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Keeping Intersections Safe for Vulnerable Users: Contributory Factors to Pedestrians' and Bicyclists' Crossing Safety

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ABSTRACT

Pedestrian- and cyclist- involved crashes at intersections remain a major concern in China due to high ratio of fatal injuries and fatalities. This paper develops the random parameters negative binominal model to determine the relationship between potential contributory factors and crash frequency involving pedestrians and bicyclists at intersection locations and identify the significant risk factors, using 4,066 observations over the period 2008–2013 from Zhengzhou and Xi'an, China. The use of random parameters' model is utilized as a mean to accommodate possible unobserved heterogeneity across intersections, and a maximum likelihood method with Halton draws is proposed to estimate the maximum likelihood of random parameters. Additionally, marginal effects are applied to assess the impact of expected instantaneous change of each dependent variable on crash frequency while keeping all the other covariates constant. Among many potential factors, passenger countdown timer, passenger push button, number of left turn lanes, left turn traffic, ratio of major direction AADT to minor direction AADT and driver's disregarding 'give-way' sign behavior,… etc. have significant association with passenger crash frequency, but a less impact on bicyclist crashes. The findings of current study could provide an important insight into traffic safety improvement projects for passengers and bicyclists at both planning and operational levels.

KEYWORDS: Risk factor, Pedestrian and cyclist crash, Intersection location, Random parameters, Negative binominal model, Countdown timer.

INTRODUCTION

In China, the rapid expansion of economy and urbanization over the past two decades has led to more and more serious traffic congestions and air pollution in many cities. As a green and healthy mode of daily traffic, walking and cycling have become increasingly popular nowadays, and a number of local governments, such as Xi'an, Xiamen and Changzhoum… etc., have proposed strategies to encourage walking and cycling as a countermeasure to congestion and environmental problems. Compared to car occupants, pedestrians and bicyclists are much more vulnerable in crash cases. Pedestrians are 23 times more likely to be injured or killed in car collisions, whereas bicyclists are 12 times more likely to be injured or killed in car collisions (Putcher and Dijkstra, 2003). In order to promote the development of walking and cycling traffic, it is crucial to conduct in-depth study with regard to pedestrian and cyclist safety issues.

Over the past decades, walking and cycling safety has drawn a lot of attention by researchers. A number of

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studies have been conducted to examine the relationship between possible contributory factors, such as vehicular characteristics, driver attributes, pedestrian and bicyclist conflicts, roadway geometry features and environmental factors (Zahabi et al., 2011; Nemunas et al., 2013; Wang et al., 2014), and crash possibility and injury severity and then identify the significant factors impacting the occurrence of pedestrian and cyclist crashes, using the mixed generalized ordered response model (Eluru et al., 2008), negative binomial and ordered proportional odds technique (Islam et al., 2014), mixed logit model (Moore et al., 2011), Bayesian Poisson-lognormal approach (Siddiqui et al., 2014), clustering regression model (Mohamed et al., 2013),… etc., which have provided valuable suggestions and measures for reducing high risk of pedestrian and bicyclist fatalities/injuries.

Compared with other locations in a roadway network, intersections are obviously more prone to be involved in traffic crashes, especially passenger- and bicyclist- involved crashes, due to the substantial factors in complex traffic environment, but how these different factors affect the occurrence and severity of crashes is still unclear (Wang et al., 2001a; Wang et al., 2011b; Delmelle et al., 2012; Siddiqui et al., 2014). Torbic et al. (2010) reported that intersections with more lanes had highest vehicle-pedestrian crashes and that crash frequency was highest when the ratio of minor road AADT to major road AADT was highest. Hamann et al. (2013) found that cycle-specific pavement markings and signage could reduce the number of cyclist-vehicle crashes and related injuries and fatalities in a crash. Kim et al. (2007) reported that large trucks' involvement, speed at impact, alcohol use, age of bicyclist, lighting and weather conditions have significant effects on the frequency of bicycle-vehicle crashes and the level of injury severity at intersections. Griswold et al. (2011) found that pedestrian-involved fatal crashes occurred more frequently during twilight and the first hour of darkness.

In view of non-motorized crashes at intersections, a number of measures have previously been proposed to improve the safety of pedestrians and bicyclists, such as changing the design standards, installing push-buttons and countdown timers, enhancing safety education and enforcing more strict regulations,… etc. Although lots of studies have been conducted with regard to non-motorized traffic safety problems, very few of them considered a comprehensive analysis of risk factors contributing to pedestrian and bicyclist crashes at intersections. Therefore, the main purpose of this study is to examine and identify the significant risk factors associated with crash frequency and severity involving pedestrians and bicyclists, using traffic accident information from 341 intersections in Zhengzhou and Xi'an during the period 2008 to 2013. The findings of the current study could provide valuable guidance for decision-making of non-motorized traffic safety improvement at intersections.

METHODOLOGY

Data Collection

The original crash data used in the research effort is extracted from Zhengzhou and Xi'an Transport Police Bureau. There is a total of 8,742 available accident records from 2008 to 2013, among which 4,066 intersection-related observations involving passengers and bicyclists, accounting for 46.51% of the total records, are selected for further analysis. Finally, this crash database includes 3281 pedestrian-motor vehicle crash samples at 341 intersections, 618 bicyclist-related crashes at 256 intersections and 167 crash samples involving both pedestrians and bicyclists at 161 intersections.

The crash sample consists of nine categories: driver attributes, passenger and bicyclist attributes, vehicle attributes, roadway attributes, environmental attributes, traffic management attributes, drivers' traffic violations, passenger and bicyclist violations and crash characteristics. All of these observations have been collected for each intersection. Table 1 summarizes description of each variable and associated mean and standard deviation values.

Table 1. Explanatory variables for crash frequency estimation

Variable	Max.	Min.	Mean	Description of coding
Driver attributes				
Vulnerable age	31.55	6.91	21.33	AAR of vulnerable drivers involved, %
Less driving experience	45.72	14.09	30.61	AAR of inexperienced drivers involved, %
Invalid license	12.88	1.77	6.15	AAR of drivers with invalid license involved, %
Alcohol / drug impairment	29.83	5.40	18.46	AAR of drunk/ drug impaired drivers involved, %
Illness/ tiredness/ sleepiness	13.39	4.88	9.22	AAR of ill/ tired/ sleepy drivers involved, %
Passenger and bicyclist attributes				
Vulnerable age	16.91	0.43	9.06	AAR of vulnerable crash victims, %
Alcohol / drug impairment	8.22	1.05	5.31	AAR of drunk/ drug impaired victims, %
Illness/ tiredness/ sleepiness	5.75	0.27	3.29	AAR of ill/ tired/ sleepy victims, %
Vehicle attributes				
Large truck	7.14	0	1.29	AAR of large trucks involved, %
Bus	15.80	0.68	5.77	AAR of buses involved, %
Taxi	21.76	1.33	12.69	AAR of taxis involved, %
Motorcycle	16.51	1.34	7.38	AAR of motorcycles involved, %
Roadway attributes				
Number of entering legs	6	3	4.18	Average number of entering legs
Number of left turn lanes	4	0	1.94	Average number of left turn lanes
Number of through traffic lanes	10	2	4.68	Average number of through traffic lanes
Mid-block crosswalk	0.84	0	0.31	1 = mid-block crosswalk exists, 0 = otherwise
Environmental attributes				
Left turn traffic	17.34	3.56	8.95	Average annual daily left turn traffic/1000, pcu[1]
Ratio of traffic volume change	3.85	0.67	2.21	AAR of major direction AADT to minor direction AADT[2]
Inclement weather	0.33	0.07	0.17	AAR of crashes during inclement weather, %
Wet/ icy pavement	0.22	0	0.12	AAR of crashes on wet/ icy roads, %
Roadway lighting	1	0	0.76	1 = if intersection has effective lighting, 0 = otherwise
Traffic management attributes				
Red-light speed camera	1	0	0.23	1 = red-light speed camera exists, 0 = otherwise
Posted speed limit	1	0	0.34	1= posted speed limit exists, 0 = otherwise
Stop sign/flasher	1	0	0.48	1 = stop sign/flasher exists, 0 = otherwise
Traffic signal	1	0.17	0.55	1 = traffic signal exists, 0 = otherwise
Passenger countdown timer	0.64	0	0.13	1 = countdown timer exists, 0 = otherwise
Passenger push button	0.58	0	0.08	1 = passenger push button exists, 0 = otherwise
Drivers' traffic violation				
Disregarding 'give-way' signs	86.13	41.55	55.64	AAR of crashes due to disregarding give-way signs, %
Running red lights	77.03	36.61	44.37	AAR of crashes due to running red lights, %
Making an illegal U-turn	13.46	1.77	9.53	AAR of crashes due to making an illegal U-turn, %
Running through restricted areas	24.41	3.60	16.69	AAR of crashes due to running through restricted areas, %
Passenger and bicyclist violations				
Jaywalkers' crossing	30.78	11.76	18.07	AAR of crashes due to jaywalkers' crossing, %
Failing to use zebra crossings	23.35	6.01	10.33	AAR of crashes due to failing to use zebra crossings, %
Crash characteristics				
Pedestrian crash frequency	2.83	0.17	1.58	Average annual pedestrian crash frequency
Bicyclist crash frequency	1.50	0.17	0.47	Average annual bicyclist crash frequency

[1] *Passenger car units*
[2] *Average annual daily traffic*

Here follows a description of each category.

- *Driver attributes*: this variable tends to examine the relation between drivers' socio-demographic features, including messages about vulnerable age (≥ 60 years old/ ≤ 20 years old), less driving experience (≤ 3 years), invalid driving license and impacts of drivers' driving conditions (alcohol/ drug impairment, sickness, tiredness and sleepiness) and frequency of passenger and bicyclist crashes at each intersection. Similar messages can be obtained in terms of passenger and bicyclist attributes.
- *Vehicle characteristics*: this variable is used to measure the impact of different categories of vehicles (large truck, bus, taxi and motorcycle) on crash frequency at each intersection.
- *Roadway attributes*: this variable presents the potential roadway factors associated with the passenger and bicyclist crashes at each intersection, including number of entering legs, number of left turn lanes, number of through traffic lanes and availability of mid-block crosswalks (yes = 1, no = 0). Here, the average annual number of left turn lanes as a dummy factor is defined as the number of left lanes × time period since they were put into use/total study period (6 years). If a left lane is relocated to each entrance at a four-legged intersection in August 2009, for example, the average number of left turn lanes of this intersection during the study period = 4×(4+5/12)/6 = 2.944. The following dummy variables can be similarly measured.
- *Environment attributes*: this variable includes the ratio of left turn traffic, ratio of traffic volume change (major direction AADT to minor direction AADT), inclement weather (rain, fog, cross wind, snow and haze), wet/ icy pavement and roadway lighting (yes = 1, no = 0).
- *Traffic management attributes*: this variable determines the potential dummy factors associated with the frequency of passenger and bicyclist crashes at each intersection, including red-light speed cameras, posted speed limit, stop sign/ flasher, traffic signal, passenger countdown timer and passenger push button.
- *Drivers' traffic violations*: this variable provides the drivers' major traffic violations contributing to intersection-related traffic crashes involving pedestrians and bicyclists, including disregarding speed limits, running red lights, making an illegal U-turn and running through restricted areas.
- *Passenger and bicyclist traffic violations*: this variable presents two major traffic violations among passengers and bicyclists while crossing intersections: jaywalkers' crossing and failing to use zebra crossings. Here, jaywalkers' crossing is also known as the 'cross the road Chinese-style', referring to those who do not wait for the 'green man' signal to cross at intersections.
- *Crash characteristics*: this variable gives the passenger and bicyclist crash frequency messages, respectively.

Model Description

Many previous studies have developed statistical models for estimating the injury severity of crashes. When the original crash data distribution is skewed, lognormal regression approach leads to better estimation results (Fletcher et al., 2005). Suppose that crash frequency x has a lognormal distribution with mean μ and variance σ^2; the density function satisfies:

$$f(\mathrm{x}) = \frac{\mathrm{Exp}\left\{\dfrac{-\left[\ln(x)-\mu\right]^2}{2\sigma^2}\right\}}{(2\pi)^{1/2}\sigma x}; \qquad (1)$$

where μ and σ are location and scale parameters corresponding to the mean deviation Exp($\mu + \sigma^2/2$) and standard deviation Exp($2\mu+2\sigma^2$) – Exp($2\mu+\sigma^2$) of the lognormal distribution, respectively.

The lognormal distribution model is especially preferred when the mean μ is relatively large. Comparably, loglinear regression approaches have extensively been used to estimate the crash severity, in which Poisson model and negative binomial model are two major types. In a Poisson regression model, the probability $P(y_i)$ of y_i crashes occurring at intersection i in a given time interval is expressed by:

$$P(\mathrm{y}_i) = \frac{\mathrm{Exp}(-\lambda_i)\lambda_i^{y_i}}{y_i\,!}; \tag{2}$$

where λ_i is the expected number of crashes at intersection i per period as a function of explanatory variables that can be determined through the log-linear approach as $\lambda_i = EXP(\beta\,\mathrm{X}_i)$. Here, X_i is the vector of explanatory variables and β is the vector of parameters to be estimated.

In Poisson estimation model, however, it is required that the mean value μ equals that of variance σ^2; otherwise, biased estimation results will be produced. A number of previous studies have concluded that traffic crash frequency is found to be significantly over-dispersed (mean less than variance). Hence, applying Poisson model could result in incorrect results.

In order to overcome the overdispersion in the original crash data, negative binomial model is proposed to expand the Poisson approach for each observation i, as follows:

$$\lambda_i = EXP(\beta\,\mathrm{X}_i + \varepsilon_i); \tag{3}$$

where, $EXP(\varepsilon_i)$ is a gamma-distributed error term with mean 1 and variance α^2, respectively, which allows the variance to differ from the mean, as shown by Eq(4).

$$VAR[\mathrm{y}_i] = \mathrm{E}[\mathrm{y}_i] + \alpha\,\mathrm{E}[\mathrm{y}_i]^2. \tag{4}$$

Here, the parameter α is the overdispersion parameter to be estimated, and then the distribution of negative binomial model is given as:

$$P(y_i) = \frac{\Gamma(1/\alpha + y_i)}{\Gamma(1/\alpha)\,y_i\,!}\left(\frac{1/\alpha}{1/\alpha+\lambda_i}\right)^{1/\alpha}\left(\frac{\lambda_i}{1/\alpha+\lambda_i}\right)^{y_i}; \tag{5}$$

where Γ is the gamma function, and y_i is crash observation at intersection i. Notably, the negative binomial model is the most commonly used approach for crash frequency modeling.

In order to deal with unobserved heterogeneity across intersections, each estimable parameter can be written as $\beta_i = \beta + \omega_i$; where ω_i is a randomly distributed term over intersection i. In this study, all random parameters are assumed to be normally distributed.

Model Evaluation

For constructing the estimation model, the significance of explanatory variables is firstly checked and the estimated coefficients for each variable should be statistically significant (p-value for the two together is 0.000). This study uses t-test to examine the significance of coefficient with a 95% confidence interval. Additionally, the ratio of log-likelihood index ρ^2 as goodness-of-fit measure is adopted to further evaluate the predictive performance of the proposed model, as follows:

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)}; \tag{6}$$

where $LL(\beta)$ is the log-likelihood value at convergence of all data model with estimated coefficient β, and $LL(0)$ is the initial log-likelihood value with all coefficients equal to 0. The value of ρ^2 varies between 0 and 1; where values close to 1 mean better fit of model.

In the proposed model, the maximum likelihood of random-parameters is estimated through a simulation-based approach with Halton draws. Additionally, marginal effects are utilized to assess the impacts of one unit change of each variable on either pedestrian or bicyclist crash frequency. R (Version 2.15.2) statistical package is applied to conduct the model estimation for normally distributed random parameters.

Table 2. Model estimation results for random parameters' negative binomial model of pedestrian crash frequency at intersections

Variables	Passenger crash			Bicyclist crash		
	β	***t*-stat. (95% CI)**	**Average marginal effect**	***β***	***t*-stat. (95% CI)**	**Average marginal effect**
Constant	1.41	12.49		0.38	4.33	
Driver attributes						
Vulnerable age	0.49	0.73	0.55	—	—	—
Less driving experience	1.14	1.41	0.83	0.45	1.91	0.87
Invalid license	—	—	—	—	—	—
Alcohol / drug impairment	0.37	2.24	1.21	0.11	2.46	0.76
Illness/ tiredness/ sleepiness	—	—	—	—	—	—
Passenger and bicyclist attributes						
Alcohol/drug impairment	0.81	1.37	1.84	0.55 (0.91)	3.14 (2.77)	1.41
Illness/ tiredness/ sleepiness	—	—	—	—	—	—
Vehicle attributes						
Large truck	0.44	0.91	0.57	—	—	—
Bus	—	—	—	—	—	—
Taxi	—	—	—	1.49	3.22	1.73
Motorcycle	0.75	1.90	0.93	1.12	2.04	1.07
Roadway attributes						
Number of entering legs	—	—	—	—	—	—
Number of left turn lanes	1.13 (0.59*)	6.91 (8.25)	2.56	0.75 (0.48)	3.44 (1.91)	1.71
Number of through traffic lanes	0.28 (1.64)	5.29 (11.37)	2.19	0.10	2.89	0.37
Mid-block crosswalk	-0.24 (0.45)	-3.89 (1.33)	-3.37	—	—	—
Environmental attributes						
Left turn traffic	0.67 (0.74)	3.45 (2.37)	2.27	0.44 (1.06)	2.50 (1.97)	1.19
Ratio of traffic volume change	0.35 (0.65)	2.71 (1.73)	0.98	0.23	1.91	1.74
Inclement weather	—	—	—	—	—	—
Wet/ icy pavement	0.51	1.77	1.03	0.23 (1.37)	5.30 (14.94)	2.61
Roadway lighting	—	—	—	0.26	1.11	0.59
Traffic management attributes						
Red-light speed camera	-1.31	-2.39	-3.47	-1.10	-2.26	-3.34
Posted speed limit	—	—	—	—	—	—
Stop sign/flasher	—	—	—	—	—	—
Traffic signal	-0.68	-2.47	-2.90	-0.55	-1.76	-2.26
Passenger countdown timer	-0.76 (-0.41)	-11.03 (-3.57)	-6.15	-0.41 (-0.59)	-4.03 (-1.42)	-1.53
Passenger push button	-0.54 (-0.27)	-3.29 (-1.02)	-4.33	—	—	—
Drivers' traffic violations						
Disregarding 'give-way' signs	0.95 (1.23)	4.76 (4.78)	2.08	0.81 (1.45)	7.80 (5.15)	2.86
Making an illegal U-turn	—	—	—	—	—	—
Running red lights	0.46 (0.50)	5.40 (2.17)	1.65	0.29 (0.52)	3.88 (1.91)	2.05
Running through restricted areas	0.70	2.77	1.94	—	—	—
Passenger and bicyclist violations						
Jaywalkers' crossing	—	—	—	—	—	—
Failing to use zebra crossings	0.33	1.33	0.86	0.64	2.27	1.22
Crash characteristics						
Pedestrian crash frequency	—	—	—	—	—	—
Bicyclist crash frequency	—	—	—	—	—	—

Dispersion parameter, α	0.38	16.49		0.65	11.76	
Number of observations	363			279		
Log-likelihood at convergence, $LL(\beta)$	-1257.31			-707.35		
Log-likelihood with constant only, $LL(0)$	-763.12			-476.08		
$\rho^2 = [1 - LL(\beta)/ LL(0)]$	0.39			0.33		

* *Standard deviation of parameter distribution*

RESULTS AND DISCUSSION

This study analyzed police-reported intersection crashes from Zhengzhou and Xi'an, China, over the period from 2008 to 2013, involving pedestrian and bicyclist observations. Table 2 shows the parameter estimation results for the negative binomial model of pedestrians and bicyclists and crash frequency, in which all random parameters are normally distributed. The log-likelihood ratio index values, ρ^2, are 0.39 and 0.33, respectively, indicating that the proposed model could explain the relationship between frequency of pedestrian and bicyclist crashes and the selected variables sufficiently.

Obviously, 10 fixed parameters are found to be significantly associated with the bicyclists' crash frequency, including 9 variables (number of left turn lanes, number of through traffic lanes, availability of mid-block crosswalks, annual average daily left-turn traffic, annual average ratio of major direction AADT to minor direction AADT, passenger countdown timer, passenger push button, disregarding 'give-way' sign behavior and running red light behavior) and 1 constant. In addition, 10 random parameters were also identified, including driver's vulnerable age, less driving experience, alcohol/ drug impairment, passenger's alcohol/ drug impairment, large truck involvement, motorcycle involvement, wet/ icy pavement, red-light speed cameras, traffic signal, running through restricted areas and passenger's failing to use zebra crossing behavior.

From the results in Table 2, it is easily concluded that the use of passenger countdown timer, push button and mid-block crosswalk as well as red-light speed camera have a positive impact on the reduction of average annual number of pedestrians' crashes, and the marginal effects in Table 2 show that a 1 unit increase in the use of countdown timer, push button, mid-block crosswalk and red-light speed camera could decrease the mean number of pedestrians' crashes per year at intersections by 6.15, 4.33, 3.47 and 3.37, respectively. Notably, the countdown timer shows the time remaining for pedestrian crossing, and thus can help passengers make better decisions about when to begin the crosswalk and how to control the rhythm of their walking. Moreover, a push-button at major intersections will help passengers push walk signal to turn to green freely and save their waiting time. Red-light speed camera, 'give-way' sign and traffic control signal also help reduce the incidence of crashes involving passengers during the crossing period. Therefore, the equipment of passenger countdown timer, push button and mid-block crosswalk can improve the efficiency of intersection crossing and level of crossing safety.

Furthermore, the number of left turn lanes is also identified to be significantly associated with the frequency of pedestrians' crashes at intersections, due to poor visibility or a history of crashes. Left lanes (inner lanes) tend to carry both through traffic and drivers who need to slow down and possibly stop to turn left, and thus the left turn traffic confronts significant conflict points with the through traffic, which in turn affects the safety of crossing pedestrians. Of course, this problem should be paid more attention at the planning and operational levels of left turn lanes. Many previous studies, such as *Safety Effectiveness of Intersection Left- and Right-Turn Lanes* (FHWA-RD-02-089) and *Left-Turn Accommodations at Unsignalized Intersections* (NCHRP Project 03-91),… etc., have examined the safety impacts of traditional left- lane design, but many problems, such as redesign of left turn lanes with isolated medians, effective measures of decreasing the conflict points,… etc., remain unsolved and thus require further deep research, especially in term of specific care for young and aged participants.

As expected, driver and passenger alcohol/ drug impaired conditions, number of left turn lanes, number of through traffic lanes, left turn traffic volume, wet/icy pavement condition, driver's disregarding red light and running through restricted area behaviors have a positive effective on the frequency of pedestrians' crashes at intersections, with the average marginal effects between 1.0 and 2.99, indicating that the decrease of these variables can improve the level of passenger crossing safety.

In view of the impacts of different variables on bicyclists' crash frequency, similar findings can be observed: 7 fixed and 10 random parameters have significant association with the bicyclist crash frequency. Compared with the observations in passenger crashes, taxi involvement, average annual ratio of major direction AADT to minor direction AADT and wet/icy pavement conditions have slightly negative and significant effects on average bicyclists' crash frequency at intersections. Additionally, bicyclists can cross the street faster than pedestrians and have less reaction time while facing the sudden oncoming traffic, particularly at night with poor visibility and under inclement weather conditions. Therefore, the crossing bicyclist can be easily involved into a collision with a turning vehicle without ever giving a turn signal. All these traffic violations, therefore, should be strictly prohibited through explicit laws and regulations.

CONCLUSIONS

This study provides an empirical evaluation of the risk factors contributing to the frequency of pedestrians' and bicyclists' crashes at intersections. Several variables including number of left turn and through traffic lanes, average annual daily left turn, as well as through traffic on major and minor directions at the intersection, existence of passenger countdown timer at the intersection,… etc., have been considered for modeling analysis. A random parameters' negative binomial model was utilized to establish the statistical relationship between pedestrian/bicyclist crash frequency and selected variables.

The degree of pedestrian and bicyclist risk depends on the complexity of traffic patterns (Sokolovskija and Prentkovskis, 2013) and availability of information about the location, direction and duration of crosswalk. Estimation results show that both planning and operational factors have close association with crash frequency and injury severity. As expected, passenger countdown timer absolutely decreases the frequency of pedestrians' and bicyclists' crashes at intersections. According to the average marginal effect values, however, the effects on the frequency of pedestrian crashes are more significant and tangible than those on the bicyclist crashes. In addition, number of left turn and through traffic lanes and number of left turn and through traffic volume are identified to have considerable effects on both pedestrians' and bicyclists' crash frequencies. Too more trucks will bring poor visibility and decreased capacity of the overall intersection; thus positive restriction of trucks would be better able to improve the crossing visibility for both drivers and pedestrians and then decrease the probability of left turning crashes as well as injury severity. Similar findings were found in the operational lane capacity studies conducted by Tenekeci et al. (2014).

All these findings could provide valuable insight into countermeasures, including forward collision warning system (FCWS) for both pedestrians and drivers, traffic violation detection system (TVDS), design of pedestrian/bicycle facilities and optimization of passenger/bicycle signal phase, as well as examination of individual factors (e.g., driver's stress, fatigue and alcohol usage) and the relationship with different issues related to specific driving performance, in order to reduce non-motorized crashes and injuries at intersections.

The results reinforce important implications for education and training countermeasures of both non-motorists and vehicle drivers on the individual's risk behaviors at intersections, such as driver's red-light running, drunk driving and passenger's sleep walking,… etc. Moreover, motorized vehicle drivers should be made aware of the dangers of driving at night time (in particular between 9 pm and 6 am), especially driving under the influence of alcohol. Similarly, non-motorists should learn the risks of night time travel by periodical education, particularly after alcohol use. Further, non-motorists during night time travel are encouraged to wear light or reflective clothing to improve visibility.

Traffic regulations and management countermeasures merit further deep consideration. More strict laws and regulations should be vigorously enforced to penalize 'high-risk' driving behaviors, such as drunk driving, over-speeding, read light running,… etc. Additionally, results suggest the need to restrict the roadway driving to a safe speed of 15 km/h or below in commercial or residential areas with heavy pedestrian and bicycle traffic, and heavy trucks should be forbidden to enter these areas during the daytime period. Effective traffic enforcement cameras and other surveillance measures play an important role in alarming both motorists and non-motorists to comply with the existing regulations and thus decrease the probability of being involved in a crash. It would also be beneficial to increase police surveillance with well-trained officers during late night periods, especially on Monday mornings and Friday afternoons. Moreover, good street lighting and illumination can also result in positive results in areas with heavy non-motorist traffic. This complies with research findings obtained by Yannis et al. (2013).

Finally, results also suggest that it could be of positive value installing the countdown timer at intersections indicating the next boat departure time for passengers and bicyclists to gauge the wait, as Markowitz et al. (2006) reported. Warning sign and pavement marking should be allocated before approaching the intersection to inform speed limit and notice of passenger and bicyclist crosswalk,… etc. Similarly, accessible information about crossing location, direction and duration should be provided to each passenger and bicyclist, including people with vision impairment. At wide intersections, pedestrian access can be enhanced through ladder marking of crosswalks, perpendicular curb ramps, curb extensions with landscaping, as well as detectable warnings, cut-through medians and adjoining good illumination. Of course, overpass or underpass is the best choice at location with heavy traffic. In addition, an off-road or a clearly demarcated bicycle lane could significantly enhance the safety performance of cycling traffic, and thus it is strongly suggested to set bicycle paths along major corridors with intersections.

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