**Traffic Injury Prevention**

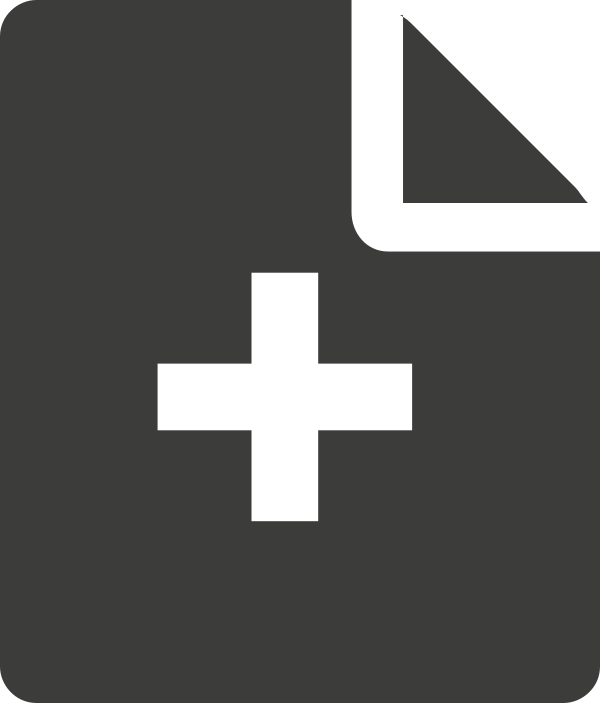
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**Investigating Factors Influencing Pedestrian Injury Severity at Intersections**

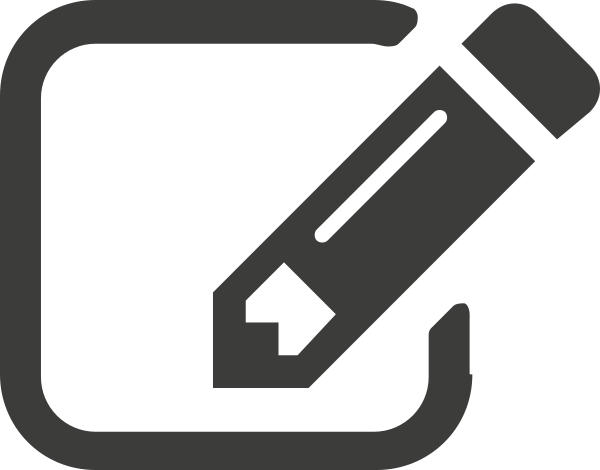
**Zhuanglin Ma, Xi Lu, Steven I-Jy Chien & Dawei Hu**

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Investigating Factors Influencing Pedestrian Injury Severity at Intersections Zhuanglin Maa,\*, Xi Lub, Steven I-Jy Chien a,c, Dawei Hu a

aSchool of Automobile, Chang’an University, Xi’an, Shaanxi, China

bChina Academy of Transportation Science, Beijing 100029, China

cJohn A. Reif, Jr. Department of Civil and Environmental Engineering, New Jersey Institute of Technology, Newark 07102, NJ, USA

Address correspondence to Zhuanglin Ma, School of Automobile, Chang’an University, Middle-section of Nan’er Huan Road Xi’an, ShaanXi Province 710064, China. E-mail: [zhuanglinma@chd.edu.cn](mailto:zhuanglinma@chd.edu.cn) **ABSTRACT**

**Objective:** Vehicle crashes which involved pedestrian at intersections have been reported occasionally. The injury severity of pedestrians in these crashes seems significantly related to driver and pedestrian attributes, vehicle characteristics, and the geometry of intersections. Identifying factors associated with pedestrian injury severity (PIS) is critical for reducing crashes and improving safety. For developing the proposed probit models, drivers who involved crashes are classified into three groups: young drivers (16

≤ age ≤ 24); middle-aged drivers (25 ≤ age ≤ 64); older drivers (age ≥ 65). This study explores that PIS is significantly but differently affected by these grouped drivers with different sets of explanatory variables. **Methods:** A total of 2,614 crash records (2011~2012) at intersections in Cook County, Illinois of the US were collected. An ordered probit modeling approach was employed to develop the proposed model and examine factors influencing PIS. The likelihood ratio test was used to assess the model performance.

Elasticity analysis was conducted to interpret the marginal effect of contributing factors on PIS associated with different drivers’ groups by age.

**Results:** The results show that four independent variables, including Pedestrian Age, Vehicle Type, Point of First Contact, and Weather Condition, significantly affect PIS at intersections for all drivers. Two additional independent variables (i.e. Number of Vehicles and Traffic Type) affect PIS for young and

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middle-aged drivers, while two other variables (i.e. Divided Type and Hit-and-run Related) are significant to PIS for both young and older drivers.

**Conclusions:** The independent variables significant to PIS at intersections for young, middle-aged, and older driver groups were identified; while the marginal effect of each variable to the likelihood of PIS were assessed.

Keywords

pedestrian injury severity; driver; age; intersection; ordered probit model; elasticity analysis; safety

## INTRODUCTION

With the increase of population and traffic volume, the crashes involving both pedestrians and vehicles are frequently reported, especially in the urban area, which has dragged significant attentions of transportation professionals. In 2015, there were approximately 5,400 pedestrians killed and 70,000 injured in the United States (NHTSA 2015), and these numbers have yielded historic high since 1996. Compared to the records in 2014, fatal pedestrian crashes increased by nearly 10%, while the number of injures increased by nearly 8%. Intersections in an urban road network are critical locations jeopardizing pedestrian’s life. To make our road safer, the safety of these locations requires a special attention and has been regarded as a priority goal of the National Highway Traffic Safety Administration (NHTSA) of the US.

As discussed in several studies, some factors influencing driving behavior may result in crashes involving pedestrians at intersections. Age has been regarded as an important factor affecting the aspects of drivers’ physiology, psychology, and behavior. On the positive side, accumulated driving experience is known to increase with age. However, some physical degradation issues, including reduction in the senses of vision and hearing as well as the ability to process information, will lead to longer perception/reaction time (Islam and Mannering 2006). Some studies (Abdel-Aty et al. 1998; Dissanayake and Lu 2001; Lam 2002) found that the age-related degradations exceed the benefits of increased driving experience.

Therefore, aged drivers are likely to involve in severer crash accidents.

Identifying factors associated with pedestrian injury severity (PIS) is critical for developing action plans for reducing crashes and improving safety. This paper proposes a method to establish the relationship of influential factors and PIS at intersections for various groups of drivers by age. These factors are embedded in various types of data, including attributes associated with drivers, pedestrians, vehicles, and intersections, and environment. The total pedestrian related crashes occurring at both signalized and un-signalized intersections (2011~2012) in Cook County, Illinois of the US were collected

and analyzed. An ordered probit model was developed and applied to identify factors influencing PIS for young, middle-aged, and older drivers. Then, the likelihood test was applied to assess the goodness-of-fit of the ordered probit model. Finally, elasticity analysis was carried out to quantify the marginal effect of each contributing factor on PIS.

## LITERATURE REVIEW

To adopt the appropriate countermeasures and to reduce PIS at intersections, several studies indicated potential factors causing pedestrian related crashes using a variety of statistical methods. Some logistic models have been employed to analyze contributing factors to pedestrian fatality. Oh et al. (2005) identified factors causing pedestrian fatality in Korea, which include pedestrian age, collision speed, and vehicle type. Sze and Wong (2007) examined the relationship between contributing factors and the probability of severe injury, including fatality. Sarkar et al. (2011) investigated the possible contributory factors to pedestrian fatality on national highways in Bangladesh.

Crash injury severity has been classified into five levels for crash victims including drivers, passengers, and pedestrians: fatal injury (K), incapacitating injury (A), non-incapacitating injury (B), possible injury (C), and no injury (O) (Eluru et al. 2008; National Safety Council 1989; Zajac and Ivan 2003). To explore the factors affecting PIS, several ordered discrete response models (e.g., ordered logit model, ordered probit model, etc.) and unordered response models (e.g., multinomial logit and probit model, nested logit model, etc.) were popularly utilized.

There is an important issue to be cautious while modeling crash injury severity, which is the ordinal nature of crash data (Savolainen et al. 2011). It was found that unordered response models usually ignored the ordinal nature of crash injury severity. The multinomial logit model has applied with limitation, which assumes the independence of irrelevant alternatives (called IIA) (Ben-Akiva and Lerman 1985) and lacks of closed-form likelihood (Greene 2002). Therefore, ordered response models, either logit or probit, have been commonly applied.

Zajac and Ivan (2003) developed an ordered probit model and found that roadway width, vehicle type, driver alcohol involvement, and pedestrian age affected PIS in rural Connecticut. Lee and Abdel-Aty (2005) developed an ordered probit model to estimate the likelihood of PIS, and found that pedestrian age, alcohol/drug use, vehicle type, vehicle speed, weather, and lighting significantly influenced PIS. Obeng and Rokonuzzaman (2013) adopted the ordered logit model to investigate PIS in vehicle- pedestrian crashes at signalized intersections in Greensboro, North Carolina, US, and the results showed that vehicle type, gender, land-use, speed limit, traffic volume, presence of sidewalk and visual- obstruction significantly influenced PIS.

Several studies employed an ordered probit approach to approximate PIS. Jang et al. (2013) found that the impact of pedestrian age, alcohol consumption, cell phone use, nighttime, weekend, rainy weather, and larger vehicles seem to increase PIS. Pei and Fu (2014) investigated the probability of PIS at non- signalized intersections and found that adverse weather, sideswiping with pedestrian on poor surface, the interaction of rear-ends and the third-class highway, winter night without illumination, and the interaction between traffic signs or marking and the third-class highway increased the probability of serious injuries. The application of the probit model seems more popular than the ordered logit model, although their performances are fairly close (Duncan et al. 1998; Garrido et al. 2014).

Many studies have been conducted to explore crash injury severity across different groups of drivers classified by age. Neyens and Boyle (2008) investigated how the driver distraction and inattention influence the injury severity to teenage drivers (16-19 years old) and their passengers. Thompson et al. (2013) examined the crash scenes as well as the attributes of drivers who are greater than 75 years old and vehicles associated with crashes. Later, Amarasingha and Dissanayake (2014) found that gender is also a factor contributing to injury severity, especially for young drivers (i.e. 15-24 years old). However, these studies focused only on one specific group of drivers (i.e., young/teenage or older/adult drivers), and the difference of influencing factors crossing different groups were not investigated.

Considering injury severity cross different ages of drivers, some studies investigate the difference in PIS incurred by young/teenage drivers versus older/adult drivers. Chen et al. (2006) examined the difference of child passenger injury risk, restraint use, and crash time caused by teenage and adult drivers. Hao et al. (2015) explored the determinants of driver injury severity by drivers’ age. Wu et al. (2016) analyzed the effect of teenage and adult drivers’ characteristics on driver injury severities. Albeit drivers were classified into younger/teenage and older/adult (Chen et al. 2006; Hao et al. 2015; Wu et al. 2016), their definitions of driver groups by age are quite different. For instance, Chen et al. (2006) and Wu et al. (2016) suggested that 20 years old is the threshold to distinguish teenage and adult drivers, but Hao et al. (2015) suggested that is 55 years old. The definition of the group by age seems heavily affected by the sufficiency of data falls in each of the group.

Some studies further classified drivers into more groups by age. However again, their definitions vary.

Kweon and Kockelman (2003) classified drivers into three groups: young (less than 20 years old), middle-aged (20-60 years old), and older (61 years old and over) driver. Islam and Mannering (2006) classified driver age into three groups: younger (16-24 years old), middle-aged (25-64 years old), and older (65 years old and over) driver. Liu et al. (2007) analyzed the difference in characteristics of crash injuries among young (16-24 years old), middle-aged (25-64 years old), and older (65 years old and over) drivers. Donmez and Liu (2015) divided drivers age into three levels: young (less than 25 years old), middle-age (25-64 years old), and older (65 years old and over) drivers, and assessed the relation of age- distraction interaction with driver injury severity. Pour-Rouholamin and Zhou (2016) divided driver age

into three groups: adult (16-24 years old), middle-age (25-64 years old), and old (more than 64 years old), and investigated the risk factors associated with PIS. Since the majority of states in the US regulated that the minimum legal age for graduated driver licensing is 16 years old, this study classified drivers into three groups: young (16 ≤ age ≤ 24), middle-aged (25 ≤ age ≤ 64), and older (age ≥ 65). It suggests that

the classification of drivers by age is location dependent and data driven (i.e. sufficiency of the data), which will affect the accuracy of estimated injury severity.

According to the review discussed above, lots of efforts have been focusing on investigating crash injury severity but the relationship between PIS at intersections associated with the age of drivers is still unknown. This relationship seems fairly critical to be established, so that the factors impacting the safety of pedestrians crossing at intersections may be recognized. The objective of this study is to investigate how driver and pedestrian attributes, vehicle characteristics, intersection environment features and crash characteristics affect PIS at intersections across different ages of drivers. Three ordered probit models were developed to predict PIS, and the likelihood ratio was used to test the model performance. Elasticity analysis was also conducted to interpret the marginal effects of contributing factors on PIS. **METHODOLOGY**

## Ordered Probit Model

As discussed earlier in this paper, we intend to introduce a new index called PIS which is estimated using an ordered probit model which represents the relationships between PIS and all potential influence factors. The general form of the ordered probit model is formulated as follows:

*zi* = **X***i* **β** + *εi*

(1)

where *zi* is a continuous latent variable, **X***i* is a vector of observed non-random independent variables including the attributes of any pedestrian victim *i*, **β** is a vector of estimated parameters associated with **X***i*, and *εi* is a unobserved random error term and normally distributed with zero mean and unit variance for the ordered probit model.

The dependent variable is PIS of pedestrian *i* denoted as *yi*, which is an integer *j* and varies from 1 to *J*

as formulated below.

1 *if*    *zi*  **1

*y*   *j if *



*i*

*j* 1

 *zi*

 * j*

(2)

 *if*

*J*



* J* 1

 *zi*

#  

where *J* is the number of PIS levels, *τj* is a threshold value for the *j*th and *j+*1th PIS levels. Then, the associated cumulative probability functions of different PIS levels can be formulated as Eqs. (3) through

(5).

*P*(*y* =

*i*

*P*(*y* = 1| **X** ) = Φ(*τ* - **X β**) (3)

*j |* **X** ) = Φ(*τ* - **X β**)*-* Φ(*τ* - **X β**) (4)

*i i* 1 *i*

*i j i j*-1 *i*

*P*(*y* = *J |* **X** ) = 1- Φ(*τ* - **X β**) (5)

*i i J* -1 *i*

where Φ(·) is a cumulative probability function of a standard normal distribution.

Since all crashes concerned in this study involving injured or fatal pedestrian(s), a pedestrian crash was defined as any reported traffic crash involving at least a vehicle and one or more pedestrian (Schneider et al. 2010). To assess the likelihood of PIS, we classified the pedestrian injuries into four levels: PIS = 1: possible injury (C); PIS = 2: non-incapacitating injury (B); PIS = 3: incapacitating injury (A); and PIS = 4: fatal injury (K). Possible injury means that a pedestrian injured in the crash, but there were no evident injury and he/she was able to walk away from the scene of the crash. Non-incapacitating injury means a pedestrian injured in the crash with visible injury observed at the scene of the crash, such as contusions, laceration, bloody nose, lump on head, and so on. Incapacitating injury means a pedestrian who injured in the crash, which prevents he/her from walking or normally continuing the activities, so the injured pedestrian must accept the help of medical assistance. Fatal injury means a pedestrian died within 30 days of the crash.

The parameters of the ordered probit model can be optimized by using the maximum likelihood (ML) method in which a log-likelihood function formulated as Eq. (6) representing the sum of the log probabilities is applied. Thus,

*n*

*L*  

*i* 1

*J*



*j* 1

log* j*

 **X β**  **

*j -* 1

 **X β** (6)

## Goodness-of-fit Test

*i*

*i*

In order to test the goodness-of-fit, the likelihood ratio (LR) test is applied to assess model performance. The LR test result shall indicate whether a global null hypothesis for a specific model should be rejected

by Eq. (7):

** 2  1  l(** )

# l(0)

(7)

where *l*(*β*) is the log-likelihood value of the developed model, and *l*(0) is the log-likelihood value of the model without independent variables included. Note that if *ρ*2 is greater than 0.2, it suggests that the developed model has sufficient explanatory and predictive power (Shankar and Mannering 1996; Ulfarsson and Mannering 2004).

## Elasticity Analysis

To investigate the effect of *βj* on the probability of PIS, elasticity analysis is conducted to assess its marginal effect. For a continuous independent variable, the marginal effect for PIS level *k* can be calculated by taking the partial derivative of the cumulative probability function of pedestrian *i* denoted as

*P*(*yi = k*) function with respect to ***Xi***. Thus,

*P*(*yi* = *k*) = [*φ*(*τ*

∂**X**

*k* -1

* **X β**)- *φ*(*τ*

*k* -2

* **X β**)]**β**

(8)

where φ(·) is the standard normal density.

*i*

*i*

On the other hand, for a binary independent variable, the marginal effect for PIS level *k* can be calculated using Eq. (9).

Δ(*y* = *k* | *x* ) = *P*(*y* = *k* | *x* = 1)- *P*(*y* = *k* | *x* = 0) (9)

*i i i i i i*

## DATA DESCRIPTION

The pedestrian crashes used in this study were obtained from the Illinois Department of Transportation (IDOT), which consist of 2,614 pedestrian-related crash records at intersections reported (2011~2012) in Cook County, Illinois of the US. Cook County is the second-most populous county in the US after Los Angeles County, California, and more than 40% of all residents of Illinois live in there.

These crash records are filed in separated categories, including crash, driver, and vehicle. Crash related data describes the details concerning occurrence time, location, number of vehicle involved, level of injury severity, geometric characteristics, and environmental conditions. Driver related data includes the details concerning driver and pedestrian demographic, driver maneuver behavior, and driver temporal impairment. Vehicle related data consists of vehicle type, vehicle maneuver prior to the crash, and point of first contact on the vehicle. It is worth noting that drivers are classified into three groups: Young drivers (16 ≤ age ≤ 24); Middle-aged drivers (25 ≤ age ≤ 64); Older drivers (age ≥ 65). Out of these 2,614 crashes, there are 311 (11.9%), 1,281 (49.0%), and 1,022 (39.1%) crashes involved young, middle-aged, and older drivers, respectively. The model variables and associated parameters are defined and illustrated in Table A1, in which the descriptive statistics of each variable is also included. The detailed definition of some independent variables is shown in Appendices.

## DISCUSSION

Three ordered probit model developed for approximating PIS caused by young, middle-aged, and older drivers are discussed in this section. The model parameters were optimized using the ML method. The hypothesis test was based on 0.10 significant level. A positive parameter of the associated independent variable encourages the increase of PIS. An elasticity analysis was conducted to quantitatively interpret the marginal effects of contributing factors on PIS by drivers’ age, which describes the behavior of each independent variable to the probability of each PIS level.

## Young Driver Model

There are 311 crash records at intersections, involving young drivers. The model parameter associated with each independent variable and the corresponding marginal effect on PIS are determined and summarized in Table 1.

Through the LR test we found in Table 1 that *ρ*2 is 0.237 indicating a reasonable goodness-of-fit of the young driver model to the data. Then, twelve independent variables, including Driver Gender, Pedestrian Age, Pedestrian Gender, Vehicle Type, Number of Vehicle, Point of First Contact, Traffic Type, Divided Type, Road Condition, Weather Condition, Traffic Control Device Condition, and Hit-and-run Related, were found significantly related to PIS. The detailed analysis of results is shown in Appendices.

## Middle-aged Driver Model

In this section, the middle-aged driver model is developed by using 1,281 crash records involved middle- aged drivers. The model parameter associated with each independent variable and the corresponding marginal effects on PIS are determined and summarized in Table 2.

In Table 2, the LR index denoted as *ρ*2 is 0.237 indicating that the middle-aged driver model fits reasonably well to the data. It was found that seven independent variables, including Pedestrian Age, Vehicle Type, Number of Vehicle, Point of First Contact, Roadway Geometry, Traffic Type, and Weather Condition, are significantly related to PIS, which are discussed next. The detailed analysis of results is shown in Appendices.

## Older Driver Model

There are 1,022 crash records at intersections involved vehicles with older drivers. The model parameter associated with each independent variable and the corresponding marginal effects on PIS are determined and summarized in Table 3.

In Table 3, the LR index denoted as *ρ*2 is 0.204, which indicates a reasonable goodness-of-fit of the older driver model to the data. The model consists of ten independent variables, including Driver License State, Pedestrian Age, Vehicle Type, Vehicle Maneuver Prior to the Crash, Point of First Contact,

Divided Type, Lighting Condition, Weather Condition, Hit-and-run Related, and Intersection Type, which are significantly related to PIS. The detailed analysis of results is shown in Appendices.

## Comparative Analysis

To further understand the different significant factor on PIS at intersection among young, middle-aged, and older drivers, the comparison analysis was conducted. Table 4 show the summary of same and different independent variables among young, middle-aged, and older drivers.

From Table 4, four common independent variables, including Pedestrian Age, Vehicle Type, Point of First Contact, and Weather Condition, are significant to PIS at intersections for all driver groups. It is worth noting that these independent variables are unrelated to the traffic volume and the design of vehicles and intersections. Some independent variables significantly affect two categories of driver age groups. For instance, two independent variables, including Number of Vehicle and Traffic Type, are significant factors associated with PIS at intersection for both young and middle-aged drivers. It is interesting that those two variables have opposite impact to PIS for young and middle-aged drivers. For “Number of Vehicle”, the reasons behind the observation are not clear and thus require further investigation, such as the difference of crash nature between single-vehicle and multi-vehicle crashes. For “Traffic Type”, the possible reason is the outcome from trade-off between roadway physical condition and the affected driving behavior due to either one-way or two-way by young and middle-aged drivers.

Divided type and Hit-and-run Related are significant factors associated with PIS at intersection for both young and older drivers. Note that some roadway improvement measures may improve pedestrian safety at intersections for young, middle-aged, or older drivers.

In general, this study identified important factors significant to PIS at intersection for various groups of drivers based on empirical data. The developed probit models would be critical to provide efficient countermeasures in the decision making process, such as elevating pedestrian safety at intersections via education, enforcement, and intersection design. Although the developed ordered probit models are

capable to adapt to both ordinal nature of crash data and IIA, they are still limited to be applied because of the assumption of a normal distribution for all unobserved component of utility. A more flexible model which can accommodate various types of distributions should be considered as an extension of this study. **ACKNOWLEDGEMENT**

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Table 1 Parameters and effects for the young driver model

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variable | Parameter | P-  value | Marginal effects | | | |
| Possible | Non-  incapacitating | Incapacitating | Fatal |
| Driver Gender (base:  female) | -0.270 | 0.044 | 0.086 | -0.031 | -0.047 | -  0.008 |
| Pedestrian Age (base:  less than 16) |  |  |  |  |  |  |
| 16-24 | 0.484 | 0.015 | -0.143 | 0.031 | 0.093 | 0.019 |
| 25-44 | 0.358 | 0.060 | -0.110 | 0.032 | 0.066 | 0.012 |
| 45-64 | 0.339 | 0.077 | -0.104 | 0.029 | 0.063 | 0.012 |
| Pedestrian Gender  (base: female) | 0.232 | 0.100 | -0.074 | 0.026 | 0.041 | 0.007 |
| Vehicle Type (base:  passenger car) |  |  |  |  |  |  |
| Other vehicle | 0.872 | 0.086 | -0.200 | -0.059 | 0.194 | 0.065 |
| Number of Vehicle  (base: single-vehicle) | -0.400 | 0.100 | 0.142 | -0.076 | -0.058 | -  0.008 |
| Point of First Contact  (base: front) |  |  |  |  |  |  |
| Back quarter  panel | 0.863 | 0.038 | -0.200 | -0.053 | 0.191 | 0.062 |
| Other | -0.451 | 0.049 | 0.161 | -0.088 | -0.064 | - |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  | 0.009 |
| Traffic Type (base:  one-way) | -0.412 | 0.037 | 0.123 | -0.028 | -0.079 | -  0.016 |
| Divided Type (base:  undivided) | 0.446 | 0.005 | -0.145 | 0.057 | 0.076 | 0.013 |
| Road Condition (base:  good) | 0.510 | 0.075 | -0.149 | 0.028 | 0.100 | 0.021 |
| Traffic Control Device  Condition (base: bad) | 0.418 | 0.046 | -0.148 | 0.079 | 0.061 | 0.008 |
| Weather Condition  (base: clear) | -0.612 | 0.040 | 0.219 | -0.122 | -0.085 | -  0.012 |
| Hit-and-run Related  (base: no) | 0.637 | 0.011 | -0.168 | -0.000 | 0.134 | 0.034 |
| *τ*1 | -0.154 |  |  |  |  |  |
| *τ*2 | 1.655 |  |  |  |  |  |
| *τ*3 | 2.779 |  |  |  |  |  |

*Note: l*(0) = -315.083, *l*(*β*) = -240.512, *ρ*2 = 0.237.

Table 2 Parameters and effects for the middle-aged driver model

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variable | Parameter | P-  value | Marginal effects | | | |
| Possible | Non-  incapacitating | Incapacitating | Fatal |
| Pedestrian Age (base:  less than 16) |  |  |  |  |  |  |
| 16-24 | 0.325 | 0.011 | -0.107 | 0.017 | 0.082 | 0.008 |
| 25-44 | 0.350 | 0.003 | -0.118 | 0.023 | 0.086 | 0.009 |
| 45-64 | 0.380 | 0.001 | -0.127 | 0.024 | 0.094 | 0.009 |
| ≥65 | 0.397 | 0.003 | -0.127 | 0.014 | 0.102 | 0.011 |
| Vehicle Type (base:  passenger car) |  |  |  |  |  |  |
| Bus-and-van | 0.219 | 0.028 | -0.073 | 0.014 | 0.054 | 0.005 |
| Truck | 0.333 | 0.089 | -0.106 | 0.010 | 0.086 | 0.010 |
| Number of Vehicle  (base: single-vehicle) | 0.271 | 0.042 | -0.089 | 0.013 | 0.069 | 0.007 |
| Point of First Contact  (base: front) |  |  |  |  |  |  |
| Side Center | -0.271 | 0.044 | 0.099 | -0.039 | -0.056 | -0.004 |
| Other | -0.339 | <0.001 | 0.125 | -0.050 | -0.070 | -0.005 |
| Roadway Geometry (base: straight and  level) |  |  |  |  |  |  |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Curve and Grade | -0.715 | 0.024 | 0.276 | -0.153 | -0.117 | -0.006 |
| Traffic Type (base:  one-way) | 0.151 | 0.058 | -0.054 | 0.017 | 0.034 | 0.003 |
| Weather Condition  (base: clear) | -0.211 | 0.008 | 0.076 | -0.026 | -0.046 | -0.004 |
| *τ*1 | -0.122 |  |  |  |  |  |
| *τ*2 | 1.344 |  |  |  |  |  |
| *τ*3 | 2.838 |  |  |  |  |  |

*Note: l*(0) = -1338.357, *l*(*β*) = -1060.462, *ρ*2 = 0.208.

Table 3 Parameters and effects for the older driver model

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variable | Parameter | P-  value | Marginal effects | | | |
| Possible | Non-  incapacitating | Incapacitating | Fatal |
| Driver License State  (base: out-of-state) | 0.308 | 0.014 | -0.117 | 0.061 | 0.051 | 0.005 |
| Pedestrian Age (base:  less than 16) |  |  |  |  |  |  |
| 45-64 | 0.307 | <0.001 | -0.113 | 0.050 | 0.057 | 0.006 |
| 65 and above | - | - | - | - | - | - |
| Vehicle Type (base:  passenger car) |  |  |  |  |  |  |
| Bus-and-van | 0.233 | 0.076 | -0.086 | 0.037 | 0.044 | 0.005 |
| Vehicle Maneuver Prior  to the Crash (base: through) |  |  |  |  |  |  |
| Left turn | -0.180 | 0.044 | 0.069 | -0.037 | -0.029 | -  0.003 |
| Right turn | -0.172 | 0.098 | 0.066 | -0.037 | -0.027 | -  0.002 |
| Point of First Contact  (base: front) |  |  |  |  |  |  |
| Side center | -0.637 | 0.004 | 0.250 | -0.170 | -0.075 | - |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  | 0.005 |
| Intersection Type (base:  signalized) | -0.359 | 0.003 | 0.137 | -0.073 | -0.059 | -  0.005 |
| Divided Type (base:  undivided) | 0.180 | 0.014 | -0.068 | 0.034 | 0.031 | 0.003 |
| Lighting Condition  (base: daylight) |  |  |  |  |  |  |
| Darkness with  lighting | 0.170 | 0.034 | -0.064 | 0.031 | 0.030 | 0.003 |
| Weather Condition  (base: clear) | -0.217 | 0.016 | 0.084 | -0.047 | -0.034 | -  0.003 |
| Hit-and-run Related  (base: no) | 0.172 | 0.052 | -0.066 | 0.035 | 0.028 | 0.003 |
| *τ*1 | -0.086 |  |  |  |  |  |
| *τ*2 | 1.460 |  |  |  |  |  |
| *τ*3 | 2.772 |  |  |  |  |  |

*Note: l*(0) = -1010.561, *l*(*β*) = -804.581, *ρ*2 = 0.204.

Table 4 Independent variables of the proposed models

|  |  |  |
| --- | --- | --- |
| Models | Independent variables | |
| Common | Additional |
| Young driver | Pedestrian Age Vehicle Type Point of First Contact Weather Condition | Driver Gender, Pedestrian Gender, Number of Vehicle, Traffic Type, Divided Type, Road Condition, Traffic Control Device Condition, Hit-  and-run Related |
| Middle-aged driver | Number of Vehicle, Roadway Geometry, Traffic  Type |
| Older driver | Driver License State, Vehicle Maneuver Prior to the  Crash, Intersection Type, Divided Type, Lighting Condition, Hit-and-run Related |