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Investigating the risk factors associated with pedestrian injury severity in Illinois



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# a r t i c l e i n f o

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# a b s t r a c t

*Introduction:* Pedestrians are known as the most vulnerable road users, which means their needs and safety re- quire speciﬁc attention in strategic plans. Given the fact that pedestrians are more prone to higher injury severity levels compared to other road users, this study aims to investigate the risk factors associated with various levels of injury severity that pedestrians experience in Illinois. *Method:* Ordered-response models are used to analyze single-vehicle, single-pedestrian crash data from 2010 to 2013 in Illinois. As a measure of net change in the effect of signiﬁcant variables, average direct pseudo-elasticities are calculated that can be further used to prioritize safe- ty countermeasures. A model comparison using AIC and BIC is also provided to compare the performance of the studied ordered-response models. *Results:* The results recognized many variables associated with severe injuries: older pedestrians (more than 65 years old), pedestrians not wearing contrasting clothing, adult drivers (16–24), drunk drivers, time of day (20:00 to 05:00), divided highways, multilane highways, darkness, and heavy vehicles. On the other hand, crossing the street at crosswalks, older drivers (more than 65 years old), urban areas, and presence of trafﬁc control devices (signal and sign) are associated with decreased probability of severe injuries. *Conclusions and practical applications:* The comparison between three proposed ordered-response models shows that the partial proportional odds (PPO) model outperforms the conventional ordered (proportional odds—PO) model and generalized ordered logit model (GOLM). Based on the ﬁndings, stricter rules to address DUI driving is suggested. Educational programs need to focus on older pedestrians given the increasing number of older peo- ple in Illinois in the upcoming years. Pedestrians should be educated to use pedestrian crosswalks and contrasting clothing at night. In terms of engineering countermeasures, installation of crosswalks where pedestrian activity is high seems a promising practice.

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1. Introduction

Despite considerable advances in the vehicle industry and safety of occupants, the safety of pedestrians as the most vulnerable road users is yet a major concern. Overall road fatalities as well as driver and pedestrian fatalities were calculated by running a query on the Fatality Analysis Reporting System (FARS) database spanning from 2004 to 2013—a 10-year time interval ([NHTSA, 2015](#_bookmark27)). Within this time period, the total number of trafﬁc fatalities decreased by 23.6% in 2013 compared to 2004 (an average decrease of 2.9% per year), and the total driver fatalities decreased by 28.9%. However, the total number of pedestrian fatalities increased by 15.9% (from 4028 fatalities in 2004 to 4668 fatalities in 2013). It should also be noted that the share of driver fatalities dropped from 54.1% in 2004 to 50.3% in 2013, while these numbers for pedestrians are 9.4% and 14.3%, respectively.

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Speciﬁcally related to Illinois, the share of pedestrians increased from 11.5% in 2004 to 12.6% in 2013, while the total number of trafﬁc fatalities dropped by 26.9%.

With the number of cars and total vehicle miles traveled (VMT) increasing in the upcoming years, the need for more robust safety inter- ventions based on actual crash data analysis is warranted. In this study, the Illinois pedestrian crash data (those caused by single vehicles with- out any passengers colliding with single pedestrians) were analyzed using ordered-response models to consider the ordered nature of crash severity. The main objective is for the results of this study to provide meaningful insight into pedestrian crash severity for the state of Illinois. Addressing this particular consideration as the main objective to save lives by suggesting safety measures, this study also compares performances of three different ordered-response models.

The rest of this paper is organized as follows: A review of prior research on pedestrian injury severity is provided in [Section 2](#_bookmark3). The da- tabase used for analysis along with descriptive statistics of the possible risk factors are presented in [Section 3](#_bookmark4). Ordered-response models (i.e., conventional ordered logit, generalized ordered logit model, and partial proportional odd model), their formulations, and their

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applications as well as pseudo-elasticity are discussed in [Section 4](#_bookmark5). In [Section 5](#_bookmark7), the proposed model is applied to the crash data set and pa- rameter estimates, and average direct pseudo-elasticities for each injury severity level are calculated. Finally, [Section 6](#_bookmark14) concludes this paper and provides safety recommendations.

1. Prior research

Several studies in the past have analyzed pedestrian crashes and the level of severity incurred by these road users and identiﬁed the role of possible risk factors as well as appropriate countermeasures using a va- riety of statistical methods ([Roudsari, Mock, & Kaufman, 2005; Nasar &](#_bookmark22) [Troyer, 2013; Al-Shammari, Bendak, & Al-Gadhi, 2009; Tarko & Azam,](#_bookmark22) [2011; Sarkar, Tay, & Hunt, 2011; Strandroth, Rizzi, Sternlund, Lie, &](#_bookmark22) [Tingvall, 2011; Oh, Kang, Kim, & Kim, 2005; Mohamed, Saunier,](#_bookmark22) [Miranda-Moreno, & Ukkusuri, 2013; Ulfarsson, Kim, & Booth, 2010;](#_bookmark22) [Eluru, Bhat, & Hensher, 2008; Cinnamon, Schuurman, & Hameed,](#_bookmark22) [2011; Gårder, 2004; Moudon, Lin, Jiao, Hurvitz, & Reeves, 2011; Tay,](#_bookmark22) [Choi, Kattan, & Khan, 2011](#_bookmark22)).

[Zajac and Ivan (2003)](#_bookmark22) used the ordered probit model to study the in-

jury severity of pedestrian crashes on rural two-lane highways without any type of control (stop sign or trafﬁc signal) in Connecticut from 1989 to 1998. The focus of their study was on roadway and area features that could possibly affect the injury severity outcome of pedestrians. They found that variables such as clear roadway width, vehicle type, driver alcohol involvement, and being older than 65 years could signiﬁcantly inﬂuence pedestrian injury severity. Furthermore, signiﬁcantly different injury severities were found in compact residential areas compared to low-density residential areas, with the latter experiencing higher pedestrian injury severity.

In another pioneering study, [Lee and Abdel-Aty (2005)](#_bookmark23) used police- reported pedestrian-involved crashes in Florida over 4 years (from 1999 to 2002) to examine the possible correlation between various factors and pedestrian crashes using the log-linear model. They discovered that middle-aged (26–64 years old) male drivers and pedestrians are more likely to be involved in such crashes. In terms of vehicle type, pas- senger cars were associated with more pedestrian crashes than any other types. Other than these factors, undivided roads, higher number of lanes, and intoxicated drivers driving during nighttime were over- represented when it comes to pedestrian crashes. A severity analysis was also conducted in this study using the ordered probit model to ﬁgure out the effect of different factors on injuries and fatalities of pe- destrians. It showed that older and intoxicated pedestrians, speeding vehicles, reduced visibility for both pedestrians and drivers, and larger vehicles are likely to worsen the injury of crashes.

[Kim, Ulfarsson, Shankar, and Kim (2008)](#_bookmark22) used a heteroskedastic

generalized extreme value model to explore the injury severity of pe- destrians in crashes. Providing a better ﬁt than the multinomial logit model, the developed model highlighted the effect of several factors in increasing the probability of fatalities. Notable factors include intoxicat- ed driving, which increases the probability of fatal pedestrian injury by

2.7 times, and darkness (with or without streetlights), which poses 2–4 times greater risk of fatalities to pedestrians. Factors such as increasing driver age, driving during PM peak hours, and crossing at crosswalks were associated with a lower risk of fatalities for pedestrians.

[Kim, Brunner, and Yamashita (2008)](#_bookmark22) analyzed a comprehensive da- tabase of police-reported pedestrian-involved accidents from 2002 to 2005 in Hawaii using logistic regression techniques. Their ﬁndings were categorized into three groups. At ﬁrst they provided a general scheme of the pedestrian crashes. This analysis was followed by com- paring at-fault drivers with at-fault pedestrians. Finally, their study was completed by providing a deeper understanding of a variety of human, temporal, and environmental factors inﬂuencing pedestrian in- juries and the at-fault party (pedestrian or driver) during a pedestrian– vehicle crash.

[Kim, Ulfarsson, Shankar, and Mannering (2010)](#_bookmark22) used a mixed logit model to explore the effect of several potential determinants on the in- jury severity of pedestrians while accounting for possible unobserved heterogeneity that is believed to be of importance, particularly in pedes- trian injury severity analysis due to unobserved pedestrian-related factors (e.g., physical health, strength, behavior). Using pedestrian crashes from 1997 to 2000 in North Carolina, their ﬁndings unveiled several signiﬁcant factors affecting the likelihood of fatal injuries for pe- destrians. For instance, darkness without streetlights, trucks, freeways, and speeding were found to increase the probability of fatalities by 400%, 370%, 330%, and 360%, respectively.

Several studies have tried to divide the existing data sets into sub- data sets either based on the geographical location or the type of facility. For example, [Aziz, Ukkusuri, and Hasan (2013)](#_bookmark15) analyzed pedestrian– vehicle crash data from 2002 to 2006 in New York City and divided it into ﬁve boroughs: the Bronx, Brooklyn, Manhattan, Queens, and Staten Island. They determined different risk factors for each of the studied boroughs by developing mixed logit models and using the likelihood ratio statistic to justify the need for separate models. Accordingly, different sets of countermeasures were suggested to be considered for these boroughs in the New York City.

Using the same approach, [Islam and Jones (2014)](#_bookmark22) investigated a 5-year pedestrian–vehicle crash data set with pedestrians being at fault and developed two separate injury severity models for rural and urban areas. Their study clearly emphasized the differences between the signiﬁcant variables based on the type of setting. For example, crashes occurring during weekends were found to signiﬁcantly affect the severity of pedestrian injuries in urban areas, while this parameter was not found to be signiﬁcant in rural areas. Furthermore, only three variables were identiﬁed to be common in both rural and urban areas, including dark light condition, 2-lane roadways, and pedestrians younger than 12 years.

[Haleem, Alluri, and Gan (2015)](#_bookmark22) hypothesized that there might be

differences in the injury outcome of pedestrians at signalized and non- signalized intersections. Two separate models for these intersections were developed by exploring this assumption and considering several factors, including geometric predictors, trafﬁc variables, road user characteristics, and environmental predictors. According to the results, differences among risk factors for these two intersections were identi- ﬁed. For example, while average annual daily trafﬁc (AADT) signiﬁcant- ly affected the injury severity of pedestrians at signalized intersections, this parameter was not found to be signiﬁcant for non-signalized intersection.

According to the aforementioned literature review and to the author's knowledge, there is no study to address pedestrian injury se- verity in Illinois. Furthermore, the studies that use partial proportional odds (PPO) model for pedestrian injury severity analysis are rare and none has compared this model with other ordered-response models. This study uses a PPO model as an ordered-response model to explore the effect of various risk factors of the pedestrian injury severity in Illi- nois as the main objective. Also, the study provides appropriate safety countermeasures and recommendations to improve the safety of pedes- trians based on the analysis results.

1. Data

The data used in this study are based on the police-reported road- way crash data in Illinois, which is accessible through the Illinois crash database. The database is separated into three different text ﬁles (crash, person, and vehicle), including a wide range of various charac- teristics and information regarding each of these categories. The crash ﬁle includes information such as type of collision (pedestrian, ﬁxed ob- ject, etc.), temporal distributions of the crash (e.g., weekend/weekday, season, time of day), number of vehicles and persons involved, number of injuries for each severity level, type of trafﬁc control device, city class in terms of the population, environmental condition (e.g., lighting,

weather), and roadway characteristics (e.g., curvature, classiﬁcation). The person ﬁle incorporates information about the type of person in- volved (e.g., driver, pedestrian), age of the person involved in the crash at the time of the crash, person's gender, person's condition (e.g., normal, under the inﬂuence), person's injury level, location of the crash (e.g., in roadway, in crosswalk), and pedestrian visibility at- tributed to the safety equipment they used at the time of the crash (e.g., contrasting clothing). The vehicle ﬁle also encompasses informa- tion about the number of occupants in the vehicle, vehicle type, vehicle defects, and vehicle age at the time of the crash. Crash records in these three ﬁles can be linked together using the variable Illinois Case Number (ICN) in all three ﬁles, which is unique to every single crash. The crash severity in these ﬁles is in the scale of KABCO, in which K is a fatal injury, A is an incapacitating injury, B is a non-incapacitating injury, C is a possible injury, and O is a property damage only (PDO).

Based on the Illinois crash database, 19,361 pedestrian–vehicle

crashes occurred on Illinois roadways from 2010 to 2013 (a 4-year peri- od). However, only those crashes that involve just one vehicle without any extra passengers other than the driver and one pedestrian were considered. The reason why this study is limited to crashes involving one driver and one passenger is to offset the possible effects that extra passengers have on a driver's behavior and that accompanying persons have on a pedestrian's behavior. Furthermore, observations with incom- plete or overly missing data were omitted from the ﬁnal data set. These considerations led to a ﬁnal sample of 14,538 crashes (more than 75% of total pedestrian–vehicle crashes) within this time period in Illinois that involved the same number of drivers and pedestrians. A review of our

intoxicants. The type of setting was also found to substantially differ among severity levels: urban areas show a higher correlation to no/possible injury crashes (31.9%), while severe crashes are more prevalent in rural areas (37.4%). This might be reﬂective of speeding and lack of timely emergency response in case of a crash that can, in turn, increase the pedestrian injury severity.

1. Methodology

As mentioned in the previous section, in this study the dependent variable (pedestrian injury severity) represents an ordered outcome (ascending from no/possible injury to severe injury). Therefore, an ordered-response model is appropriate to analyze the data. Three ordered-response models that have previously been used in the litera- ture will be introduced in the following sub-sections, including conven- tional ordered logit (proportional odds—PO) model, generalized ordered logit model (GOLM), and partial proportional odds (PPO) model.

* 1. *Ordered logit (proportional odds) model*

Let *j* denotes the crash severity level (1 = no/possible injury; 2 = minor injury; 3 = severe injury), and *J* represents the number of severity levels (here *J* = 3), then the standard form of the conventional ordered logit or PO model is as follows:

data showed that in all pedestrian–vehicle crashes in our database, the

Pr *Y j*

exp(*Xi*β−α *j*)

*j* 1 2 … *J*−1 1

pedestrian incurs the highest injury severity and determines the injury ð *i* N Þ ¼ 1 þ exp(*X* β−α )] ¼ ; ; ; ð Þ

severity of the crash. The distribution (frequency; percentage) of the pe- *i j*

destrian injury severity across all levels is as follows: no injury (343;

2.4%), C-injury (4220; 29.0%), B-injury (7213; 49.6%), A-injury (2431;

16.7%), and fatal (331; 2.3%). As can be seen, the number of observations in the no injury and fatality categories are so few that they may cause computational problems. Hence, the no injury category was combined with C-injury crashes making the “no/possible injury” category. A- injury and fatal categories were also joined together forming “severe in- jury” category to ensure sufﬁcient crash records for the new categories. The ﬁnal three injury severity categories are now as follows: no/possible injury; minor injury (representing non-incapacitating injury); and severe injury.

The explanatory variables used in this study are cross-tabulated with the three-level injury severity and are presented in [Table 1](#_bookmark6). This kind of cross-tabulation provides a more detailed representation of the vari- ables and their distribution and enables a better understanding of the developed model and its results presented in the next sections. It should be noted that the Other/Unknown categories for the variables are not presented in this table; therefore, the total number for some variables under the columns may not sum up to the corresponding injury severity frequency.

When looking at [Table 1](#_bookmark6), a few points are worthy of mentioning. An increasing trend in the severe injuries is observable as the pedestrians grow older. The same trend is also obvious in no/possible injuries. However, the percentage of minor injured pedestrians decreases as

where *Yi* represents the observed severity for crash *i*, *Xi* is a vector of explanatory variables, β is a vector of the corresponding parameter estimations, and α*j* is the cutoff term for the threshold in the model. The goal in this model is to estimate β's and α*j*'s values ([Long, 1997](#_bookmark25)). As can be seen in the PO model, the parameter estimate β is assumed to be constant across each severity level for each variable, and the only difference between *J* − 1 regression lines is the parameter α. This causes regression lines that are parallel to each other and is called par- allel regression assumption or proportional odds assumption ([Boes &](#_bookmark16) [Winkelmann, 2006](#_bookmark16)). According to this assumption, each variable may either increase or decrease the likelihood of higher injury severities, while, in reality, this assumption is often violated. The GOLM can appropriately handle this shortcoming, which is explained next.

* 1. *Generalized ordered logit model (GOLM)*

As mentioned previously, and in order to overcome the issue arose from parallel line assumption, the GOLM model is developed that relaxes this assumption for all the variables in the model. This model can be formulated as follows:

the pedestrians grow older. This might be due to physiological differ-

ences and behavioral patterns of various pedestrian age-groups. In

Prð*Yi* N

exp *X* β −α

1 þ exp(*X* β −α )]

( )*i jjj*Þ ¼

*j* ¼ 1; 2; …; *J*−1 ð2Þ

terms of the location, crashes that happen at crosswalks generally tend to be less severe compared to those that happen in roadways. The drivers' awareness of pedestrian presence at crosswalks can explain this difference. Older drivers (more than 65 years old) are less involved in pedestrian severe crashes mainly due to their driving behav- iors, as they are more cautious and experienced compared to other age- groups ([Joanisse, Gagnon, & Voloaca, 2012](#_bookmark22)). Intoxicated drivers are disproportionally over-represented compared to those under normal condition in severe crashes (58.6% vs. 19.8%), which is obviously related to their impaired driving behaviors due to being under the inﬂuence of

*i j j*

where β*j* is the vector of parameter estimations that, despite the PO model, do vary across equations for different crash severities ([Williams, 2006](#_bookmark22)). The other factors were previously introduced. Another possibility, in terms of proportional odds assumption, is that this assumption might not be violated by all the variables of the model. In other words, there might be just one or more variables in the model that necessitate considering varying β's across those severity levels. This situation caused the emergence of the PPO model.

Table 1

Descriptive statistics of the explanatory variables.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Explanatory variable | No/possible injury | Minor injury |  | Severe injury |  | Total |
| Total | 4563 | 7213 |  | 2762 |  | 14,538 |
| Pedestrian variables |  |  |  |  |  |  |
| Age |  |  |  |  |  |  |
| Child (less than 15) | 704 28.9% | 1349 | 55.3% | 386 | 15.8% | 2439 |
| Adult (16–24) | 911 31.4% | 1491 | 51.3% | 503 | 17.3% | 2905 |
| Middle-age (25–64) | 2374 31.7% | 3616 | 48.3% | 1504 | 20.1% | 7494 |
| Old (more than 65) | 574 33.8% | 757 | 44.5% | 369 | 21.7% | 1700 |
| Gender |  |  |  |  |  |  |
| Male | 2382 30.6% | 3837 | 49.2% | 1577 | 20.2% | 7796 |
| Female | 2119 32.0% | 3326 | 50.2% | 1180 | 17.8% | 6625 |
| Visibility |  |  |  |  |  |  |
| No contrasting clothing | 2654 28.1% | 4849 | 51.4% | 1940 | 20.5% | 9443 |
| Contrasting clothing | 658 29.2% | 1129 | 50.2% | 464 | 20.6% | 2251 |
| Driver variables Age |  |  |  |  |  |  |
| Adult (less than 24) | 390 24.7% | 808 | 51.1% | 383 | 24.2% | 1581 |
| Middle-age (25–64) | 2191 30.2% | 3549 | 49.0% | 1505 | 20.8% | 7245 |
| Old (more than 65) | 1982 34.7% | 2856 | 50.0% | 874 | 15.3% | 5712 |
| Gender |  |  |  |  |  |  |
| Male | 1971 30.0% | 3197 | 48.6% | 1408 | 21.4% | 6576 |
| Female | 1293 30.7% | 2112 | 50.1% | 812 | 19.3% | 4217 |
| Condition |  |  |  |  |  |  |
| Normal | 2810 29.8% | 4752 | 50.4% | 1864 | 19.8% | 9426 |
| DUI | 46 13.0% | 100 | 28.3% | 207 | 58.6% | 353 |
| Temporal variables Year |  |  |  |  |  |  |
| 2010 | 1113 32.7% | 1653 | 48.6% | 638 | 18.7% | 3404 |
| 2011 | 1221 32.5% | 1825 | 48.6% | 712 | 18.9% | 3758 |
| 2012 | 1151 31.3% | 1821 | 49.5% | 709 | 19.3% | 3681 |
| 2013 | 1078 29.2% | 1914 | 51.8% | 703 | 19.0% | 3695 |
| Season |  |  |  |  |  |  |
| Spring | 1124 31.2% | 1852 | 51.4% | 625 | 17.4% | 3601 |
| Summer | 1052 29.4% | 1827 | 51.1% | 699 | 19.5% | 3578 |
| Autumn | 1261 32.2% | 1897 | 48.4% | 758 | 19.4% | 3916 |
| Winter | 1126 32.7% | 1637 | 47.5% | 680 | 19.8% | 3443 |
| Day of week |  |  |  |  |  |  |
| Weekday | 3583 31.7% | 5614 | 49.7% | 2100 | 18.6% | 11,297 |
| Weekend | 980 30.2% | 1599 | 49.3% | 662 | 20.4% | 3241 |
| Time of day |  |  |  |  |  |  |
| 10:00–15:59 | 1510 34.1% | 2191 | 49.4% | 730 | 16.5% | 4431 |
| 16:00–19:59 | 1370 31.3% | 2189 | 50.0% | 819 | 18.7% | 4378 |
| 20:00–5:59 | 907 27.2% | 1628 | 48.9% | 797 | 23.9% | 3332 |
| 6:00–9:59 | 776 32.4% | 1205 | 50.3% | 416 | 17.4% | 2397 |
| Environmental variables City Population and class |  |  |  |  |  |  |
| Less than 10,000 | 156 23.5% | 317 | 47.8% | 190 | 28.7% | 663 |
| 10,000 to 25,000 | 315 23.6% | 647 | 48.5% | 373 | 27.9% | 1335 |
| 25,000 to 50,000 | 369 26.8% | 655 | 47.6% | 353 | 25.6% | 1377 |
| More than 50,000 | 578 27.5% | 1022 | 48.6% | 505 | 24.0% | 2105 |
| Chicago | 3055 35.4% | 4392 | 50.9% | 1188 | 13.8% | 8635 |
| Type of setting |  |  |  |  |  |  |
| Urban | 4459 31.9% | 6956 | 49.8% | 2546 | 18.2% | 13,961 |
| Rural | 104 18.0% | 257 | 44.5% | 216 | 37.4% | 577 |
| Type of trafﬁcway |  |  |  |  |  |  |
| Not divided | 1544 30.8% | 2496 | 49.9% | 966 | 19.3% | 5006 |
| Divided—ﬂush median | 1604 29.7% | 2702 | 50.1% | 1089 | 20.2% | 5395 |
| Divided—raised median | 281 25.6% | 543 | 49.5% | 274 | 25.0% | 1098 |
| One way | 478 36.5% | 626 | 47.8% | 205 | 15.7% | 1309 |
| Number of lanes |  |  |  |  |  |  |
| One-lane | 577 35.4% | 822 | 50.5% | 229 | 14.1% | 1628 |
| Two-lane | 1634 31.0% | 2645 | 50.2% | 986 | 18.7% | 5265 |
| Multilane | 1148 28.3% | 1959 | 48.4% | 944 | 23.3% | 4051 |
| Location |  |  |  |  |  |  |
| In roadway | 2125 29.1% | 3569 | 48.9% | 1612 | 22.1% | 7306 |
| In crosswalk | 1652 33.0% | 2591 | 51.7% | 766 | 15.3% | 5009 |
| Trafﬁc control device |  |  |  |  |  |  |
| No control | 2011 29.8% | 3353 | 49.7% | 1388 | 20.6% | 6752 |
| Trafﬁc signal | 1510 32.4% | 2366 | 50.8% | 785 | 16.8% | 4661 |
| Trafﬁc sign | 704 35.4% | 1005 | 50.6% | 278 | 14.0% | 1987 |
| Weather condition |  |  |  |  |  |  |
| Clean | 3609 30.9% | 5786 | 49.6% | 2276 | 19.5% | 11,671 |
| Rain | 538 30.5% | 888 | 50.3% | 338 | 19.2% | 1764 |
| Snow/slush | 147 38.1% | 186 | 48.2% | 53 | 13.7% | 386 |
| Surface condition |  |  |  |  |  |  |
| Dry | 3392 30.7% | 5498 | 49.8% | 2151 | 19.5% | 11,041 |

Table 1 (*continued*)

Explanatory variable No/possible injury Minor injury Severe injury Total

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Wet | 747 | 30.0% | 1251 | 50.2% | 492 | 19.8% | 2490 |
| Snow/slush | 143 | 38.1% | 176 | 46.9% | 56 | 14.9% | 375 |
| Lighting condition |  |  |  |  |  |  |  |
| Daylight | 2961 | 33.1% | 4523 | 50.5% | 1468 | 16.4% | 8952 |
| Dawn/dusk | 195 | 31.5% | 319 | 51.5% | 106 | 17.1% | 620 |
| Dark—not lit | 344 | 24.4% | 642 | 45.5% | 425 | 30.1% | 1411 |
| Dark—lit | 983 | 29.4% | 1625 | 48.7% | 730 | 21.9% | 3338 |
| Vehicle variables Type |  |  |  |  |  |  |  |
| Passenger car | 3045 | 32.0% | 4821 | 50.7% | 1645 | 17.3% | 9511 |
| Pickup | 232 | 26.5% | 416 | 47.4% | 229 | 26.1% | 877 |
| Van/minivan | 338 | 31.5% | 509 | 47.4% | 226 | 21.1% | 1073 |
| SUV | 477 | 29.5% | 778 | 48.1% | 363 | 22.4% | 1618 |
| Bus | 30 | 13.5% | 103 | 46.2% | 90 | 40.4% | 223 |
| Truck | 80 | 28.8% | 127 | 45.7% | 71 | 25.5% | 278 |

* 1. *Partial proportional odds (PPO) model*

The PPO model accounts for the fact that not every single variable might violate the parallel line assumption and is speciﬁed as:

where Pr(*Yi* N *j*) is deﬁned by Eqs. [(1), (2), or (3)](#_bookmark5) (whichever applies) and *xjnk* is the *k*th explanatory variable associated with the injury sever-

ity *j* for the individual crash *n*. The average direct pseudo-elasticities can then be calculated for each injury severity to represent the whole data

set ([Kim et al., 2010](#_bookmark22)).

Prð*Y* N *j*Þ ¼ exp(*X*1*i*β1 þ *X*2*i*β2−α *j*)

*j* ¼ 1; 2; …; *J*−1 ð3Þ

*i* 1 þ exp(*X*1*i*β1 þ *X*2*i*β2−α *j*)]

where β1 and β2 are the vectors of parameter estimations that does and does not violate the parallel line assumption, respectively. The corre- sponding vector of independent variables that does and does not violate this assumption are *X*1*i* and *X*2*i*, respectively. This model, which has pre- viously been employed by some studies ([Kaplan & Prato, 2012; Quddus,](#_bookmark22) [Wang, & Ison, 2010; Wang & Abdel-Aty, 2008](#_bookmark22)), can be ﬁtted by gologit2 program in Stata ([Williams, 2006](#_bookmark22)).

Before ﬁtting the model, it is necessary to test whether this assump- tion is valid. There are several tests to examine the validity of this as- sumption, such as the likelihood ratio test, the Wolfe Gould test, and the Brant test. In this study, a Brant test ([Brant, 1990](#_bookmark17)) is proposed prior to model estimation in order to determine whether any of the var- iables violate this assumption. This test estimates the coefﬁcients for the underlying binary logistic regressions and examines the equality of all parameter estimates for individual variables using a chi-square statistic. If the test statistic is statistically signiﬁcant, the parallel line assumption is violated for that particular variable.

* 1. *Elasticity*

The interpretation of the results from ordered-response models needs more attention as the sign and value of the β's do not always de- termine the direction and magnitude of the effect of the intermediate levels for crash severity ([Kaplan & Prato, 2012](#_bookmark22)). In other words, the estimated coefﬁcients are not sufﬁcient to determine the net change in the outcome probabilities given the change in the explanatory variables. The reason is that the marginal effect of one speciﬁc variable depends on the parameter estimates of all other variables in the model ([Khorashadi, Niemeier, Shankar, & Mannering, 2005](#_bookmark22)). Therefore, elasticities can be used for interpretation purposes instead of single co- efﬁcients. It should be noted that elasticities are applicable to continu- ous variables, whereas—given the nature of explanatory variables in this study that are dummy variables taking the value of 0 or 1—direct pseudo-elasticities can instead be used for each injury severity and each crash. This measure is calculated as the change in the percentage of the crash severity probability when the dummy variable is switched from 0 to 1, or vice versa. Direct pseudo-elasticity can be computed as ([Kim, Ulfarsson, Kim, & Shankar, 2013](#_bookmark22)):

1. Results and discussion

While ﬁtting any ordered-response model using the available data, the parallel line assumption needs to be checked in order to choose be- tween three abovementioned models (PO, GOLM, and PPO). In doing so, a Brant test was used, and as mentioned earlier, this test can be conduct- ed for both the entire model (including all the variables) and each single parameter separately. Using the Brant test, it was found that the parallel line assumption for some variables is violated, therefore necessitating the development of a PPO model. [Table 2](#_bookmark9) identiﬁes the signiﬁcant vari- ables that affect the injury severity of pedestrians during crashes and their corresponding parameter estimates as well as highlighting those variables violating parallel line assumption. Average direct pseudo- elasticities for these parameters across all severity levels are also calcu- lated to present the net effect of each explanatory variable on each crash severity. It is worthy of mentioning that to make a more parsimonious model, explanatory variables with a *p*-value of less than 0.10 on at least one of the thresholds were kept in the ﬁnal model. The Wald chi- square statistic of 1014.42 with 32 degrees of freedom—which is sub- stantially larger than the respective chi-square values at any reasonable conﬁdence level—demonstrates that the presence of exogenous variables signiﬁcantly improves the quality of the model's estimation.

* 1. *Model comparison*

In order to check the performance of the PO and GOLM models and make a comparison of these two models with the PPO model, the same data set was used, and PO and GOLM models were ﬁt. Two popular in- formation criteria (Akaike Information Criterion, or AIC, and Bayesian Information Criterion, or BIC) for comparing maximum likelihood models were used to this end. The AIC and BIC can be formulated as follows:

AIC ¼ −2LLFull þ 2*k* ð5Þ

BIC ¼ −2LLFull þ ln ð*N*Þ x *k* ð6Þ

where LLFull is the log-likelihood of the full model with statistically sig- niﬁcant explanatory variables, *k* is the number of parameters estimated

in the model, and *N* is the number of observation (14,538). In addition

*E* Prð*Yi* N *j*Þ

Prð*Yi* N *j*Þ Given *xjnk* ¼ 1]− Prð*Yi* N *j*Þ Given *xjnk* ¼ 0]

4Þ to comparing the model ﬁt, these two measures can account for the

*xjnk* ¼

Prð*Yi* N *j*Þ Given *xjnk* ¼ 0] ð

complexity of the model by penalizing the criterion for the number of

Table 2

Estimation results and average direct pseudo-elasticities for pedestrian injury severity.



29,400

29,300

29,298.70

29,173.83

Explanatory variable

Parameter estimates Average direct

pseudo-elasticities

29,200

29,100

29,109.61

Pedestrian variables Age

[a](#_bookmark13)

Threshold 1

[⁎⁎⁎](#_bookmark10)

Threshold 2

[⁎⁎⁎](#_bookmark10)

No/possible injury

Minor injury

Severe injury

29,000

28,900

28,800

28,904.31

28,851.74

29,006.97

Child (less than 15)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Adult (16–24)[a](#_bookmark13) | 0.006 | −0.215[⁎⁎⁎](#_bookmark10) | −0.4% | 6.7% | −17.4% |
| Old (more than 65)[a](#_bookmark13) | −0.070 | 0.184[⁎⁎⁎](#_bookmark10) | 4.8% | −8.5% | 14.9% |

Visibility

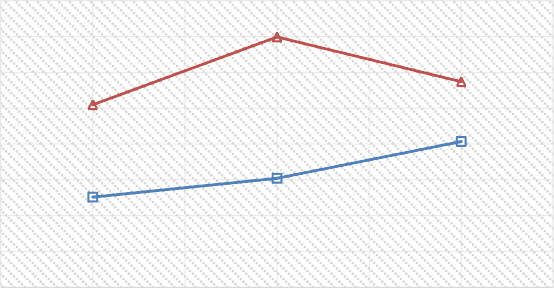
0.142

−0.268

−9.8% 14.1% −21.7%

28,700

28,600

PPO GOLM PO

No contrasting clothing

Driver variables Age

0.153[⁎⁎⁎](#_bookmark10) 0.153[⁎⁎⁎](#_bookmark10) −10.5% 1.9% 12.4%

AIC BIC

Fig. 1. AIC and BIC values for PO, GOLM, and PPO models.

Adult (less than 24) 0.172[⁎⁎⁎](#_bookmark10) 0.172[⁎⁎⁎](#_bookmark10) −11.8% 2.1% 13.9%

Old (more than 65) −0.190[⁎⁎⁎](#_bookmark10) −0.190[⁎⁎⁎](#_bookmark10) 13.0% −2.4% −15.4% Condition

DUI[a](#_bookmark13) 0.851[⁎⁎⁎](#_bookmark10) 1.430[⁎⁎⁎](#_bookmark10) −58.4% −6.9% 115.8%

Temporal variables Season

Summer 0.116[⁎⁎⁎](#_bookmark10) 0.116[⁎⁎⁎](#_bookmark10) −8.0% 1.4% 9.4% Time of day

20:00–5:59 0.103[⁎⁎](#_bookmark11) 0.103[⁎⁎](#_bookmark11) −7.1% 1.3% 8.4%

Environmental variables City population and class

Chicago[a](#_bookmark13) −0.347[⁎⁎⁎](#_bookmark10) −0.640[⁎⁎⁎](#_bookmark10) 23.8% 4.5% −51.9% Type of setting

Urban −0.397[⁎⁎⁎](#_bookmark10) −0.397[⁎⁎⁎](#_bookmark10) 27.3% −4.9% −32.2%

Type of trafﬁcway

Accordingly, child and adult pedestrians are found to be more likely to suffer from minor injuries, while, in contrast, the older pedestrians show completely reversed behaviors. More speciﬁcally, the probability of incurring severe injuries for child and adult pedestrians shows a reduction of 21.7% and 17.4%, respectively, while older pedestrians are associated with higher probability of severe injuries by 14.9%. This result is consistent with [Wier, Weintraub, Humphreys, Seto, and Bhatia](#_bookmark22) [(2009)](#_bookmark22) and [Retting, Ferguson, and McCartt (2003)](#_bookmark22).

Pedestrian gender is not presented in the ﬁnal model estimations as

this variable was not found to be signiﬁcantly related to the crash injury severity. The existing literature also shows contradicting results in

Divided—ﬂush median Divided—raised median

Number of lanes

0.131[⁎⁎⁎](#_bookmark10) 0.131[⁎⁎⁎](#_bookmark10) −9.0% 1.6% 10.6%

0.265[⁎⁎⁎](#_bookmark10) 0.265[⁎⁎⁎](#_bookmark10) −18.2% 3.3% 21.5%

terms of this variable and incurred severity. Notably, a study by [Kim,](#_bookmark22) [Ulfarsson, Shankar and Kim (2008)](#_bookmark22) showed that male pedestrians are

1.2 times more likely to be seriously injured compared to their female counterparts. [Zhu, Zhao, Coben, and Smith (2013)](#_bookmark24) also demonstrated

Multilane[a](#_bookmark13) 0.145[⁎⁎⁎](#_bookmark10) 0.275[⁎⁎⁎](#_bookmark10) −9.9% −2.1% 22.3%

Location

In crosswalk[a](#_bookmark13) 0.039[⁎](#_bookmark12) −0.152[⁎⁎⁎](#_bookmark10) −2.7% 6.3% −12.3% Trafﬁc control device

Trafﬁc signal −0.090[⁎⁎](#_bookmark11) −0.090[⁎⁎](#_bookmark11) 6.2% −1.1% −7.3%

Trafﬁc sign −0.255[⁎⁎⁎](#_bookmark10) −0.255[⁎⁎⁎](#_bookmark10) 17.5% −3.2% −20.6% Weather condition

Snow/slush −0.312[⁎⁎⁎](#_bookmark10) −0.312[⁎⁎⁎](#_bookmark10) 21.4% −3.9% −25.3%

Lighting condition

Dark—not lit[a](#_bookmark13) 0.241[⁎⁎⁎](#_bookmark10) 0.426[⁎⁎⁎](#_bookmark10) −16.5% −2.6% 34.5%

Dark—lit[a](#_bookmark13) 0.130[⁎⁎](#_bookmark11) 0.263[⁎⁎⁎](#_bookmark10) −8.9% −2.4% 21.3% Vehicle variables

Type

that the pedestrian death rate per person-year for men was 2.3 times that for women. On the other hand, [Islam and Jones (2014)](#_bookmark22) indicated that female pedestrians are 3.3% more likely to endure major injuries compared to male pedestrians.

According to the obtained results, pedestrians who wear no con- trasting clothing are more vulnerable to severe injuries compared to others who wear contrasting clothing. Speciﬁcally, the probability of no/possible injuries in these groups decreases by 10.5%, and, on the other hand, the probability of severe injuries increases by 12.4%. It is be- lieved that wearing bright or contrasting clothes makes pedestrians

more visible while no contrasting clothes render them invisible to

Pickup 0.152[⁎⁎](#_bookmark11)

[⁎⁎](#_bookmark11)

0.152[⁎⁎](#_bookmark11) −10.4% 1.9% 12.3%

drivers as the human visual system is organized to respond to contrast-

SUV 0.107

0.107[⁎⁎](#_bookmark11) −7.3% 1.3% 8.6%

Bus 0.282[⁎⁎](#_bookmark11) 0.282[⁎⁎](#_bookmark11) −19.4% 3.5% 22.9%

Constant 1.192[⁎⁎⁎](#_bookmark10) −0.971[⁎⁎⁎](#_bookmark10) – – –

Number of observations 14,538 Wald χ2 (32) 1014.42

ing objects ([Noy & Karwowski, 2004](#_bookmark22)). More importantly, during night- time conditions, a driver is more likely to see the pedestrian by reﬂection of the headlight illumination from bright/contrasting clothing

since the background is dark or there is little light ([Borzendowski,](#_bookmark18)

Log-likelihood at convergence

−14,391.869

[Rosenberg, Sewall, & Tyrrell, 2013](#_bookmark18)). This reﬂection and resulting

Log-likelihood at zero −14,928.701



⁎⁎⁎ Signiﬁcant at the 99% conﬁdence interval.

⁎⁎ Signiﬁcant at the 95% conﬁdence interval.

\* Signiﬁcant at the 90% conﬁdence interval.

a Explanatory variable violating parallel line assumption.

explanatory variables included in the model. This penalization is carried out by either 2*k* or ln(*N*)×*k* terms in the equations. Having the models ﬁt on the same data set, the model with lower AIC and BIC is considered to out- perform the others. Using Eqs. [(5) and (6)](#_bookmark8), the AIC and BIC for all three models were calculated and depicted in [Fig. 1](#_bookmark9). As can be seen in this ﬁgure, the PPO model yields lower values for both AIC and BIC compared to the other two models, providing a better ﬁt than the GOLM and PO models.

* 1. *Pedestrian variables*

Considering the speciﬁc estimation results presented in [Table 2](#_bookmark9), pe- destrian age is found to be a signiﬁcant factor for crash injury severity.

visibility provides the driver with more time to react to the pedestrian,

reducing the likelihood of severe injuries.

* 1. *Driver variables*

For this variable, drivers at the age of 25 to 64 (middle-aged) were used as the reference group. The different effect of driver age on pedes- trian crash severity is also worthy of investigation. The present study found that adult drivers (less than 24) and older drivers (65 years and above) signiﬁcantly affect the pedestrian injury severity but with con- tradictory effects. Pedestrian–vehicle crashes caused by adult drivers are more likely to result in severe crashes, whereas those caused by older drivers are more likely to result in no/possible injuries. According to [Table 1](#_bookmark6), as drivers get older, the propensities of higher injury levels decrease. This ﬁnding, which is consistent with the study by [Kim,](#_bookmark22) [Ulfarsson, Shankar and Kim (2008)](#_bookmark22), can be explained so that as the drivers grow older, they follow more cautious and conservative driving behaviors by driving at safer speeds. Part of this cautious driving

behavior is related to experience of the older drivers and their dimin- ished visual visibility that make these drivers drive at lower speeds to compensate for this issue. A study by [Wood, Lacherez, and Tyrrell](#_bookmark22) [(2014)](#_bookmark22) showed that older drivers (63 to 80 years old) are capable of recognizing pedestrians at approximately half the distance required for younger drivers (18 to 38 years old), which can be translated to less reaction time to pedestrians.

Among signiﬁcant variables in the ﬁnal model, driver condition (being under the inﬂuence) has the strongest positive effect on the crash severity outcome for pedestrians. Driving while intoxicated increases the probability of severe crashes by 115.8% compared to driving while apparently normal. As can be seen from [Table 1](#_bookmark6), 58.6% of pedestrian–vehicle crashes involved DUI driving and led to severe injuries in Illinois. In a nationwide scale, from 2005 to 2010, DUI drivers were responsible for 59.8% of pedestrian deaths ([Stimpson, Wilson, &](#_bookmark22) [Muelleman, 2013](#_bookmark22)).

* 1. *Temporal variables*

Pedestrian crashes during summer season were associated with an increase in the risk of severe injuries by 9.4%. Many studies have shown higher pedestrian activities during summer compared to other seasons and so related the risk of higher severities to the higher pedes- trian activities. According to [Table 1](#_bookmark6), however, summer is not the season with the highest pedestrian activity while it encompasses a higher percentage of minor and severe injuries compared to other seasons.

In terms of time of day, crashes occurring from 20:00 to 5:59 are found to encompass a higher probability of severe injuries (8.4%) to pe- destrians. This ﬁnding is in line with prior studies ([Aziz et al., 2013; Kim,](#_bookmark15) [Ulfarsson, Shankar and Kim, 2008](#_bookmark15)). The possible explanation for this ﬁnding is that during these time periods, trafﬁc on roadways is lower than other time intervals during the day. This condition causes pedes- trians to disobey trafﬁc laws (crossing at crosswalk) and take the risk. Combined with darkness, these factors increase the likelihood of severe injuries during this time period. [Campbell, Zegeer, Huang, and Cynecki](#_bookmark19) [(2004)](#_bookmark19) have also shown the prevalence of a higher likelihood of fatal pedestrian–vehicle crashes during the night.

* 1. *Environmental variables*

Under city population and class variable, pedestrian crashes that happened in different size cities are signiﬁcantly related to crash injury severity. Accordingly, such crashes, if happened in Chicago, tend to be less severe compared to similar crashes that happened in areas with a population of less than 10,000. Despite the fact that high population areas experience more pedestrian activities and thus more trafﬁc conﬂicts, some driving behaviors and trafﬁc patterns might explain this outcome. In other words, due to higher number of side streets, in- tersections, vehicular activities and turning movements, and pedestrian crossings in Chicago (or any other highly populated areas), drivers may be restricted to lower speeds, which decreases the probability of severe injuries in the possibility of conﬂict with a pedestrian. However, in less populated areas trafﬁc interruptions are less observed, which further allows vehicles to drive at higher speeds and intensiﬁes the probability of higher risks. Furthermore, in such areas, midblock crossings are observed to be more prevalent ([Chu, 2006](#_bookmark20)). [Zajac and Ivan (2003)](#_bookmark22) also observed higher injury severity for pedestrians in medium- and low-density areas compared to compact areas.

Urban areas compared to rural areas are associated with higher

probability of no/possible injuries (27.3%) and lower probability of severe injuries (32.2%). This difference in injury severity outcome between these two settings can be explained so that generally urban areas accommodate lower speeds compared to rural areas. Additionally, emergency medical services (EMS) are more accessible and faster in urban areas, which may reduce the severity of injuries when a crash happens. Better said, EMS confronts several challenges speciﬁc to rural

areas such as getting notiﬁed, locating, and transporting victims in a timely and effective manner ([Minge, 2013](#_bookmark26)). This ﬁnding is consistent with the previous studies ([Islam & Jones, 2014; Lee & Abdel-Aty,](#_bookmark22) [2005; Wang, Abdel-Aty, & Brady, 2006](#_bookmark22)).

The analysis of crashes shows that divided highways, regardless of the type of median (ﬂush vs. raised), generally pose a higher risk of severe injuries to pedestrians. While there are similarities between these two signiﬁcant trafﬁcway variables in terms of the change in prob- ability of injury severities, the decrease in the probability of no/possible injury and increase in the probability of severe injury is more pro- nounced for divided roads with raised medians. As for ﬂush medians, an increase of 10.6% in severe injuries is observed compared to undivid- ed roadways. However, the magnitude of the change in the probability is higher for divided highways with raised medians so that the probabil- ity of no/possible injuries when crossing such trafﬁcways decreases by 18.2%, and the probability of severe injuries increases by 21.5%. Al- though raised medians on divided highways are supposed to provide a refuge for pedestrians when crossing the trafﬁcway, these facilities generally are considered for higher speed highways that consequently worsen the injury outcome when a pedestrian is involved in the crash. When compared to one-lane roadways as the reference group, multilane roadways (more than 2 lanes) are responsible for higher probability of severe injuries (22.3%). Designing roadways with a higher number of lanes is a result of higher vehicular demands and corresponding speed, which increases the injury severity, as previously discussed. Additionally, pedestrians, and especially older ones ([Dommes, Cavallo, Dubuisson, Tournier, & Vienne, 2014](#_bookmark22)), need extra time to cross multilane roadways, which makes these vulnerable road

users more exposed to crash risk.

The location of the crash was also found to signiﬁcantly affect the type of injury. Being at crosswalks helps decrease the probability of being severely injured by 12.3%, while the probability of minor injuries is increased by 6.3%. The reason of lower probability of severe injuries might be the fact that the presence of crosswalk and related pedestrian crossing signs alerts drivers of the possible presence of the pedestrian, thus causing drivers to drive more cautiously. These pedestrian facilities also account for more pedestrian volume and activities at such location which, in turn, increase the probability of getting involved in a crash, though less severe due to the abovementioned reason. This result cor- roborates the role of pedestrian crosswalk in mitigating the sever injury issues raised from crashes and suggest considering crosswalks where it is warranted by pedestrian volume. [Kim, Ulfarsson, Shankar and Kim](#_bookmark22) [(2008)](#_bookmark22) also calculated an almost 16% reduction in the probability of fatalities when pedestrians were crossing streets at crosswalks.

The presence of trafﬁc control devices (signal and sign) can signiﬁ-

cantly and effectively reduce the probability of severe injuries. Pedestri- an volume at an intersection is one of the warrants that justify the need for trafﬁc signal installation; therefore, pedestrians will be given the right-of-way at these locations. As for the signs, drivers normally exert more caution and drive at relatively lower speeds compared to locations without any type of control devices.

Compared to clear weather, snowy weather conditions decrease the probability of severe injuries by 25.3%. The possible explanation for this effect might be the fact that not only drivers drive more cautiously dur- ing snowfall as a result of restricted visibility and driving on slippery roadways, but also pedestrian activity is lower during this weather con- dition. These factors decrease the probability of severe injuries in case of a crash. Based on the [Table 1](#_bookmark6), only 2.7% of pedestrian–vehicle crashes have occurred when it was snowing.

* 1. *Vehicle variables*

Of the vehicle type, pickup, sport utility vehicle (SUV), and bus are found to signiﬁcantly increase pedestrian injury severities in pedestri- an–vehicle crashes; however, their inﬂuence differs from each other. Regarding the net change in the probabilities, having a crash with

pickup, SUV, and bus increases the probability of being severely injured by 12.3%, 8.6%, and 22.9%, respectively. These vehicles, compared to passenger cars, are known with their larger vehicle masses, higher bum- pers, and their blunt frontal proﬁle ([Leﬂer & Gabler, 2004](#_bookmark24)). [Ballesteros,](#_bookmark21) [Dischinger, and Langenberg (2004)](#_bookmark21) also demonstrated that being hit by an SUV or pickup increases the likelihood of severe injury and fatality

1.48 and 1.72 times, respectively.

1. Conclusions and recommendations

This paper employed a partial proportional odds (PPO) model to analyze and identify risk factors of pedestrian injury severity in pedes- trian–vehicle crashes using Illinois crash data from 2010 to 2013. To off- set the effect of the presence of other accompanying passengers in the vehicle and accompanying persons with the pedestrian, the focus of this research was set at single-driver, single-pedestrian crashes. Three severity levels based on the injury severity sustained by the pedestrian (as the road user that governed the crash injury severity) were deﬁned: no/possible injury, minor injury, and severe injury. A comparison of the PPO model with two other commonly used ordered-response models (PO and GOLM) using information criteria (AIC and BIC) conﬁrmed that the PPO model surpasses the performance of the other two models. The ﬁndings of this paper identiﬁed several risk factors at pedestrian, driver, temporal, environmental, and vehicle levels that signiﬁcantly change the probability of injury severity. Accordingly, older pedestrians, wearing no contrasting clothing, adult drivers, summer season, time of day (20:00 to 05:59), crossing divided highways, multilane highways, darkness, and collision with pickup, SUV, and busses are associated with more severe injuries for pedestrians in Illinois. In contrast, child and adult pedestrians, older drivers, crossing at designated crosswalks, highly populated areas (i.e., Chicago), urban settings, presence of trafﬁc control devices (signal and sign), and snowy weather are associated with lower injury severities (i.e., no/possible injury). The direct pseudo-elasticities for the categorical variables presented in this paper can help prioritize possible countermeasures when the implementation of all countermeasures is not possible due to budget constraints. Accordingly, the priority can be given to those variables with a higher increase in the severity of crashes, as addressing these variables is potentially related to more effectively alleviating the pedestrian injury

crashes.

Based on the empirical ﬁndings of the present study and, speciﬁcally, the obtained average direct pseudo-elasticities, several countermea- sures can be suggested to help mitigate the pedestrian crash issues in Il- linois. These countermeasures can be grouped into three categories: engineering, education, and enforcement. Educational programs and behavior-based countermeasures should speciﬁcally target older pedes- trians, as they are signiﬁcantly associated with the higher injury sever- ities, mainly due to their unsafe street-crossing decisions. Training for older pedestrians has shown promising short- and long-term outcomes, as a result of the change in the decision criteria ([Dommes, Cavallo,](#_bookmark22) [Vienne, & Aillerie, 2012](#_bookmark22)). Given the increasing percentage of the older population in Illinois,2 this age-group should be given special attention. The ﬁndings also show that drunk driving increases the likelihood of se- vere injuries by 115.8%, which is the highest among all the studied risk factors. This ﬁnding substantiates the signiﬁcant role of intoxicated driving and necessitates the establishment of DUI driving prevention campaigns and the promotion of stricter rules. Illinois has already pub- lished the DUI Fact Book to enhance awareness of driving while intoxi- cated. Furthermore, community members (i.e., both pedestrian and drivers) should be educated to understand and respect crosswalk laws through education and outreach efforts. Pedestrians need to learn about jaywalking, and drivers need to yield the right-of-way to pedes- trians at crosswalks. The ﬁndings of the present study demonstrate

2 There has been a 7.28% increase in the number of population aged 65 and over from 2000 to 2010 in Illinois, according to [Census.gov](http://Census.gov/).

the role of crosswalks, signals, and signs in reducing the severity of injuries and recommends installation of pedestrian signals where it is warranted by pedestrian volume.

Pedestrian crashes during darkness are more associated with higher probability of severe injuries, and no contrasting clothing also increases the likelihood of severe injuries. A difference in the probability of severe crashes between lighted roads and others without any lighting is also observed, with the not-lighted road being responsible for higher probability of severe injuries. Therefore, the appropriate use of contrast- ing clothing, as well as reﬂectors, can be of great help if incorporated in educational efforts in Illinois. Drivers should also be educated to use more compensating driving behaviors during darkness, such as reduc- ing driving speed.

The results of the study also show a considerably increased probabil- ity of severe crashes on multilane (22.3%) and divided highways (10.6% with ﬂush median and 21.5% with raised median). By conducting further studies to identify such highways with high pedestrian activities, several countermeasures can be proposed. For instance, any improvement in lighting condition and installing crosswalks can ascer- tain promising results (based on the ﬁndings of this paper). Additional- ly, given the higher speed and heavy trafﬁc at such highways, trafﬁc calming techniques can be useful. These techniques may include installing speed bumps and narrowing the travel lanes.

Similar to most studies, this study also has some limitations. For ex- ample, the data used in this study are just from one U.S. state, per the de- ﬁned objective. Incorporating more data from other states can lead to a more comprehensive result and help in developing nationwide counter- measures and strategies. It will also be made possible to evaluate the ef- fectiveness of already implemented countermeasures in various states and learn from successful programs. Another limitation of this study comes from the inevitable role of human error in data collection process by police ofﬁcers that affects the level of detail and accuracy for the ob- tained signiﬁcant variables. Pedestrian condition (whether under the inﬂuence) was also a missing variable in the database. As this factor has previously been found to signiﬁcantly affect the behavior of pedes- trian and resulting injury severity ([Dultz & Frangos, 2013; Jang, Park,](#_bookmark22) [Chung, & Song, 2010](#_bookmark22)), it is recommended that this parameter be consid- ered by the responsible entity in future crash data collection process. The other variables, such as AADT and speed limit, can also be incorpo- rated into the model for future studies; however, due to high variations between AADT and speed limits in rural and urban areas, developing two separate models based on the type of setting might be more appropriate.

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