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# Mixed logit approach to analyzing pedestrian injury severity in pedestrian-vehicle crashes in North Carolina: Considering time-of-day and day-of-week

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## ABSTRACT

**Objective:** The objective of this research is to identify and compare contributing factors to pedestrian injury severities in pedestrian-vehicle crashes considering both time-of-day and day-of-week.

**Methods:** The pedestrian-vehicle crash data are collected from 2007 to 2018 in North Carolina with categorical factors of pedestrian, driver, vehicle type, crash group, geography, environment, and traffic control characteristics. The final dataset includes 17,904 observations with 69 categorized variables. Four mixed logit models are developed to analyze the crash dataset with segmentations of weekday daytime, weekday nighttime, weekend daytime, and weekend nighttime.

**Results:** A total number of 31 fixed significant factors and 6 random parameter factors to the pedestrian injury severity are detected in four mixed logit models. According to marginal effects, large vehicle involved, pedestrians with age over 65, hit and run, drunk pedestrian, down/dusk light, dark without roadside light, and industrial land use are identified as the contributing factors that result in more than a 0.08 increase in the probability of fatal injury. Compared to the daytime, most factors are found to have more impact on severe injuries in the nighttime. Also, most factors are found to result in more severe injuries on weekends than on weekdays.

**Conclusions:** This study identifies and compares the factors to pedestrian injury severity in pedestrian-vehicle crashes considering the temporal variance in time-of-day (i.e., daytime vs. nighttime) and day-of-week (i.e., weekdays vs. weekends). Random effects are explored in mixed logit models. Differences and possible reasons for the significant factors' impact within and across time-of-day and day-of-week are also investigated. Corresponding countermeasures and suggestions to mitigate the impacts of major factors are also discussed, which give practical guidance to planners and engineers, and provide a solid reference to further explore the temporal variance of the crash data.

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## KEYWORDS

Pedestrian-vehicle crashes; severity; time-of-day; day-of-week; mixed logit model; contributing factors


## Introduction

According to the Centers for Disease Control and Prevention (CDC), compared to other entities, pedestrians are among the most vulnerable on American roadways, and on average, a pedestrian was killed every 88 min in a traffic crash in 2017. Therefore, the safety of pedestrians is a crucial issue despite continual traffic safety improvements in the US, and a further investigation of the contributing factors to the pedestrian injury severity is needed. Also, within the scope of temporal analysis of pedestrian injury severity in crashes, though previous research has already pointed out the positive correlation between the injury severity level with the nighttime (Mohamed et al. 2013). Wang et al. (2020) considered time-of-day as a temporal factor in the pedestrian-injury severity model. To further investigate

time-of-day variations of the pedestrian crash factors, Li et al. (2021) segmented the pedestrian injury crash data by time-of-day into three periods. Furthermore, Song et al. (2021) segmented the pedestrian crash data by spatial and temporal features, and the spatial patterns with different temporal tendencies were further investigated in Song et al. (2020). The temporal relationship between injury severity levels and contributing factors including both time-of-day and day-of-week, is not clearly understood. Hence, to improve the safety and mitigate the pedestrian injury severity, this study explores the contributing factors to the pedestrian injury severity in pedestrian-vehicle crashes and investigates the temporal variations in factors considering both time-of-day and day-of-week (i.e., weekday daytime, weekday nighttime, weekend daytime, and weekend nighttime).

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Since discrete outcome models with fixed parameters, such as the multinomial logit model (Chen and Fan 2019), ordered logit/probit model (Yasmin et al. 2014; Song and Fan 2021), and partial proportional odds model (Song and Fan 2020), might ignore the unobserved heterogeneity inherent in the crash data and could result in biased estimations and therefore make wrong conclusions, a method that considers the heterogeneity is needed to model the pedestrian injury severity (Mannering et al. 2016). The mixed logit (ML) model, which captures the unobserved heterogeneity with random parameters, has been proved to have better performance in outcome accuracy compared to fix parameter models (Gong et al. 2016; Li et al. 2021). Thus, ML model is further utilized to explore the potential unobserved heterogeneity across pedestrian injury observations and to identify major factors that significantly affect the pedestrian severities.

In this article, four ML models are employed to the pedestrian-vehicle crashes data from 2007 to 2018 in North Carolina by considering the time-of-day and day-of-week features. Associated parameter estimates and marginal effects are also calculated to further explain the impact of contributing factors to the pedestrian injury severity. Finally, analysis results and policy-related recommendations are provided to help improve the safety and mitigate the risk for pedestrians.

## Data description

The data utilized in this study are retrieved from the North Carolina Department of Transportation (NCDOT). A total of 17,904 pedestrian-vehicle crash observations from 2007 to 2018 in North Carolina are filtered and utilized after data cleaning. The pedestrian severities are categorized into four levels (i.e., fatal injury (K), incapacitating injury (A), non-incapacitating injury (B), and no/possible injury (C/O)) considering both the severity features and crash frequency, and the pedestrian with the most severe injury is selected in one observation. The explanatory variables are classified and dummied according to the characteristics of driver and pedestrian, vehicle type, crash group, geography, environment, and traffic control.

To explore contributing factors considering the temporal variance in the time-of-day and day-of-week, an examination on such temporal characteristics is conducted. Figure 1 shows the total pedestrian crash frequency by time-of-day and day-of-week (red-color denotes weekdays and blue-color denotes weekends). The result indicates that different temporal variation patterns do exist between weekdays and weekends and across time-of-day. Meanwhile, a significant frequency difference is also shown between daytime and nighttime (6:00 AM and 5:00 PM as breakpoints). Moreover, the data used in this study are summarized and displayed in the online Appendix (Table A1, [supplementary material](#)) by category and injury severity level.

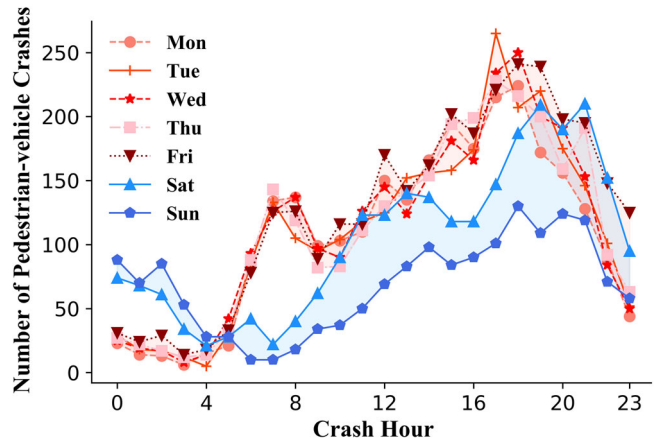


Figure 1. Total pedestrian crash frequency in time-of-day by day-of-week.

## Methodology

### Mixed logit model

The mixed logit (ML) model is a highly flexible model that includes both fixed and random parameters. In this study, the linear utility function for pedestrian  $i$  with severity level  $j$  is defined as:

$$U_{ij} = \beta_i X_{ij} + \zeta_{ij} + \varepsilon_{ij} \quad (1)$$

where  $X_{ij}$  denotes a vector of explanatory variables, and  $\beta_i$  indicates the corresponding estimated coefficient.  $\zeta_{ij}$  marks the error term that follows a general distribution correlated among severity levels and heteroscedastic for pedestrians.  $\varepsilon_{ij}$  represents the random term that is independent and identically Gumbel distributed over severity levels of pedestrians (McFadden and Train 2000).

The probability that pedestrian  $i$  suffers injury severity  $j$  can be calculated by the integral of the conditional choice probability  $P_i(j|\zeta_{ij})$  over the distribution of  $\zeta_{ij}$

$$P_i(j) = \int P_i(j|\zeta_{ij}) f(\beta \zeta_{ij} | \varphi) d\zeta_{ij} \quad (2)$$

where  $f(\zeta_{ij} | \varphi)$  represents the probability density function of the  $\zeta_{ij}$ , and  $\varphi$  is the corresponding distribution parameter of the  $\zeta_{ij}$  (e.g., when  $\zeta_{ij}$  obeys the normal distribution, and  $\varphi$  denotes the mean and variance).

$$P_i(j|\zeta_{ij}) = \frac{\exp(\beta_i X_{ij} + \zeta_{ij})}{\sum_{j=1}^J \exp(\beta_i X_{ij} + \zeta_{ij})} \quad (3)$$

The normal distribution is set for the random parameters after the examination of the model fit. Considering that the  $P_i(j)$  does not always have a closed-form solution, this article utilizes 200 Halton draws in the simulation procedure for parameter estimation by calling the MDC PROC in SAS 9.4.

### Marginal effect analysis

In this article, all explanatory variables are categorized and dummied into 1 for the event happened and 0 otherwise. Marginal effect analysis is utilized to give a straightforward

**Table 1.** Summary of overall variable results of models.

Dataset	Number of fixed variables	Number of random variables	Significant random variables [Injury severity level]
Weekday daytime	20	2	Dash/dart-out [Injury severity level: B]; Local streets [Injury severity level: K]
Weekday nighttime	22	2	No ambulance rescue [Injury severity level: K]; Public vehicular area [Injury severity level: B]
Weekend daytime	8	1	24 < PedAge <= 54 [Injury severity level: K]
Weekend nighttime	14	1	No ambulance rescue [Injury severity level: B]

Note. K, fatal injury; A, incapacitating injury; B, non-incapacitating injury.

interpretation on the impacts of significant variables on the probability outcome change of the pedestrian injury severity

$$E_{X_{ijk}}^{P_{ij}} = \frac{P_{ij}(X_{ijk} = 1) - P_{ij}(X_{ijk} = 0)}{P_{ij}(X_{ijk} = 0)} \quad (4)$$

where the  $P_{ij}$ , the probability of pedestrian  $i$  suffered severity level  $j$ , is calculated when the  $k$ th explanatory variable  $X_{ijk}$  changes from 0 to 1, respectively. The final marginal effect for each explanatory variable is calculated by averaging the marginal effects over all observations.

### Temporal instability test

To test the temporal instability of the factors in four temporal segmented crashes, likelihood ratio tests are applied according to (Washington et al. 2011).

$$X^2 = -2 \left[ LL(\beta_{total}) - \sum_i^n LL(\beta_{time\ i}) \right] \quad (5)$$

where  $LL(\beta_{total})$  is the log-likelihood at the convergence of a model containing the converged parameters based on the total crash data.  $LL(\beta_{time\ i})$  denotes the log-likelihood at the convergence of a model containing the converged parameters based on the crashes at time period  $i$ . The same variables are utilized in models with the whole dataset and segmented datasets. The degrees of freedom are calculated by the summation of the number of estimated parameters in all temporal segmented models minus the number of estimated parameters in the whole dataset model. The  $X^2$  is  $\chi^2$  distributed with the null hypothesis that the parameters for the segmented subsets are equal.

Based on the basic multinomial logit models, the log-likelihood value for the models with the whole, weekday daytime, weekday nighttime, weekend daytime, and weekend nighttime data are  $-16,926$ ,  $-7248$ ,  $-5500$ ,  $-1583$ , and  $-2426$ , respectively. The value of  $X^2$  is 338 with 243 degrees of freedom. This gives a 99.995% confidence level to reject the null hypothesis that the parameters for four temporal segmented subsets are the same. This result indicates significant distinctions (or temporal instability) between the factors of the crashes within these four time periods, which requires a segmentation of the whole dataset according to the time-of-day and day-of-week.

## Results

The detailed ML model results including both fixed and random parameters during each period (i.e., weekday daytime, weekday nighttime, weekend daytime, and weekend nighttime) are provided in the online Appendix (Tables A2 and

A3, [supplementary material](#)). Table 1 summarizes the number of significant fixed and random variables for all four models. Figures 2–3 exhibit the marginal effects for each significant explanatory variable on the fatal injury in four periods, and detailed marginal effect results at all severity levels are showed in online Appendix Tables A4 and A5 ([supplementary material](#)). This article utilizes the marginal effects to illustrate the impact of all significant contributing factors on the fatal injury in the following subsections.

### Human characteristics

Age, gender, and alcohol involvement of both pedestrians and drivers are found to have significant impacts on pedestrian injury severities. This study divides the age into four groups considering different physical conditions and corresponding severity proportions of different age stages (Kim et al. 2010; Li and Fan 2019). Compared to young pedestrians (i.e., age  $\leq 24$ ), elder age pedestrians (i.e., age  $\geq 25$ ) are more likely to suffer fatal injuries. Furthermore, compared with daytime models in the same day-of-week periods, such chances are much higher in nighttime models. These findings are in line with (Wang et al. 2020), which also indicated elder age pedestrians and nighttime periods would result in severer injuries. For instance, elder pedestrians with age over 65 would have a 0.035 and a 0.148 probability increase in the fatal injury in the weekday daytime and weekday nighttime, respectively. Meanwhile, random-effects observed in the pedestrians of medium age ( $24 < \text{PedAge} \leq 54$ ) also indicate the heterogeneity in the physical state of medium age pedestrians. Mohamed et al. (2013) also observed a decrease in the injury severity among medium age pedestrians. Compared to the daylight circumstance, dark conditions with/without roadside light could both increase the probability of fatal injury, and dark without roadside light has a higher probability increase in the fatal injury than dark with light condition. A possible explanation for this is that drivers/pedestrians are sensitive to light intensity. According to (Sullivan and Flannagan 2002), in some cases, such sensitivity could result in seven times more likely for pedestrians involving in a crash and a higher probability for the fatal injury at night over the daytime. The intoxicated pedestrians are found to result in severer injury for pedestrians on weekends than weekdays (also higher in the nighttime than the daytime). Female pedestrians are found to have a little higher chance to suffer fatal injuries (increase 0.012 and 0.01 on weekdays and weekends) than male pedestrians only in nighttime models. One possible reason might be the difference of the physical

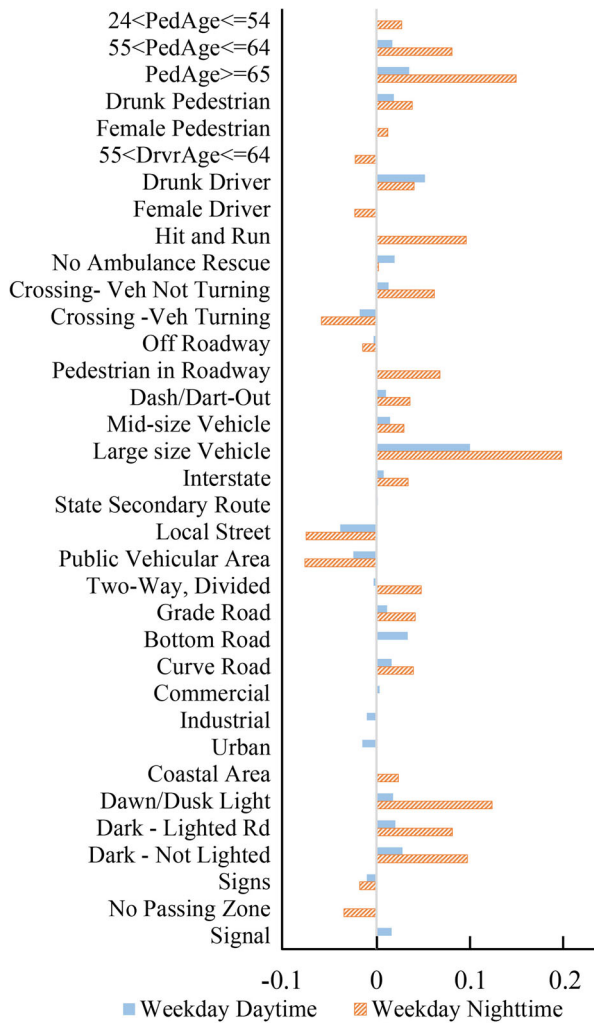


Figure 2. Marginal effects of weekday daytime and nighttime model for fatal injury.

condition between female and male, and female is more vulnerable in a crash.

Drivers with age between 25 and 54 are found to result in a lower risk of fatal injury (decrease  $-0.022$ ) for pedestrians in the weekday nighttime. It is found that pedestrians in the Weekday Nighttime model are less likely to experience fatal injury by female drivers. One possible reason for this is that male drivers are more likely to take risks and engage in aggressive driving (Kim et al. 2010). Also, the drunk driver is found to have about a 0.05 probability increase of the pedestrian being killed in all models except Weekend Daytime. This is also in line with (Kim et al. 2017).

**Vehicle characteristics**

This study classifies vehicles into three types based on the associated vehicle weight. Such classification could also be seen in (Aziz et al. 2013), whose results indicated that the crash severity is highly relevant to the vehicle weight. In general, heavier vehicles would result in severer injuries. Compared to small vehicles, mid-size and large vehicles show an increase in fatal severities in all models except Weekend Daytime in this study. Crashes involved with large

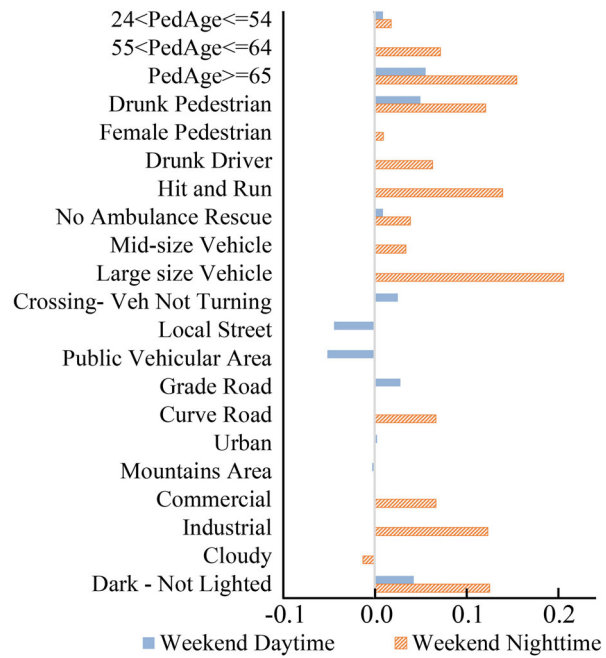


Figure 3. Marginal effects of weekend daytime and nighttime model for fatal injury.

vehicles increase the possibility of the fatal injury by 0.099, 0.196, and 0.207 in the Weekday Daytime, Weekday Nighttime, and Weekend Nighttime, respectively. It is also noted that such effects are larger in large-size vehicles than mid-size vehicles and larger in the nighttime than in the daytime.

**Crash characteristics**

Factors within this category are highly related to both drivers’ and pedestrians’ behaviors. No ambulance rescue increases the risk of suffering a severer injury for pedestrians in all periods. Meanwhile, no ambulance rescue is found to have random-effects in the nighttime. One possible reason for this might be that pedestrian-injury crashes are less likely to be timely reported due to the decrease of the witnesses at night. Also, “Hit and run” increases the probability of fatal injury for both nighttime models. It is noted that timely professional emergency medical rescue could mitigate the severity of the pedestrian injury. Compared to the scenario that pedestrians are walking along the roadways, crashes involving pedestrians crossing roadways with vehicles not turning could increase the probability of the fatal injury in all models except Weekend Nighttime. Meanwhile, both factors of “Crossing Roadway with Vehicle Turning” and “Off Roadway” could reduce the probability of pedestrians being killed in both weekday daytime and nighttime. One possible reason for that might be the slow speed when the vehicle is turning or on off-roadways. For the crash when the pedestrian is on the roadway, marginal effects indicate an increase of the probability for both fatal and incapacitating injuries in the weekday nighttime. Also, the random-effects observed in Dash/Dart-out behavior in the Weekday Daytime might indicate that pedestrians are more careless and impatient in the Weekday Daytime than other periods. And this

incautious behavior increases the probability of the fatal injury in both Weekday models.

### **Geography characteristics**

Within this category, variables such as commercial areas, coastal region, two-way divided roadways, grade and bottom roadway, curved roadways, interstate, and state secondary route are found to increase pedestrians' injury severity, while urban areas, local streets, and public vehicular areas are found to decrease pedestrians' injury severity. The random-effects observed in the local street and public vehicular areas might be caused by the mixed environment of pedestrians and vehicles in those areas. Heterogeneity effects are observed in urban and industrial areas. Compared to rural areas, crashes located in urban areas show a 0.015 probability decrease and a 0.003 probability increase in the fatal injury in the weekday daytime and weekend daytime, respectively. Also, marginal effects of urban areas indicate a reversed effect on the probabilities of the incapacitating injury in two models (i.e., Weekday Daytime 0.002 vs. Weekend Daytime  $-0.046$ ). Possible reasons for such heterogeneity might be the variations of the vehicle's speed, travel behavior, and traffic volume in urban areas. Compared to the piedmont regions, coastal regions are found to have a 0.023 probability increase for the fatal injury in the weekday nighttime. Meanwhile, mountainous regions show a 0.002 probability decrease for the fatal injury and a 0.039 probability increase for the incapacitating injury in the weekend daytime. Additionally, compared to residential areas, commercial areas exhibit a 0.003 and a 0.067 possibility increase for fatal injuries in the weekday daytime and weekend nighttime, respectively. While, industrial areas indicate a 1% probability decrease and a 0.124 probability increase for the fatal injury in the weekday daytime and weekend nighttime, respectively.

Compared to straight roadways, curved roadways are found to increase the probability of fatal injuries (i.e., Weekday Daytime 0.016, Weekday Nighttime 0.039, and Weekend Nighttime 0.067). Li et al. (2021) also found that curved roadways have temporally stable impacts on increasing severe injury possibilities during periods between 2010 and 2018. Also, compared to level roadways, gradient roadways and bottom roadway all indicate a probability increase of fatal injury for pedestrians. One possible reason for that is the bad sight condition in these locations. Compared to one-way not divided roadways, two-way divided roadways raise the risk of the pedestrians being killed (increase 0.048) in Weekday Nighttime. Moreover, compared to the US routes, local streets and public vehicular areas could overall mitigate the risks of the pedestrians being fatally injured in both daytime models. However, interstate and state secondary routes increase the probability of the pedestrians being killed in Weekdays.

### **Environmental characteristics**

Variables such as dawn/dusk light, dark with/without roadside light, and traffic signal are found to increase

pedestrians' injury severity, while cloudy weather, traffic signs, roadways with double yellow line and no passing zone are found to decrease pedestrians' injury severity. Compared to the clear weather, cloudy weather shows a 0.013 possibility decrease for the fatal injury in the weekend nighttime. This might be explained as the cautious driving of the drivers with less natural light due to the cloudy weather. Compared to no traffic control conditions, traffic signs are detected to help mitigate both fatal and incapacitating injuries for pedestrians in both Weekday models. Also, roadways with the double yellow line and no passing zone exhibit a 0.034 probability decrease for the fatal injury in the weekday nighttime. On the other hand, traffic signals indicate a 0.016 probability increase for the fatal injury in the weekday daytime. This might be caused by the high speed of the vehicle and complex traffic in signal control intersections. Compared to daylight condition, dawn/dusk light and dark with/without roadside light are all found to increase the risk of the pedestrian being killed, but with different magnitudes. Especially for dark without roadside light situation, it increases the probability of the fatal injury by 0.126 in the weekend nighttime.

### **Discussions**

According to (Behnood and Mannering 2016), the shifts of human behaviors and environments in different periods are all possible reasons for the temporal instability of the pedestrian-injury severity factors. It should be noted that factors are found to result in severer injuries in the nighttime than the daytime, and this might be caused by the poor sight of the drivers and pedestrians in the dark environment. Also, factors are found to contribute to more severe injuries on weekends than weekdays, and one possible reason for that is the difference of the pedestrian's traveling purpose and behavior on weekdays and weekends. Additionally, large vehicle involved, pedestrians with age larger than 65, hit and run, drunk pedestrian, dawn/dusk light, dark without roadside light, and industrial land use are identified as contributing factors that result in more than 0.08 probability increase in the fatal injury. Countermeasures for these factors are summarized as follows (1) modifying the crossing facilities (i.e., setting pedestrian refuge or pedestrian bridge at intersections) in industrial areas to provide better protection of pedestrians; (2) strengthening law and education to prohibit hit and run, drunk driving, and even drunk walking in/across the roadways for pedestrians; (3) setting roadside light and flashing light to notify drivers of the pedestrians on roadways; (4) increasing the frequency of the patrol and alcohol tests; and (5) limiting the permit travel time for large vehicles in industrial areas.

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- Aziz HMA, Ukkusuri SV, Hasan S. 2013. Exploring the determinants of pedestrian-vehicle crash severity in New York City. *Accid Anal Prev.* 50:1298–1309. doi:10.1016/j.aap.2012.09.034
- Behnood A, Mannering FL. 2016. An empirical assessment of the effects of economic recessions on pedestrian-injury crashes using mixed and latent-class models. *Anal Methods Accid Res.* 12:1–17. doi:10.1016/j.amar.2016.07.002
- Chen Z, Fan W. 2019. A multinomial logit model of pedestrian-vehicle crash severity in North Carolina. *Int J Transp Sci Technol.* 8(1): 43–52. doi:10.1016/j.ijtst.2018.10.001
- Gong L, Fan W, Washing EM. 2016. Modeling severity of single vehicle run-off-road crashes in rural areas: model comparison and selection. *Can J Civ Eng.* 43(6):493–503. doi:10.1139/cjce-2015-0449
- Kim M, Kho SY, Kim DK. 2017. Hierarchical ordered model for injury severity of pedestrian crashes in South Korea. *J Safety Res.* 61:33–40. doi:10.1016/j.jsr.2017.02.011
- Kim J, Ulfarsson GF, Shankar VN, Mannering FL. 2010. A note on modeling pedestrian-injury severity in motor-vehicle crashes with the mixed logit model. *Accid Anal Prev.* 42(6):1751–1758. doi:10.1016/j.aap.2010.04.016
- Li Y, Fan W. 2019. Modelling severity of pedestrian-injury in pedestrian-vehicle crashes with latent class clustering and partial proportional odds model: A case study of North Carolina. *Accid Anal Prev.* 131:284–296. doi:10.1016/j.aap.2019.07.008
- Li Y, Song L, Fan W. 2021. Day-of-the-week variations and temporal instability of factors influencing pedestrian injury severity in pedestrian-vehicle crashes: a random parameters logit approach with heterogeneity in means and variances. *Anal Methods Accid Res.* 29: 100152. doi:10.1016/j.amar.2020.100152
- Mannering FL, Shankar V, Bhat CR. 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. *Anal Methods Accid Res.* 11:1–16. doi:10.1016/j.amar.2016.04.001
- McFadden D, Train K. 2000. Mixed MNL models for discrete response. *J Appl Econ.* 15(5):447–470. doi:10.1002/1099-1255(200009/10)15:5 < 447::AID-JAE570 > 3.0.CO;2-1
- Mohamed MG, Saunier N, Miranda-Moreno LF, Ukkusuri SV. 2013. A clustering regression approach: a comprehensive injury severity analysis of pedestrian-vehicle crashes in New York, US and Montreal. *Canada Saf Sci.* 54:27–37. doi:10.1016/j.ssci.2012.11.001
- Song L, Fan W. 2020. Combined latent class and partial proportional odds model approach to exploring the heterogeneities in truck-involved severities at cross and T-intersections. *Accid Anal Prev.* 144:105638. doi:10.1016/j.aap.2020.105638
- Song L, Fan W. 2021. Exploring truck driver-injury severity at intersections considering heterogeneity in latent classes: a case study of North Carolina. *Int J Transp Sci Technol.* 10(2):110–120. doi:10.1016/j.ijtst.2020.12.006
- Song L, Fan W, Li Y, Wu P. 2021. Exploring pedestrian injury severities at pedestrian-vehicle crash hotspots with an annual upward trend: A spatiotemporal analysis with latent class random parameter approach. *J Safety Res.* 76:184–196. doi:10.1016/j.jsr.2020.12.008
- Song L, Li Y, Fan W, Wu P. 2020. Modeling pedestrian-injury severities in pedestrian-vehicle crashes considering spatiotemporal patterns: Insights from different hierarchical Bayesian random-effects models. *Anal Methods Accid Res.* 28:100137. doi:10.1016/j.amar.2020.100137
- Sullivan JM, Flannagan MJ. 2002. The role of ambient light level in fatal crashes: Inferences from daylight saving time transitions. *Accid Anal Prev.* 34(4):487–498. doi:10.1016/S0001-4575(01)00046-X
- Wang J, Huang H, Xu P, Xie S, Wong SC. 2020. Random parameter probit models to analyze pedestrian red-light violations and injury severity in pedestrian-motor vehicle crashes at signalized crossings. *J Transp Saf Secur.* 12(6):818–837. doi:10.1080/19439962.2018.1551257
- Washington SP, Karlaftis MG, Mannering FL. 2011. *Statistical and Econometric methods for transportation data analysis.* Boca Raton, (FL): Chapman and Hall/CRC.
- Yasmin S, Eluru N, Ukkusuri SV. 2014. Alternative ordered response frameworks for examining pedestrian injury severity in New York City. *J Transp Saf Secur.* 6(4):275–300. doi:10.1080/19439962.2013.839590