 2011 collision data from the NSCRD. Injury severity is modeled on a five-point ordered scale: 1) no injury; 2) minor injury; 3) moderate injury; 4) major injury; and 5) fatal injury. To address the ordinal nature of injury severity as well as latent heterogeneity within the modeling framework, an LSOL model is developed. Individual victims are allocated into discrete latent segments based on the victims' and drivers' profile, and collision characteristics. This study extensively tests the effects of built environment attributes.

The segment allocation model results suggest that individuals are allocated into two segments, which can be identified as high-risk and low-risk injury severity segments. Vehicle occupants are assigned to the segments on the basis of gender and age of the individual victim, driver under the influence of alcohol, vehicle hitting a stationary object, going straight, negotiating a curve, head-on collision, and vehicle type (i.e., car and SUV). The model results of the injury severity component suggest that built environment and environmental factors significantly influence collision injury severity. For example, curved roads, freeways, and mid-block road sections are positively associated with injury severity. Higher mixed land use, higher population density, and longer sidewalk reduce the probability of injury severity. The model results reveal that significant heterogeneity exists between the latent segments. For instance, straight road alignment increases the probability of higher severity in the high-risk segment; in contrast, it decreases the likelihood of higher severity in the low-risk segment. The model confirms the interplay between built environment and distraction type. For example, inattentive driving is found to aggravate vehicle occupants' injury at the intersections of parking lots. The use of a communication device is also positively associated with a higher level of injury at curved road sections.

The findings of this study offer important insights for policy making that focuses on mitigating the injury severity from crashes involving distracted driving. For example, this study identifies that inattentiveness at the parking lot aggravates injury severity. This finding has important implications as many of the existing policies mainly mitigate the effects of distractions because of the use of cell phones. Developing policies for inattentive driving is a challenging task. One of the beneficial policy interventions might be to provide feedback to inattentive drivers with regard to where they should be more careful, for instance, at parking lots. Another important implication is with regard to the use of communication devices. The findings suggest that the drivers need to be more careful in using communication devices when negotiating curved road alignments. The heterogeneity captured across the discrete latent segments of individual victims needs to be addressed when making the road safety policies. For example, straight road segments are found to pose a higher injury risk in the high-risk segment, and a lower injury risk in the low-risk segment. Road safety policy interventions should address such heterogeneity. The marginal effect analysis assists road safety engineers and planners in identifying the factors that reduces the crash injury severity of vehicle occupants. For example, older victims, and drivers under the influence of alcohol are found to be more likely to experience severe injury. This finding sheds light on the need for policies that target specific segments of the populations. Additionally, collisions occurring in the evening and overnight and head-on collisions substantially affect the probability of moderate and fatal injury. Rain, freeways, curved roads, mid-block road sections, vehicle hitting stationary objects, and negotiating curves are found to aggravate injury severity. On the other hand, higher mixed land use, longer length of sidewalk, and higher population density are found to mitigate the severity of injury.

This study has certain limitations. It derives land use and neighborhood variables at a 250-m buffer distance from the collision locations. One of the reasons for adopting a buffer of 250 m is to avoid correlations with the macro-level location attributes of crashes such as urban or rural areas. However, the 250-m buffer might introduce some correlations, which is a limitation of this study. In the case of collisions involving multiple victims, the unobserved factors influencing injury severity across multiple involved parties might be correlated. This study does not consider such correlation among multiple victims involved in one collision. One of the restrictive assumptions of the models developed in this study is the constant estimation of parameters across the injury severity levels, which is known as the parallel regression assumption. This restrictive assumption might also attribute to the low pseudo-R^2 value of the models. Alternative model structures, such as the generalized LSOL model, should be tested to relax the parallel regression assumption and improve the goodness-of-fit measures (*25*). Another limitation of this study is the unbalanced distribution of the dependent variable (injury severity level), which might result in biased estimation. Future research should address this skew in the data by reducing the multicategory injury severity level into series of two-category phenomenon. Artificial neural network (ANN) is a potential modeling approach to tackle this skewness, as ANN accommodates such conversion and yields a significantly improved model fit (*33*). In summary, this study provides important insights toward the interplay between distraction types and built environment for different population groups and collision profiles, which will be beneficial to identify and prioritize road safety strategies and plans.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: MRF, MAH; data collection: MAH, MRF; analysis and interpretation of results: MRF, MAH; draft manuscript preparation: MRF, MAH. Both authors reviewed the results and approved the final version of the manuscript.

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