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DEVELOPMENT OF A PARTIAL PROPORTIONAL ODDS MODEL FOR PEDESTRIAN INJURY SEVERITY AT INTERSECTIONS

ABSTRACT

Pedestrian injury in crashes at intersections often results from complex interaction among various factors. The factor identification is a critical task for understanding the causes and improving the pedestrian safety. A total of 2,614 crash records at signalized and non-signalized intersections were applied. A Partial Proportional Odds (PPO) model was developed to examine the factors influencing Pedestrian Injury Severity (PIS) because it can accommodate the ordered response nature of injury severity. An elasticity analysis was conducted to quantify the marginal effects of contributing factors on the likelihood of PIS. For signalized intersections, seven explanatory variables significantly affect the likelihood of PIS, in which five explanatory variables violate the Proportional Odds Assumption (POA). Local driver, truck, holiday, clear weather, and hit-and-run lead to higher likelihood of severer PIS. For non-signalized intersections, six explanatory variables were found significant to the PIS, in which three explanatory variables violate the POA. Young and adult drivers, senior pedestrian, bus/van, divided road, holiday, and darkness tend to increase the likelihood of severer PIS. The vehicles of large size and heavy weight (e.g. truck, bus/van) are significant factors to the PIS at both signalized and non-signalized intersections. The proposed PPO model has demonstrated its effectiveness in identifying the effects of contributing factors on the PIS.

KEY WORDS

pedestrian; safety; crash injury severity; intersection; partial proportional odds model;

1. INTRODUCTION

Though considerable advances have been made in vehicle and roadway design, pedestrians are still the most vulnerable road users under the concern of the transportation authorities and researchers. The data of the Fatality Analysis Reporting System (FARS) maintained by the National Highway Traffic Safety Administration (NHTSA) showed that one in every six traffic-related fatalities involved pedestrians in the US in 2016 [1]. The number of fatal crashes decreased by 8% and the total number of fatalities decreased by 9.21% in 2016 compared to those in 2007. However, the total number of pedestrian fatalities increased by 27.41% from 4,699 in 2007 to 5,987 in 2016, which indicates that one pedestrian was killed every 88 minutes. A pedestrian crash defined here is a motor vehicle crash involving at least one pedestrian injured or killed, who travels on foot (i.e. walking, running, or jogging).

Intersections are critical locations threatening the pedestrian safety. On one hand, the risk to the pedestrian is directly caused by the conflict of right-of-way between pedestrians and vehicles (through and turning). On the other hand, the complex design and environment of an intersection result from roadway geometry, lane configurations, presence of traffic control devices and markings, the density of buildings and the volume of other road users, which might result in the drivers overlooking the potential risks. Therefore, when vehicles approach an intersection the drivers must be attentive with respect to the conflicting traffic and pedestrians. Some studies investigated the impact of intersections on the driver's visual scanning, decision-making, and performance [2, 3]. The complexity of an intersection was found to significantly affect the crash risk, which is of particular concern among pedestrians. Therefore, the pedestrian safety at intersections has been regarded as a priority goal of traffic authorities.

Since pedestrian(s) involved in a crash in general would suffer more severe consequences, which may result in injury and even cost a life, identifying the factors contributing to the likelihood of Pedestrian Injury Severity (PIS) would be the first step to recognize the appropriate countermeasures and then to assess the pedestrian safety. Some previous studies investigated various factors associated with pedestrian fatality. Oh et al. [4] developed a probabilistic model and found that the collision speed, pedestrian age, and vehicle type were significant factors. Sarkar et al. [5] also applied a logistics model to assess the PIS and found that the pedestrian(s) under the age of 15 or older than 55 at non-signalized intersections in rain, and buses/trucks would increase the likelihood of a fatal crash. As the studies discussed above focused on two PIS levels: fatal injury and non-fatal injury, some recent studies [6, 7] focused on investigating the significance of factors to the likelihood of various PIS levels.

To further explore the potential factors affecting Crash Injury Severity (CIS), some unordered and ordered response models were developed. The most conventionally used unordered response model to predict the CIS is the Multinomial Logit (MNL) model [8]. The limitation of the MNL model is that it not only does not account for the ordinal nature of CIS, but it could also fulfil the assumption of the Independence of Irrelevant Alternatives (IIA). As the ordered levels inherent to CIS are usually ignored by unordered response model, the ordered response models were commonly applied, which can be classified into Ordered Logit (OL) and Ordered Probit (OP) models. The OL models were preferred to analyse the CIS by some researchers [9]. Relatively few studies applied the OL models to assess the PIS. Obeng & Rokonuzzaman [10] analysed the PIS based on vehicle-pedestrian crashes that occurred at signalized intersections, and the results showed that the vehicle type, gender, land-use, speed limit, traffic volume, presence of sidewalk and visual-obstruction are significant factors. Some studies also applied the OP models to explore the significance of the factors on the PIS. Zajac and Ivan [11] evaluated the effect of road and area type features on the PIS in rural Connecticut. Jang et al. [12] found that the pedestrian characteristics, environmental characteristics, and vehicle type significantly affected PIS. Pei and Fu [13] investigated the likelihood of PIS at unsignalised intersections and found that adverse weather, sideswiping with pedestrian on poor condition of road surface, winter night without illumination, and the interaction of traffic signs/markings and the third-class highway would increase the likelihood of serious injuries and fatalities.

To investigate the performance of OL and OP models, some studies investigated the relationship between potential factors and injury severity [14, 15]. It was found that if the random term has a logistics distribution, the OL modelling approach shall be applied. However, if the random term follows a normal distribution, the OP modelling approach is suggested. Albeit both the OL and OP models consider the inherent hierarchical nature of CIS, those models assume that the estimated parameters of explanatory variables are constant across different injury severity levels. The Proportional Odds Assumption (POA) deals with the estimated parameters in the OL and OP models in the same way except for cut-off points. Considering that POA may be violated by one or few explanatory variables, Peterson and Harrel [16] proposed a Partial Proportional Odds (PPO) modelling approach, where POA can be a relaxed subject to special conditions for some explanatory variables when it is not justified and allows non-proportional odds for some explanatory variables.

Some studies evaluated the performance of the PPO models for analysing the CIS. Wang et al. [17] found that the PPO model outperformed the OP model when they analysed the effects of ramp-lane arrangements on the CIS. Wang et al. [18] found the PPO model outperformed the OL model for analysing CIS at signalized intersections. Zhao et al. [19] applied the OL and PPO models to determine the influence factors of the CIS on highway tunnels and concluded that the developed PPO model performs more realistically. Liu and Fan [20] found that the PPO model took a more parsimonious consideration than both the OL and MNL models in the analysis of head-on CIS. Other studies also applied the PPO for examining the CIS [6, 21].

The review discussed above suggests that the PPO model is a sound approach for CIS analysis, and no study yet has adopted it to analyse the contributing factors towards the likelihood of the PIS at intersections. In addition, some new potential factors such as the driver license and vehicle manoeuvre prior to the crash, have not been considered in previous studies.

2. METHODOLOGY

The main purpose of this section is to develop a PPO model and to assess the potential factors (i.e. driver and pedestrian attributes, vehicle characteristics, intersection environment features, and crash characteristics) affecting the likelihood of the PIS at signalized and non-signalized intersections. The elasticity analysis of explanatory variables to various PIS levels has also been conducted.

2.1 PPO model

An OL model formulated as *Equation 1* was applied to determine the significance of each potential factor on the PIS.

$$P(Y_i > j) = \frac{\exp(\alpha_j + \mathbf{X}_i\boldsymbol{\beta})}{1 + \exp(\alpha_j + \mathbf{X}_i\boldsymbol{\beta})},\quad j = 1,\dots,J-1, i = 1,\dots,N \tag{1}$$

where Y_i is the PIS of crash i; J is the number of the PIS levels (i.e. $J = 4$ here); $\mathbf{X}_i$ is a vector of explanatory variables associated with crash i; N is the number of crashes; $\boldsymbol{\beta}$ is a vector of the corresponding parameter estimations associated with $\mathbf{X}_i$; and α_j is the cut-off point for the j-th cumulative logit.

The estimation of β and α_j is the key step for developing the OL model. The parameters in β are assumed constant across the PIS levels, while α_j varies. According to the POA, each explanatory variable may affect the likelihood of higher PIS in either a positive or a negative way. Therefore, POA can be appropriately handled with the Generalized Ordered Logit (GLO) model as formulated in *Equation 2*.

$$P(Y_i > j) = \frac{\exp(\alpha_j + \mathbf{X}_i\boldsymbol{\beta}_j)}{1 + \exp(\alpha_j + \mathbf{X}_i\boldsymbol{\beta}_j)} \tag{2}$$

where $\boldsymbol{\beta}_j$ is a vector of estimated parameters for PIS level j.

However, the POA might not violate by all explanatory variables. Justification can be made from *Equation 1* to fulfil the POA, but others violate it. Thus, a general PPO model can be formulated as *Equation 3*.

$$P(Y_i > j) = \frac{\exp[\alpha_j + (\mathbf{X}_i\boldsymbol{\beta} + \mathbf{T}_i\boldsymbol{\gamma}_j)]}{1 + \exp[\alpha_j + (\mathbf{X}_i\boldsymbol{\beta} + \mathbf{T}_i\boldsymbol{\gamma}_j)]} \tag{3}$$

where $\mathbf{X}_i$ is a p×1 vector associated with crash i on the full set of p explanatory variables; $\boldsymbol{\beta}$ is a p×1 vector of the corresponding parameter estimations associated with the p variables in $\mathbf{X}_i$ (the elements of β are denoted by β_l, l=1,…, p); $\mathbf{T}_i$ is a q×1 vector associated with crash i on the subset of q explanatory variables which the POA has not fully fulfilled ($q \le p$); $\boldsymbol{\gamma}_j$ is a q×1 vector of the estimated parameters associated with covariates in $\mathbf{T}_i$; and the elements of $\boldsymbol{\gamma}_j$ are denoted by γ_{jl}, l=1, …,q.

In *Equation 3*, since $\mathbf{r}_1$=0, the model uses only (α_1+$\mathbf{X}_i\boldsymbol{\beta}$) to estimate the odds ratio associated with the dichotomization of Y into Y=1 versus Y>1, whereas the estimation of the odds ratios associated with the remaining cumulative probabilities involve incrementing (α_j+$\mathbf{X}_i\boldsymbol{\beta}$) by $\mathbf{T}_i\gamma_j$. Therefore, each explanatory variable fulfilled with POA has one β parameter, and each explanatory variable unfulfilled with POA has one β parameter and (J-2) γ parameters. There are (J-1) α parameters reflecting the cut-off points, and the vector of $\boldsymbol{\gamma}$ represents the deviations from proportionality. This gamma parameterization combines all the features of the OL model while allowing for non-proportionality in some or all variables in the model [22].

For variable X_{im} where non-proportional odds exist in relation to the response, (α_j-$\beta_m X_{im}$) is incremented by regression coefficient $\gamma_{jm}T_{im}$, which is the effect associated with each j-th cumulative logit, having accounted for all the covariates. The number of the PIS is divided into four levels in this paper, then three parameters of α and two parameters of γ are estimated. In the first cumulative logit, γ_1 is equal to 0, so the first cut-off point is based on (α_1-$\beta_m X_{1m}$). In the second cumulative logit, γ_2 is estimated, then the second cut-off point is based on $(\alpha_2-(\beta_m+\gamma_{2m})X_{2m})$. Similarly, in the third cumulative logit, γ_3 is estimated, then the third cut-off point is based on $(\alpha_3-(\beta_m+\gamma_{3m})X_{3m})$.

It is worth noting that if γ_j is a zero vector, *Equation 3* is an OL model. If $\boldsymbol{\beta}$ is a zero vector, *Equation 3* is a GLO model.

The PPO model in this study can be fitted using a user-written program *gologit2*, which is optimized by the maximum likelihood method [22]. One should be very cautious in interpreting the coefficients of intermediate categories, because the sign of β does not always determine the direction of the effect of the intermediate outcomes [23, 24].

Likelihood ratio (L_R) as formulated in *Equation 4* is a typical measure of model performance which indicates whether a global null hypothesis for a specific model should be rejected.

$$L_R = 1 - \frac{l(\beta)}{l(0)} \tag{4}$$

where $l(\beta)$ represents a log-likelihood value of the developed model at convergence with parameter vector $\boldsymbol{\beta}$, and $l(0)$ is the log-likelihood value of the developed model only including interception. If $L_R > 0.2$, the developed PPO model is sufficient to explain and/or predict the PIS [21].

2.2 Elasticity analysis

To assess the effect of explanatory variables on the PIS, an elasticity analysis is conducted. Elasticity here is quantified as the ratio of the percentage change in one explanatory variable to the percentage change in the dependent variable, when the former variable has a causal influence on the latter. A more precise definition is given in terms of differential calculus as formulated in *Equation 5*, where $P(Y_i>j)$ represents the probability of PIS level j and X_{ijl} represents the l-th explanatory variable associated with PIS level j for crash i. Thus,

$$E_{X_{ijl}}^{P(Y_i>j)} = \frac{\partial P(Y_i>j)}{\partial X_{ijl}} \cdot \frac{X_{ijl}}{P(Y_i>j)},\ l=1,\ldots,p \tag{5}$$

where l is l-th explanatory variable, p is the number of explanatory variables.

Equation 5 is computed from the partial derivative for each crash and it is useful in measuring the responsiveness of $P(Y_i>j)$ to changes in another causative variable (e.g. X_{ijl}).

If the l-th explanatory variable is a binary variable (i.e. 0 or 1), the classic elasticity measure cannot be applied since the probability function is not differentiable. To address this issue, the pseudo-elasticity can be applied to quantify the marginal effect of a binary variable [21]. Thus,

$$E_{X_{ijl}}^{P(Y_i>j)} = \frac{P(Y_i>j)[X_{ijl}=1] - P(Y_i>j)[X_{ijl}=0]}{P(Y_i>j)[X_{ijl}=0]},\quad l=1,\ldots,p \tag{6}$$

which is used to measure the change of the PIS probability [e.g. $P(Y_i>j)$] in percentage when the dummy variable (e.g. X_{ijl}) is switched from 0 to 1 or vice versa. *Equation 6* can be applied to determine the pseudo elasticity for each crash i with injury severity j. With that the average pseudo-elasticity for all crashes with PIS level j can be calculated.

3. DATA

The crash data for this study are police-reported crashes involving at least one motor vehicle and one injured pedestrian from the Cook County, Illinois, USA. After excluding the records with missing variables, the crash data in this study included a total of 2,614 crash records occurring at signalized (1,677 records) and non-signalized (937 records) intersections over a period of two years (2011-2012).

The PIS defined here is an ordered-response discrete variable which can be classified into Level 1: fatal injury, Level 2: incapacitating injury, Level 3: non-incapacitating injury, and Level 4: possible injury. Fatal injury means at least one pedestrian died within 30 days after a crash has taken place. Incapacitating injury means the most injured pedestrian in a crash needs the assistance of medical rescue and cannot walk or normally continue subsequent activities. Non-incapacitating injury means the most injured pedestrian in a crash has a visible injury, such as laceration, contusions, lump on the head, bloody nose, etc. Finally, possible injury means that at least one pedestrian has been injured in the crash without evident injury and can walk away from the crash scene by themselves.

According to the definition of the PIS, the distribution of the PIS at signalized and non-signalized intersections is presented in *Table 1*. There are about 16.5% and 11.9% pedestrians associated with fatal/incapacitating injury at signalized and non-signalized intersections, respectively, which indicate a certain percentage of pedestrians who are likely to be seriously or fatally injured.

Table 1 – Distribution of crash records over various PIS levels

PIS level	Summary statics: crash frequency (percentage)	
	Signalized intersection	Non-signalized intersection
1: Fatal injury	14 (0.8%)	10 (1.1%)
2: Incapacitating injury	263 (15.7%)	101 (10.8%)
3: Non-incapacitating injury	862 (51.4%)	488 (52.1%)
4: Possible injury	538 (32.1%)	338 (36.1%)
Total	1,677 (100%)	937 (100%)

Table 2 – Summary statistics of explanatory variables

Variable	Signalized intersection	Non-signalized intersection
Driver age	"16-24" = 188, "25-44" = 511, "45-64" = 371, "> 64" = 607	"16-24" = 123, "25-44" = 223, "45-64" = 176, "> 64" = 415
Driver gender	Female = 488, Male = 1,189	Female = 296, Male = 641
Driver license	Non-local driver=572, Local driver=1,105	Non-local driver=20, Local driver=917
Alcohol usage	No = 1,662, Yes = 15	No = 415, Yes = 522
Driver vision	Bad = 185, Good = 1,492	Bad = 97, Good = 840
Aggressiveness	No = 702, Yes = 975	No = 439, Yes = 498
Pedestrian age	"< 16" = 145, "16-24" = 337, "25-44" = 539, "45-64" =456, "> 64" = 200	"< 16" = 154, "16-24" = 198, "25-44" = 248, "45-64" =231, "> 64" = 200
Pedestrian gender	Female = 910, Male = 767	Female = 530, Male = 407
Vehicle type	Passenger car = 1,191, Bus/van = 164, Truck = 36, Other = 286	Passenger car = 820, Bus/van = 74, Truck = 14, Other = 29
No. of vehicles	Single-vehicle=1,589, Multi-vehicle = 88	Single-vehicle = 889, Multi-vehicle = 48
Manoeuvre prior to the crash	Straight ahead = 476, Left-turn = 689, Right-turn = 308, Other = 204	Straight ahead = 418, Left-turn = 190, Right-turn = 76, Other = 253
Road contour	Straight/level = 1,604, Straight/grade = 37, Curve/level =4, Curve/grade = 32	Straight/level = 913, Straight/grade = 17, Curve/level =5, Curve/grade = 2
Traffic type	One-way = 257, Two-way = 1,420	One-way = 281, Two-way = 656
Divided type	Undivided = 740, Divided = 937	Undivided = 588, Divided = 349
Road surface	Dry = 1,275, Wet = 402	Dry = 751, Wet = 186
Day	Working day = 1,312, Holiday = 365	Working day = 732, Holiday = 205
Lighting condition	Daylight =1,073, Darkness with lighting = 445, Darkness w/o lighting = 159	Daylight = 646, Darkness with lighting = 213, Darkness w/o lighting = 78
Area type	Urban=1,480, Suburban=126, Rural=71	Urban = 820, Suburban = 76, Rural = 41
Weather	Clear = 1,336, Adverse = 341	Clear = 760, Adverse = 177
Hit-and-run	No = 1,223, Yes = 454	No = 658, Yes = 279

After investigating the data in each category, twenty explanatory variables were identified. The detailed statistics of explanatory variables is summarized in *Table 2*.

4. RESULTS AND DISCUSSION

The explanatory variables listed in *Table 2* affecting the PIS were examined using the PPO model corresponding to the crashes at signalized and non-signalized intersections individually. The model parameters are optimized by the maximum likelihood method, and the significance level applied for selecting explanatory variables is 0.05 (i.e. 95% confidence interval).

4.1 Signalized intersections

The parameters and the associated explanatory variables of the PPO model for signalized intersections are illustrated in *Table 3*. In *Table 3*, L_R is 0.204 indicating that the model outcome is significant to explain the likelihood of the PIS for crashes that occurred at signalized intersections. Seven explanatory

Table 3 – Model parameters for signalized intersections

	Explanatory variable	Parameter	P-value
β	Driver license	-1.897	0.014
	Vehicle type (base: other)		
	Truck	-2.645	0.001
	Vehicle manoeuvre prior to the crash (base: other)		
	Left-turn	0.204	0.046
	Right-turn	0.403	0.002
	Road contour (base: curve/grade)		
	Straight/level	1.786	0.027
	Day	-1.070	0.043
	Weather	0.427	<0.001
	Hit-and-run	-2.017	0.003
γ^2	Driver license	1.343	0.046
	Vehicle type (base: other)		
	Truck	1.911	0.012
	Road contour (base: curve/grade)		
	Straight/level	-2.239	0.002
	Day	1.004	0.049
	Hit-and-run	1.784	0.006
γ^3	Driver license	1.801	0.021
	Vehicle type (base: other)		
	Truck	2.171	0.012
	Road contour (base: curve/grade)		
	Straight/level	-2.432	0.003
	Day	1.252	0.019
	Hit-and-run	2.147	0.002
α	α_1	5.511	<0.001
	α_2	2.301	<0.001
	α_3	-0.395	0.045
	L_R	0.204	

Table 4 – Elasticity analysis of the PPO model for signalized intersections

Variable definition	PIS = 1	PIS = 2	PIS = 3	PIS = 4
Driver license state (base: non-local drivers)	0.007	0.063	-0.049	-0.021
Vehicle type (base: other)				
Truck	0.054	0.070	-0.030	-0.094
Vehicle manoeuvre prior to the crash (base: other)				
Left-turn	-0.001	-0.026	-0.017	0.044
Right-turn	-0.002	-0.048	-0.041	0.091
Road contour (base: curve/grade)				
Straight and /level	-0.021	0.073	0.099	-0.151
Day (base: working day)	0.007	0.002	-0.049	0.040
Weather (base: clear)	-0.002	-0.051	-0.043	0.096
Hit-and-run (base: no)	0.017	0.016	-0.061	0.028

variables, including driver license, vehicle type (truck), vehicle manoeuvre prior to the crash (left-turn, right-turn), road contour (straight/level), day, weather, and hit-and-run, are significant, while five of them (i.e. driver license, vehicle type (truck), road contour (straight/grade), day, and hit-and-run) violate the POA. Meanwhile, *Table 4* summarizes the average pseudo-elasticity of explanatory variables on the probabilities of the PIS.

Variables fulfilling the POA at signalized intersections

For "Vehicle manoeuvre prior to the crash", other (e.g. starting in traffic, slow/stop, and backing) is the base category. There is no significant difference between straight ahead and other. However, both left-turn- and right-turn are found significant, and the associated parameter values are 0.204 and 0.403, respectively. By comparing with left-turn, other manoeuvres, such as starting in traffic, slow/stop, and backing, have a 0.1%, 2.6%, and 1.7% greater probability of involving fatal, incapacitating, and non-incapacitating injuries, respectively. While comparing with right-turn, other manoeuvres, such as starting in traffic, slow/stop, and backing, have a 0.2%, 4.8%, and 4.1% greater probability of involving fatal, incapacitating, and non-incapacitating injuries, respectively. The presumable reason could be related to the lag time and proper turning speed in reacting pedestrians crossing the street. This finding is in line with the previous studies conducted by Roudsari et al. [25].

For "Weather", clear weather is selected as the base category. Adverse weather is found significant to the PIS and the parameter value is 0.427. The probability of pedestrian possible injury increases by 9.6% occurring under adverse weather compared to that with clear weather. The presumable reason is that the adverse weather increases the risk of pedestrian injury, but the drivers and pedestrians are relatively more cautious while crossing the street which may then result in minor pedestrian injury. This finding seems consistent with the results suggested by Kim et al. [26].

Variables violating the POA at signalized intersections

For explanatory variable "Driver license", non-local driver is the base. The estimated parameter value of the first panel (i.e. PIS = 1 vs. PIS = 2 + 3 + 4) is -1.897, and the estimated parameter of the second panel (i.e. PIS = 1 + 2 vs. PIS = 3 + 4) is -0.554 (= -1.897 + 1.343), and the estimated parameter of the third panel (i.e. PIS = 1 + 2 + 3 vs. PIS = 4) is -0.096 (= -1.897 + 1.801). The probabilities of pedestrian fatal and incapacitating injury increase by 0.7% and 6.3%, respectively, for local against non-local drivers. We would expect that the local drivers have better knowledge of the roadway and intersection environment than the non-local drivers. However, we found that the familiarity with the roadway and intersection environment will not reduce the risk of being involved in pedestrian crash for the local drivers. We may even speculate that the local drivers might unconsciously drive more aggressively than the non-local drivers. This result is consistent with what was found by Kemel [27].

For "Vehicle type", other (e.g. motorcycle, motor-driven cycle, and snowmobile) is selected as the reference category. There is no significant difference between passenger car and other, just as bus/van and other. However, truck is found significant to the PIS, and it violates the POA. The estimated parameter of the first panel is -2.645, and the estimated parameter of the second panel is -0.734, and the estimated parameter of the third panel is -0.474. The probabilities of pedestrian fatal and incapacitating injury increase by 5.4% and 7%, respectively, for truck drivers compared with other drivers. Since a truck is of larger size, greater weight, and longer stopping distance compared to other vehicles, the results are not surprising. Pedestrians involved in a crash with heavy vehicles are the most vulnerable ones and very likely to suffer from the severest injuries. Similar findings were also discussed by Zajac and Ivan [11] and Kim et al. [26].

For "Road contour", curve/grade is the base category. There is no significant difference between straight/grade and curve/grade, and also for curve/level and curve/grade. It was found that straight/level is not only significant to the PIS but also violates the POA. The estimated parameter values of the first panel, the second panel and the third panel are 1.786, -0.453, and -0.646, respectively. The probabilities of pedestrian incapacitating and non-incapacitating injuries increase by 7.3% and 9.9%, respectively, at straight/level signalized intersections compared with that of curve/grade ones, but the probabilities of fatal injury decrease by 2.1%. The result seems contradictory, and it should be thoroughly investigated as more data are available.

For “Day”, working day is the base. It was found that Holidays is not only significant to the PIS, but also violates the POA. The estimated parameters of the first, the second and the third panel are -1.070, -0.066, and 0.182, respectively. The potential crashes with possible injury were more likely to occur on “holiday” than on a “working day” (i.e. by 4%). The more frequent and relaxing outside activities on holidays might increase the likelihood of crash occurrence which usually results in minor pedestrian injury.

For “Hit-and-run”, “No” is selected as the base. It was found that Hit-and-run is not only significant to the PIS but also violates the POA. The estimated parameter values of the first panel, the second panel and the third panel are -2.017, -0.233, and 0.130, respectively. It was also found that hit-and-run crashes have 1.7%, and 1.6% greater probability of involving fatal, and incapacitating injuries, respectively. The presumable reason is that the pedestrian who is struck in a hit-and-run crash will not be treated immediately due to the driver fleeing the scene of the crash. Therefore, higher probabilities of injury and fatality can be expected. This result is consistent with the findings concluded by Aidoo et al. [28].

4.2 Non-signalized intersections

The parameter estimation result at non-signalized intersections is presented in *Table 5*. As shown in *Table 5*, L_R is 0.205 which indicates that the developed model is sufficient to explain and predict the likelihood of the PIS at non-signalized intersections. Six explanatory variables, including driver age (16-24, 25-44), pedestrian age (<16), vehicle type (bus/van), divided type, day, and lighting condition, have significant associations with the pedestrian injury severity, while three of them (i.e., driver age (16-24), vehicle type (bus/van), and day) violate the

Table 5 – Model parameter for non-signalized intersections

	Explanatory variable	Parameter	P-value
β	Driver age (base: >64)		
	16-24	-1.757	0.041
	25-44	-0.342	0.026
	Pedestrian age (base: >64)		
	<16	0.650	<0.001
	Vehicle type (base: others)		
	Bus/van	-2.408	<0.001
	Divided type	-0.391	0.003
	Day	-2.390	0.002
	Lighting condition (base: darkness w/o lighting)		
	Daylight	0.445	0.050
	Darkness with lighting	0.556	0.034
γ^2	Driver age (base: >64)		
	16-24	1.923	0.030
	Vehicle type (base: others)		
	Bus/van	1.484	0.006
	Day	2.217	0.003
γ^3	Driver age (base: >64)		
	16-24	1.410	0.036
	Vehicle type (base: others)		
	Bus/van	2.094	0.001
	Day	2.709	<0.001
α	α_1	6.057	<0.001
	α_2	1.859	<0.001
	α_3	-0.909	0.045
	L_R	0.205	

Table 6 – Elasticity analysis of the PPO model for non-signalized intersections

Variable Definition	PIS = 1	PIS = 2	PIS = 3	PIS = 4
Driver age (base: >64)				
16-24	0.016	-0.032	0.092	-0.076
25-44	0.002	0.034	0.040	-0.076
Pedestrian age (base: >64)				
<16	-0.002	-0.052	-0.101	0.155
Vehicle type (base: others)				
Bus/van	0.035	0.087	-0.053	-0.069
Divided type (base: undivided)	0.002	0.038	0.048	-0.088
Day (base: working days)	0.025	-0.007	-0.093	0.075
Lighting condition (base: darkness w/o lighting)				
Daylight	-0.002	-0.045	-0.052	0.099
Darkness with lighting	-0.002	-0.047	-0.083	0.132

POA. *Table 6* summarizes the average pseudo-elasticity of explanatory variables on the probabilities of the PIS.

Variables fulfilling the POA at non-signalized intersections

For "Pedestrian age", "65 and above" is the reference category. There is no significant difference between pedestrian age of "25-44" and "65 and above", just as "45-64" and "65 and above". But the pedestrian age of "less than 16" is found significant and the estimated parameter is 0.650. By comparing with young pedestrians (less than 16 years of age), the elder pedestrians (65 years and above) have a 0.2%, 5.2%, and 10.1% greater probability of getting involved in a fatal, incapacitating, and non-incapacitating injury, respectively. The possible reason is that the relative worse physical condition of the elder pedestrians would result in higher risk of involving injury during the crash. The result is consistent with the previous studies [29, 30].

For "Divided type", undivided road is selected as the base category. Divided type is found significant and the estimated parameter value is -0.391. By comparing with undivided road, a divided road has a 0.2%, 3.8%, and 4.8% greater probability of involving fatal, incapacitating, and non-incapacitating injuries, respectively. A possible explanation could be that the divided road is a multi-lane road, and it has a greater number of lanes than the undivided road, which results in the pedestrians having to cross a wider road thus increasing the risk at intersection, especially at non-signalized intersection. This result is consistent with the findings suggested by Olszewski et al. [30].

For "Lighting condition", darkness without lighting is the base category. Both daylight and darkness with lighting are found significant. The values of estimated parameters are 0.445 and 0.556 for daylight and darkness with lighting, respectively. By comparing with daylight, darkness without lighting has a 0.2% and 4.5% greater probability of involving fatal and incapacitating injuries, respectively. While comparing with darkness with lighting, darkness without lighting has a 0.2% and 4.7% greater probability of involving fatal and incapacitating injuries, respectively. The presumable reason is that darkness without lighting at non-signalized intersections offers bad vision for drivers which leads to longer reacting time for drivers to brake or take fewer effective actions to avoid an emergency situation. This result is consistent with the previous findings [26, 31].

Variables violating the POA at non-signalized intersections

For explanatory variable "Driver age", "65 and above" is defined as the reference category. There is no significant difference between "45-64" and "65 and above". The driver age of "16-24" is not only found significant associated with the PIS, but also violates the POA. The estimated parameters of the first panel, the second panel and the third panels are -1.757, 0.166, and -0.347, respectively. In addition, the driver age of "25-44" is found significant and the estimated parameter is -0.342. In comparison to the older group (65 years old and above), the driver age of "16-24" group has 1.6 % higher probability of involving pedestrian fatal injury, and the driver age of "25-44" group has 0.2% greater probability of suffering pedestrian fatal injury at non-signalized intersection. The probability of pedestrian possible injury decreases by 7.6% for the driver age of "65 and above" group compared with that of "16-24" group. Meanwhile, the probability of pedestrian possible injury also decreases by 7.6% for the driver age of "65 and above" group compared with that of "25-44" group. A possible explanation could be that the driving behaviour is becoming more and more cautious with the increase in the driver age. Elder drivers will follow more cautious and conservative driving behaviours at a low and safe speed. However, both young and adult drivers will drive in a more ambitious manner due to their good visibility and reaction capacity. This result is consistent with the findings of Pour-Rouholamin and Zhou [6].

For "Vehicle type", other is the base category. There is no significant difference between passenger car and other, just as truck and other. However, bus/van is found significantly associated with the PIS, and it violates the POA. The estimated parameters of the first panel, the second panel, and the third panel are -2.408, -0.924, and -0.314, respectively. The probabilities of pedestrian fatal and incapacitating injuries increase by 3.5% and 8.7%, respectively, for bus/van drivers compared with other drivers. The presumable reason is that the pedestrians have a higher possibility of sustaining fatal or severe injury by larger vehicles, like bus-and-van because of their heavy weight and longer braking time. This result is consistent with the findings summarized by Zajac and Ivan [11].

For "Day", working days is the reference category. Holidays is not only found significant associated with the PIS, but also violates the POA. The estimated parameters of the first panel, the second panel and the third panel are -2.390, -0.173, and 0.319, respectively. The probability of pedestrian possible injury increases by 7.5% for holidays compared with the working days. This variation trend is similar to signalized intersections, which shows that there is no difference in the crash day between signalized and non-signalized intersections.

4.3 Comparative analysis

To further understand the difference between the significant factors affecting the PIS at signalized and non-signalized intersections, a comparative analysis was conducted. *Table 7* shows a summary of explanatory variables for the PPO models for signalized and non-signalized intersections.

Table 7 shows that the common explanatory variables, including Vehicle type and Day, are significant factors for the PIS of crashes at both signalized and non-signalized intersections. It is worth noting that those variables are unrelated to the characteristics of drivers and pedestrians according to the data applied to this study. For Vehicle type, truck is found significantly associated with the PIS at signalized intersections, but bus/van is found significant to the PIS of crashes at non-signalized intersections. Since truck or bus/van are hard to manoeuvre and heavier than other types of vehicles, the pedestrian will suffer severer injury. "Day" has the same impact on the PIS at both signalized and non-signalized intersections.

Five explanatory variables, including the driver license, vehicle manoeuvre prior to the crash, road contour, weather, and hit-and-run, have an exclusive effect on the PIS for signalized intersections. While, four explanatory variables, including the driver age, pedestrian age, divided type, and lighting condition, have an exclusive effect on the PIS for non-signalized intersections.

Table 7 – Explanatory variables of the PPO model for signalized and non-signalized intersections

Model	Explanatory variable	
	Common	Additional
Signalized intersection	Vehicle type, Day	Driver license, Vehicle manoeuvre prior to the crash, Road contour, Weather, Hit-and-run
Non-signalized intersection	Vehicle type, Day	Driver age, Pedestrian age, Divided type, Lighting condition

5. CONCLUSION

Considering the limitations of the POA, the PPO model has been developed to investigate the PIS at signalized and non-signalized intersections based on crashes that occurred in the Cook County, Illinois, in the US. For signalized intersections, seven explanatory variables, including the driver license, vehicle type (truck), vehicle manoeuvre prior to the crash (left-turn, right-turn), road contour (straight/level), day, weather, and hit-and-run, show significant associations with the PIS, and five of them (i.e. driver license, vehicle type (truck), road contour (straight/level), day, and hit-and-run) violate the POA. Local drivers, truck, holiday, clear weather, and hit-and-run are associated with severer PIS (e.g. fatal and incapacitating injury) at signalized intersections. For non-signalized intersections, six explanatory variables, including the driver age (16-24, 25-44), pedestrian age (<16), vehicle type (bus/van), divided type, day, and lighting condition, show significant association with the PIS, and three of them (i.e. driver age (16-24), vehicle type (bus/van), and day) violate the POA. Young and adult drivers, senior pedestrians, bus/van, divided road, holiday, and darkness without lighting are associated with severer PIS (e.g. fatal and incapacitating injuries) at non-signalized intersections. Furthermore, only two variables were identified to be common at both signalized and non-signalized intersections, including vehicle type and day.

This study investigates the effects of factors affecting the PIS at signalized and non-signalized intersections, respectively, which would identify significant countermeasures and be applied to improve the traffic safety and the PIS at intersections. In general, these countermeasures can be classified into education, engineering, and enforcement fields.

In the field of education, training for young/adult drivers and senior pedestrians have shown promising outcomes. The drivers, especially young and adult drivers, should be educated to fully understand and respect the pedestrian and crosswalk laws through systematic education and outreach programs. The emphasis of the education program should focus on the driving behaviour of making the turning at intersections to keep the right-of-way of the pedestrians. And with the increasing percentage of the senior population in the US, the education of senior pedestrians' self-protection awareness should also be given special attention, because of the higher injury severities at non-signalized intersections due to unsafe street-crossing decisions.

In addition, the senior pedestrians' high proportional severe injuries at intersections suggest that the existing road crossing environment and the solutions cannot meet the safety requirements of the ageing society, which indicates that the engineering improvements at intersections should be highly recommended. For instance, adding signal control system at non-signalized intersections with high pedestrian or vehicle flow can be implemented to remind the drivers to slow down at intersections. Similarly, a pedestrian involved in a crash at a non-signalized intersection in dark environment usually suffers severer injuries, so that the lighting infrastructure and reflection signs should be installed to improve the pedestrian visibility at intersections. And installing appropriate traffic calming techniques, such as speed bumps, would also be efficient for reducing the PIS.

Although educational campaigns have been successfully applied to change the drivers' attitudes and reduce the crash severities, risky driving behaviours such as hit-and-run should be efficiently prevented by administrative and legal measures rather than by education programs only. Therefore, it is strongly suggested that more traffic enforcement efforts, such as the presence of more police patrols, should be implemented to reduce the likelihood of hit-and-run behaviours.

The traffic volume of each approach at intersections (AADT at 15-minute intervals) is not considered as a parameter in the study due to the data unavailability, which could be an extension of this study. Another extension is to analyse the PIS by types of intersection (e.g. T intersections, 4-leg and more than 4-leg intersections), design of intersection (e.g. markings, warning signs, flash lights, sight distance, etc.) and the presence of pedestrian-activated crosswalk system. Additionally, the Mixed Logit (ML) model could be promoted in the follow-up studies due to considering the individual differences among injury severities in different crashes.

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摘要

交叉口行人交通事故常常是多种因素相互作用的结果。识别这些影响因素是理解交叉口行人交通事故原因和改善行人安全的关键。　研究收集了发生在信号控制和无信号控制交叉口的*2,614*起交通事故数据,采用部分优势比模型研究行人受伤严重程度的影响因素，以适应受伤严重程度的有序反应本质，并采用弹性分析方法定量研究各影响因素对行人受伤严重程度发生概率的边际影响。对于信号控制交叉口，*7*个解释变量对行人受伤严重程度有显著影响，其中*5*个解释变量违反了比例优势假设。本地驾驶人、卡车、节假日、晴天和肇事逃逸都可能导致更严重的行人受伤严重程度。对于无信号控制交叉口，6个解释变量对行人受伤严重程度有显著影响，其中*3*个解释变量违反了比例优势假设。年轻和成年的驾驶人、老年行人、公交车/大巴车、分隔的道路、节假日和夜晚都可能导致更严重的行人受伤严重程度。那些体积大、质量重的车辆（如卡车、公交车/大巴车）是信号控制和无信号控制交叉口行人受伤严重程度的显著影响因素。本文提出的部分优势比模型在确定行人受伤严重程度影响因素的影响具有良好的效果。

关键词

行人；安全；事故受伤严重程度；
交叉口；部分优势比模型

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