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Diagnostic Analysis of the Effects of Weather Condition on Pedestrian Crash Severity

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Abstract

Pedestrians are vulnerable to severe injury and mortality in road crashes. Numerous studies have attempted to identify factors contributing to crashes and pedestrian injury risks. As an active transport mode, the act of walking is sensitive to changes in weather conditions. However, comprehensive real-time weather data are often unavailable for road safety analysis. In this study, we used a geographical information system approach to integrate high-resolution weather data, as well as their corresponding temporal and spatial distributions, with crash data. Then, we established a mixed logit model to determine the association between pedestrian crash severity and possible risk factors. The results indicate that high temperature and the presence of rain were associated with a higher likelihood of Killed and Severe Injury (KSI) crashes. Also, we found the interaction effects of weather condition (hot weather and presence of rain) on the association between pedestrian crash severity and pedestrian and driver behaviors to be significant. For instance, the effects of jaywalking and risky driving behavior on crash severity were more prevalent under rainy conditions. In addition, the effects of driver inattention and reckless crossing were more significant in hot weather conditions. This has critical policy implications for the development and implementation of proactive traffic management systems. For instance, real-time weather and traffic data should be incorporated into dynamic message signs and in-vehicle warning systems. Doing so will enhance the levels of safety awareness of drivers and pedestrians, especially in adverse weather conditions. As a result, pedestrian safety can be improved over the long term.

Keywords: Pedestrian crash, Weather condition, Injury severity, Random-parameter logistic regression

1. Introduction

Walking not only alleviates the problems of traffic emissions and congestion, but also improves human well-being. This is particularly true in compact cities like Hong Kong. In Hong Kong, 89% of trips are made by bus and metro, and walking has been the primary means for accessing public transport services. The walkability of a city can be characterized by its accessibility, environment, connectivity, and safety. Pedestrians are vulnerable to severe injury and mortality in road crashes (Haleem et al., 2015). In Hong Kong, 17% of the 20,381 road casualties in 2015 were pedestrians. However, of the people killed on the roads, 66% were pedestrians (Transport Department, 2015). Taking into account the travel distance, the fatality rate (per kilometer traveled) of pedestrians has been found to be 1.4 times and 23 times that of motorcyclists and vehicle occupants, respectively (Pucher and Dijkstra, 2003). As such, it is imperative to identify the factors contributing to the high crash and injury risk of pedestrians. Numerous studies have indicated that the road environment, vehicular speed, crash circumstances, traffic control, and driver and pedestrian behaviors affect pedestrian safety (Sze and Wong, 2007; Cambon de Lavalette et al., 2009; Jian et al., 2005; Dai. 2012; Gårder. 2004; Aziz, et al. 2013; Zajac and Ivan. 2003).

As an active transport mode, walking is sensitive to adverse weather conditions. In this era of climate change, with the increasing variations in air temperature and precipitation, extreme weather events including heat waves, storms, and heavy rainfall are occurring more frequently. The weather condition has been recognized as one of the major environmental factors contributing to pedestrian crashes (Kim et al., 2010). Mariana et al. (2017) found the crash likelihood of pedestrian to be 77% lower than that of cyclists under favorable weather conditions. Increases in the frequency and intensity of rainfall are reported to be associated with poor visibility and low pavement friction, and thus increased crash risk (Maze et al. 2004; Mohamed et al., 2013, Theofilatos and Yannis, 2014). Furthermore, weather conditions may have interaction effects on the association between the severity of pedestrian injury and possible risk factors. Li et al. (2017) found that the light conditions could affect pedestrian injury severity in good weather conditions, but no evidence was established for an association in adverse weather conditions. It is therefore necessary to examine the effects of weather and its extremes on pedestrian injury risk.

In conventional road safety analysis, weather information is obtained from police crash reports. However, the reliability of the weather information recorded depends on the judgment of the attending police officers and is not often rigorously assessed (Naik et al. 2016). For an effective assessment, it is essential to obtain real-time weather data from local weather agencies and incorporate it into crash prediction models. Researchers have attempted to evaluate the crash severity of single-vehicle (Jung et al., 2010), multi-vehicle (Jung et al., 2012), and truck-related (Naik et al., 2016) crashes, as well as crashes on a mountainous freeway (Yu and Abdel-Aty, 2014) based on real-time weather data, and have obtained enhanced prediction performances. The results of a study of Wisconsin interstate highways indicated that increased rainfall intensity 15 minutes prior to a crash was correlated with an increase in the likelihood of more severe single-vehicle crashes, whereas increased wind speed was associated with a reduction in the likelihood of more severe single-vehicle and multivehicle crashes (Jung et al., 2010; 2012). Reduction in temperature has also been attributed to an increase in the likelihood of more severe crashes on a mountainous freeway (Yu and Abdel-Aty, 2014). For vehicular crash analysis, the weather attributes typically considered have been air temperature, humidity, visibility, wind speed, and the amount of precipitation (Naik et al., 2016). However, the effect of weather conditions on the severity level of pedestrian crashes has rarely been attempted using comprehensive real-time weather data.

Our objective in this paper is twofold: (1) to examine the effects of weather conditions on the severity level of pedestrian crashes, using high-resolution weather data and its temporal and spatial variations; and (2) to identify possible factors contributing to pedestrian crash severity and the interaction effects of weather conditions on this association.

Changes in weather conditions can moderate travel behavior, and thus the risks of road crash and injury. In Hong Kong, the mean daily maximum temperature is 26 °C. However, the average annual number of extremely hot days (with a daily maximum temperature higher than 33 °C) exceeded 10 during the period from 1981 to 2010. Also, the average annual number of rainy days and days with strong monsoonal wind were 116 and 35, respectively (Hong Kong Observatory, 2015). In this study, we devoted considerable effort to the collection and aggregation of high-quality regional weather records from a selection of 18 automatic weather stations (AWS) operated by the Hong Kong Observatory (HKO) for various districts of the Hong Kong territory. Conventional meteorological variables including air temperature, wind speed, humidity, and rainfall are available at 1-min intervals (the highest frequency used in similar analyses). We used a geographic information system (GIS) approach to integrate the crash and real-time weather data with respect to crash location and time. We considered meteorological variables, as well as driver and pedestrian attributes, road environments, and traffic characteristics. To incorporate the effects of unobserved heterogeneity, we used a mixed logit approach. In the remainder of this paper, we first describe our data collection and aggregation method. We discuss our analysis method in section 3. In section 4, we present our results, and in sections 5, we discuss these results and consider their implications. Finally, we make our concluding remarks and recommendations for future research in section 6.

2. Data

For this study, we extracted 2015 Hong Kong crash data from the Traffic Information System (TIS) maintained by the Hong Kong Police Force and Transport Department. The TIS has two components: (i) a casualty profile and (ii) a vehicle profile, both of which contain information related to crash attributes, including the precise crash time and location, number of vehicles and casualties involved, road type, traffic control, and crash circumstances. In the casualty profile, there is information about the role (driver, passenger, and pedestrian), demographics, injury characteristics, locations during crash, and behavior of each casualty involved. In the vehicle profile, there is information about the driver age and gender, vehicle class, and risky driver behavior. Despite the presence of information about the weather conditions (i.e., clear, dull, fog/mist, strong wind, not raining, light rain, and heavy rain) in the TIS, it was descriptive only.

We obtained high-frequency regional weather data from the Hong Kong Observatory, which is the official weather agency of Hong Kong. We used records from a selection of 18 AWSs that span the entire Hong Kong territory, which has a total land area of 1,100 km^2. Variations in the weather conditions with respect to time and space are considerable in Hong Kong. The high-density of the AWSs provide very precise weather information for determining the association between crash severity, road environment, traffic attributes, and weather conditions. The raw weather data, including wind direction, wind speed, gust speed, air temperature, humidity, and precipitation, have a high temporal resolution (1-min intervals). We are unaware of any previous traffic safety research that incorporated such high-frequency weather data. We matched each crash with its corresponding weather data from the nearest AWS using the GIS approach (with the software ArcGIS 10.0).

Prior to statistical analysis, we integrated the vehicle and casualty profiles. In 2015, there were 3,218 road crashes involving pedestrians. As the proposed analysis aimed to identify possible vehicle and pedestrian characteristics that had contributed to crash severity, we excluded crashes involving more than one pedestrian and/or more than one vehicle (which constituted 5.4% of total crashes). Also, we excluded cases with incomplete or missing data. Therefore, the number of observations in the final dataset totaled 2,794. In Hong Kong, crash severity is divided into three categories: fatal, serious, and slight (Sze and Wong, 2007). Of the selected crashes, only 81 (2.90%) were fatal. Therefore, we combined fatal and severe injury crashes to generate the category killed and severe injury (KSI) crashes (Haleem et al., 2015; Sze and Wong, 2007). Possible factors considered were pedestrian characteristics (age, gender, pedestrian location, pedestrian action, special circumstance, and pedestrian contributing factors), driver characteristics (driver age, gender, and contributing factors), vehicle class, road geometry, traffic control type, weather conditions (wind speed, guest speed, air temperature, humidity, rainfall) and crash circumstance (time of the day, day of the week, and geographical region). Table 1 presents summary statistics of the information considered. As shown in the table, we considered both the general distributions (mean, standard deviation and range) as well as the distributions by category of weather condition. We established the weather condition classifications according to their physical meaning. For instance, we classified wind and gust speeds according to the wind rating scale, and humidity according to the humidity rating scale (Jung et al., 2014). Prior to determining the association, we conducted a multi-collinearity test to ensure that the variables considered were not highly correlated.

Table 1. Summary Statistics of Variables

Factor	Attribute	Count(proportion)	Factor	Attribute	Count(proportion)
Injury severity	Killed or severe injury (KSI)	702 (25.1%)	Pedestrian contributor	Pedestrian jay walking	536 (19.2%)
	Slight injury	2092 (74.9%)		Pedestrian inattentiveness	497 (17.8%)
District	New territory	1026 (36.7%)		No pedestrian factor	1674 (59.9%)
	Kowloon	1101 (39.4%)		Other pedestrian factors*	87 (3.1%)
	Hong Kong island*	667 (23.9%)	Driver age (years)	Young (≤30) *	303 (10.8%)
Time of the day	7:00-9:59	447 (16.0%)		Younger-middle (31–45)	803 (28.7%)
	10:00-15:59	1101 (39.4%)		Older-middle (46–65)	1350 (48.3%)
	16:00-18:59	604 (21.6%)		Old (66)	338 (12.1%)
	19:00-6:59*	642 (23.0%)	Driver gender	Male	2475 (92.0%)
Day of week	Weekday	2114 (75.7%)		Female*	214 (8%)
	Weekends*	680 (24.3%)	Driver contributor	Driving negligently	445 (15.9%)
Within 20m of junction	Yes	814 (29.1%)		Driving inattentively	996 (35.6%)
	No*	1980 (70.9%)		No driver factor	1086 (38.9%)
Junction control	Signalized	410 (14.7%)		Others*	267 (9.6%)

	Not at junction	2229 (79.8%)	Class of vehicle	Private car	1105 (39.5%)
	Other control type*	155 (5.5%)		Goods vehicle	503 (18%)
Road type	One way	1505 (59.3%)		Bus	310 (11.1%)
	Two-way	1218 (43.6%)		Taxi	594 (21.3%)
	Multi-/dual carriageway*	71 (2.5%)		Others*	282 (10.1%)
Pedestrian age (years)	Child (≤11)*	174 (6.3%)	Wind speed (m/s)	Calm (<0.2) *	250(9.0%)
	Young (12–25)	335 (12.1%)		Light air (0.2-1.6)	581 (20.8%)
	Younger-middle (26–45)	665 (24.0%)		Light breeze (1.6-3.4)	1193 (42.7%)
	Older-middle (46–65)	937 (33.8%)		Gentle breeze (3.4-5.5)	628 (22.5%)
	Younger-old (66–80)	425 (15.3%)		More than breeze (>5.5)	141 (50.0%)
	Older-old (81)	235 (8.5%)	Gust speed (m/s)	Calm (<0.2) *	179(6.4%)
Pedestrian gender	Male	1454 (52.1%)		Light air (0.2-1.6)	300 (10.7%)
	Female*	1337 (47.9%)		Light breeze (1.6-3.4)	926 (33.1%)
Pedestrian location	Footpath or verge	842 (30.1%)		Gentle breeze (>5.5)	937 (33.5%)
	On or within 15M of controlled crossing	526 (18.8%)		Moderate breeze (5.5-8.0)	370 (13.2%)
	On carriageway (no crossing control)	1180 (42.2%)		More than moderate breeze (>8.0)	81(3.0%)
	Others*	246 (8.8%)	Air temperature (℃)	Cold (≤ 20) *	631 (22.6%)
Pedestrian action	Walking back to traffic	410 (14.7%)		Cool (20-25)	538 (19.2%)
	Walking facing traffic	1078 (38.6%)		Warm (25-30)	1020 (36.5%)
	Crossing from near side	692 (24.8%)		Hot (> 30)	466 (16.7%)
	Crossing from off side	335 (12.0%)	Humidity (%)	Extremely dry (<30) *	15(0.6%)
	Others*	279 (10.0%)		Dry (30-40)	51 (1.8%)
Pedestrian special circumstance	Overcrowded footpath	190 (6.8%)		Less comfortable (40-60)	281 (10.1%)
	Ran onto the road	1251 (44.8%)		Most comfortable (60-80)	1447 (51.8%)
	No special circumstance	1283 (45.9%)		Moist (>80)	999 (35.7%)
	Others*	70 (2.5%)	Rainfall (mm)	No raining (none)*	2710 (97.0%)
				Raining (0-15)	84 (3.0%)

	Mean	S.d.	Max	Min
Wind speed (m/s)	2.60	1.662	10.80	0.00
Gust speed (m/s)	3.59	2.106	12.20	0.00
Air temperature (℃)	24.40	5.533	36.10	9.10
Humidity (%)	74.90	0.137	100	21
Rainfall (mm)	0.26	2.289	70.00	0.00

Note 1: * represents the variable attributes treated as control.

Note 2: Descriptive terms of weather conditions pertain only to this paper and differ from the conventions used in weather reporting by HKO in Hong Kong (http://www.hko.gov.hk/wxinfo/currwx/flw_description/flw_e.htm)

3. Methodology

Our aim in this study was to measure the association between the severity of pedestrian crashes, road environment, vehicle attributes, pedestrian behaviors, and weather conditions. Traditionally, crash severity is modeled using binary logit or Probit approaches (Sze and Wong, 2007; Tarko and Azam, 2011), ordered logit or Probit approaches (Lee et al., 2018; Zahabi et al., 2011), a generalized logit approach (Clifton et al., 2009), a multinomial logit approach (Tay et al., 2011), a latent class approach

(Yu et al., 2017), or a mixed (random parameter) logit approach (Chang et al., 2016; Haleem et al., 2015; Islam and Jones, 2014; Kim et al., 2010). These analyses were disaggregated, as they modeled the likelihood of incurring more severe injury upon a crash. They allowed the characteristics of an individual crash and the vehicle and pedestrian involved to be retained. Random parameters and latent classes are among the most advanced methodological approaches currently used in crash-injury severity analysis (Behnood and Mannering, 2016). In this study, we applied a mixed logit approach, which can estimate unobserved effects by allowing the parameters of observed attributes to vary across observations. Its performance is superior since a number of factors are considered, including physical fitness, height, weight, and mental well-being, which can affect crash severity and are often not measured.

The dependent variable of the proposed model is dichotomous (KSI crash versus slight injury crash), therefore we established binary logistic regression and mixed logit regression models to measure the association between crash severity, possible risk factors, and weather conditions. We formulated the models as follows.

Suppose the probabilities of a crash being KSI (y = 1) or slight injury (y = 0) are p and 1−p, respectively, then:

$$y \sim Binomial(p)$$
$$\log it(p) = \log(\frac{p}{1-p}) = \mathbf{X}_i\boldsymbol{\beta} + \varepsilon_i, \quad (1)$$

where **X** is the vector of explanatory variables, $\boldsymbol{\beta}$ is the vector of corresponding coefficients (i.e., β_1, β_2, . . . , β_t), and ε_i is the random error term assumed to be identically and independently distributed.

One restriction of the above basic model is that it assumes that the effects of individual variables are fixed across observations. This assumption ignores the effects of possible unobserved heterogeneity (i.e., physical health) on the association between crash severity, crash circumstances, and pedestrian demographics. To this end, we applied a mixed logit model. In particular, the coefficients are assumed to be randomly distributed with the formulation of the random parameter β_i as follows:

$$\beta_i = \beta + \varphi_i, \quad (2)$$

where φ_i is normally distributed with a mean of zero and variance of σ^2.

We established a random parameter model using conditional probability, as follows:

$$\Pr ob\left[y_i = 1 \middle| x_i, \beta_i\right] = F\left(\beta_i' x_i\right). \quad (3)$$

We estimated the parameters of the proposed mixed logit model using the maximum likelihood approach with NLOGIT5 software (Greene, 2012). In this study, we assumed the parameters to be normally distributed as this provided the best statistical fit (Christoforou et al., 2010; Milton et al., 2008). For individual parameter estimates, we considered a parameter to be random if the corresponding standard error of the assumed distribution was different from zero at the 10% level of significance; otherwise, we considered it to be fixed. We generated results from 200 Halton draws. For details of this modeling approach and Halton draws, the reader may refer to the paper by Train (2003). In addition, we used a stepwise iterative process to determine whether a parameter was fixed or random (see Islam and Jones (2014)).

To assess the prediction performance of candidate models, we estimated their Akaike information criterion (AIC), which considers both the goodness-of-fit and model complexity. The AIC can be specified as follows:

$$AIC = -2\ln(L) + 2K\,, \tag{4}$$

where L is the maximum likelihood function and K is the number of parameters in the model.

4. Results

We utilized the basic binary logit model and mixed logit model to identify the risk factors associated with crash severity. First, we separately estimated the weather and other potential contributing factors (basic model). Then, we considered the interaction effects of significant weather variables on the association with pedestrian and driver characteristics (refined model). Therefore, four models were ultimately calibrated. We screened all possible candidate factors, and included in the final model only those factors contributing to crash severity, at the 10% level of significance. To present the effects on crash outcome by individual factor attributes, we estimated the odds ratios.

Table 2 presents the goodness-of-fit measures of the proposed models. Compared with the binary logit models, the mixed logit models were superior in terms of their lower AIC values and likelihood-ratio test results. Therefore, in the following section, we present the parameter estimation results obtained from the mixed logit models.

Table 2. Goodness-of-fit Measures for Binary and Mixed models

	Basic Model		Refined Model	
	Binary Logit	Mixed Logit	Binary Logit	Mixed Logit
AIC	2907.6	2890.0	2903.0	2884.5
Log likelihood at zero, LL(0)	-1575.00	-1575.00	-1575.00	-1575.00
Log likelihood at convergence, LL(β)	-1435.82	-1421.11	-1431.49	-1417.27
Number of parameters, K	18	24	20	25
$X^2 = -2[\mathrm{LL}(\beta) - \mathrm{LL}(0)]$	14.711		14.220	
Degree of freedom	6		5	
p-value	0.023		0.014	

Table 3. Parameter Estimation Results of Basic and Refined Models

Factor	Attributes	Basic Model				Refined Model			
		Coefficient	Odds ratio	S.d.	Z-value	Coefficient	Odds ratio	S.d.	Z-value
Constant		-1.684***	0.19	0.1652	-10.19	-1.538***	0.21	0.1514	-10.16
District	Kowloon	0.529***	1.70	0.0910	5.82	0.463***	1.59	0.0874	5.30
	s.d. Kowloon	*0.906****	--	*0.1019*	*8.90*	*0.729****	--	*0.0954*	*7.64*
Road type	One way	-0.275***	0.76	0.0836	-3.28	-0.243***	0.78	0.0807	-3.01
Time of the day	10:00-16:00	-0.337***	0.71	0.0877	-3.84	-0.319***	0.73	0.0840	-3.80
Casualty age	46-65	0.426***	1.53	0.0946	4.51	0.385***	1.47	0.0925	4.16
	66-80	1.242***	3.46	0.1185	10.48	1.228***	3.41	0.1127	10.90
	s.d. 66-80	*0.971****	--	*0.1416*	*6.86*	--	--	--	--
	>80	0.683***	1.98	0.1876	3.64	0.737***	2.09	0.1729	4.26
	s.d. >80	*3.338****	--	*0.3716*	*8.98*	*2.735****	--	*0.3180*	*8.60*
Pedestrian location	On carriageway	-0.888***	0.41	0.1078	-8.23	-0.851***	0.43	0.1043	-8.16
	s.d. On carriageway	*2.467****	--	*0.1517*	*16.26*	*2.352****	--	*0.1459*	*16.12*
Pedestrian action	Walking facing to traffic	0.189*	1.21	0.1079	1.75	--	--	--	--
	Crossing from near side	0.459***	1.58	0.1185	3.87	0.359***	1.43	0.0932	3.85
	s.d. Crossing from near side	*1.128****	--	*0.1257*	*8.98*	*0.904***	--	*0.1162*	*7.78*
	Crossing from offside	0.521***	1.68	0.1416	3.68	0.357***	1.43	0.1204	2.97
Driver Contributor	Negligently Driving	0.561***	1.75	0.1266	4.43	0.627***	1.87	0.1344	4.66
Vehicle class	Private car	0.372**	1.45	0.1496	2.49	0.378***	1.46	0.1464	2.58
	Goods vehicle	0.994***	2.70	0.1631	6.09	0.950***	2.59	0.1588	5.98
	Bus	1.346***	3.84	0.1829	7.36	1.310***	3.71	0.1745	7.51
	s.d. Bus	*2.355***	--	*0.2442*	*9.65*	*1.833****	--	*0.2102*	*8.72*
	Taxi	0.647***	1.91	0.1578	4.10	0.619***	1.86	0.1540	4.02
Temperature	Above 30 ℃	0.297***	1.35	0.1104	2.69	--	--	--	--
Rain	Raining	0.638***	1.89	0.2062	3.10	--	--	--	--
Weather interactions	Raining & pedestrian jay walking	--	--	--	--	0.680**	1.97	0.2649	2.57
	Raining & driver contributor	--	--	--	--	0.434***	1.54	0.1666	2.61
	Raining & Footpath overcrowded	--	--	--	--	-1.699**	0.18	0.6809	-2.50
	Above 30 ℃ & driver inattention	--	--	--	--	0.578*	1.78	0.2958	1.95
	Above 30 ℃ & pedestrian run onto the road	--	--	--	--	0.385***	1.47	0.1455	2.64

Notes:

, **, and * denote the statistical significance at 10%, 5% and 1% levels, respectively.*

s.d. denotes the abbreviation for standard deviation.

Random parameters were highlighted using italics.

Basic model

First part of Table 3 shows the results of the basic model, in which the factors, district area, time of day, road type, casualty age, pedestrian location, pedestrian action, driver contributory factor, vehicle class, temperature, and presence of rain, all contributed to the pedestrian crash severity. In particular, crashes in Kowloon (odds ratio = 1.70) involving pedestrians older than 46 years (ages 46 – 65 years (1.53), ages 66–80 years (3.46), and age 80 years or above (1.98)) that involved pedestrian walking while facing traffic (1.21); crossing from the near side (1.58) and from the off side (1.68); negligent driving (1.75); crashes involving a private car (1.45), goods vehicle (2.70), bus (3.84), or taxi (1.91); air temperature of 30 °C or above (1.35); and the presence of rain (1.89) all had a higher likelihood of KSI. In contrast, crashes during the period between 10:00 am and 4:00 pm (0.71) on one-way roads (0.80), and involving a pedestrian being on the carriageway (0.41) all had lower likelihood of KSI. Also, the effects of factor attributes including Kowloon (mean = 0.529, s.d. = 0.906), pedestrian age of 66–80 years (mean = 1.242, s.d. = 0.971), pedestrian age above 80 years (mean = 0.683, s.d. = 3.338), pedestrian on the carriageway (mean = –0.89, s.d. = 2.47), and pedestrian crossing from the near side (mean = 0.459, s.d. = 1.128) on crash severity were found to vary across observations.

Refined model

We added terms denoting interactions between weather conditions (significant weather variables revealed in the basic model, i.e., air temperature and rain) and possible risk factors (i.e., road type, pedestrian demographics, pedestrian location, pedestrian behavior, vehicle class, and driver contributory factor) into the refined model. We included interaction terms that had significantly contributed to crash severity at the 10% level in the final model. The second part of Table 3 presents the parameter estimation results for the refined model. Since the effects of most of the risk factors were consistent with that of the basic model, here, we discuss only the intervention effects of weather conditions in the refined model. Interactions between (i) raining and jaywalking behavior (odds ratio = 1.97), (ii) raining and driver contributing factor (1.54), (iii) raining and overcrowded footpath (0.18), (iv) temperature above 30 °C and driver inattention (1.78), and (v) temperature above 30 °C and pedestrian running onto the road (1.47) all significantly contributed to crash severity at the 10% level.

5. Discussion

Pedestrian Characteristics

Crashes involving pedestrians older than 45 years had a higher likelihood of KSI, especially those involving elderly pedestrians aged 66–80 years, which could be due to vulnerabilities associated with their physiological conditions and the poor safety perceptions of elderly pedestrians. Also, elderly pedestrians may take longer to respond to hazardous situations. This is consistent with the findings of previous studies (Abay, 2013; Xu et al., 2016). Also, the parameters of pedestrian aged 66–80 years and older than 80 years were normally distributed. We found that the probabilities of incurring KSI were 90.0% and 58.1% for pedestrian aged 66 – 80 years and older than 80 years, respectively. This echoes findings that the physiological conditions of people in the same age group can vary significantly (Islam and Jones, 2014). This is an alarming issue for traffic management and control and road-user education. As in other modern societies, the ageing population is a matter of increasing concern in Hong Kong. The proportion of the population older than 65 years is projected to increase from 16% in 2016 to over 25% in 2035. To improve road safety, special attention should be paid to elderly pedestrians. The safety awareness of this vulnerable pedestrian group could be enhanced by education and promotional campaigns, especially for areas with high levels of pedestrian activities, vehicle – pedestrian interactions, and attraction points for elderly citizens (i.e., hospital, clinic, and recreation and welfare services). Other possible remedial measures are improving sidewalk design and installing pedestrian signals that emphasize the needs of the elderly.

Vehicle and Driver Attributes

It is not surprising that negligent driving behavior is correlated with a higher likelihood of KSI crashes. Negligent driving behaviors include reversing, U-turning, overtaking, and turning recklessly. To tackle these problems, enforcements and penalties could be enhanced to combat risky driving behavior. Also, targeted safety campaigns could be implemented to emphasize the hazards associated with aggressive driving and unexpected vehicle maneuvers (Sze and Wong, 2007).

With respect to vehicle class, crashes involving private cars, goods vehicles, buses, and taxis all had higher likelihoods of KSI, compared to those involving bicycles and motorcycles. This finding is expected considering the differences in mass, speed, and energy dissipated for different crash types (Haleem et al., 2015). These results indicate the importance of better traffic control and management, and in particular, the use of warning signs at locations that serve as access points to public transport interchanges and loading/unloading areas, where interactions between pedestrians, buses, taxis, and goods vehicles are frequent (Sze and Wong, 2007).

Road Environment and Traffic Control

We found pedestrian crashes that occur on one-way roads and roads with no crossing control to have lower likelihood of KSI. This could be attributed to lower vehicular speed on one-way roads and higher driver and/or pedestrian awareness due to frequent roadside activities and unexpected crossings, therefore reducing the risk of more severe pedestrian crashes (Tulu et al., 2015). Indeed, the crash location parameter was normally distributed. The probability of slight injury crashes on roads with no crossing control was 64.1%. This indicates a significant variation in traffic condition and vehicular speed, and thus the varying effect of road environment on crash severity (Pei et al. 2012).

Pedestrian crashes at crosswalks have tended to have higher risk of fatality or serious injury (Sarkar et al., 2011; Brosseau et al., 2013). Consistently, the results of this study indicate that a number of pedestrian actions, including crossing from the off side or near side of the road and walking while facing traffic were all correlated with a higher likelihood of KSI. It is essential to combat risky pedestrian and driver behaviors such as jaywalking, speeding, and driving under the influence by increasing traffic surveillance and penalty levels (Sze et al., 2011). Also, the installation of barriers and warning signs to drivers regarding the presence of pedestrians could enhance pedestrian safety at locations with high levels of pedestrian activity.

Time and Space Distribution

With respect to temporal distribution, we found that crashes occurring between 10:00 am and 4:00 pm (non-peak period) had lower likelihood of KSI, compared to those occurring at night. Sze and Wong (2007) found better visual conditions and increased awareness of drivers to be correlated with lower injury risk. With respect to geographical distribution, crashes that occurred in Kowloon (densely developed urban area) had a higher likelihood of KSI. These results are consistent with those of a previous study. The number of points of attraction, i.e., restaurant, recreation, and shopping mall both for local residents and tourists, was high in Kowloon, and roadside and loading/unloading activities were very frequent. These factors may all have increased the crash and injury risks (Wong et al., 2007). Noland and Quddus (2005) found dense urban areas with a higher population density, road density, and pedestrian activity near public transportation stations to be positively associated with mortality and severe injury, especially during congested periods. Also, the 'Kowloon' parameter variable was normally distributed, with a 72% probability that injury risk in Kowloon was higher than that on Hong Kong Island and in the New Territories. Variations in the association between crash severity and geographical distribution could be attributed to the regular (day-to-day variation) and irregular (traffic incident) fluctuations in traffic conditions.

Weather Condition

As also shown in Table 3, crashes occurring when the air temperature was higher than 30 °C and in rainy conditions tended to have higher likelihood of KSI. This finding is consistent with those of previous studies, which found that pedestrians and drivers tended to be less patient and more likely to violate traffic rules in undesirable environmental conditions (Li and Fernie, 2010; Naik et al., 2016). Indeed, rain has long been recognized as a common factor contributing to increases in crashes and injury risk (Eisenberg. 2004; Caliendo et al., 2007; Khorashadi et al., 2005; Qiu and Nixon. 2008; Theofilatos et al., 2012).

When other factors are unchanged, weather conditions could affect driver and pedestrian behaviors. Therefore, the association between crash severity and possible risk factors may be moderated by weather conditions. In particular, in hot weather conditions, crashes attributed to driver inattention and reckless crossing by pedestrians had higher likelihoods of KSI. This could be attributed to an increased sensitivity to risky pedestrian and driver behaviors to changes in traffic conditions in hot weather. Also, the capabilities of drivers and pedestrians to execute a defensive response to an emergency situation could be reduced in poor weather conditions. Moreover, increases in tire pressure might result in the tire bursting in continuously extreme hot weather conditions. All these factors have adverse impacts on crash and injury risk. Perhaps the higher risk of road injury in hot weather could be emphasized in promotional campaigns for pedestrians.

Similarly, in rainy conditions, crashes attributable to jaywalking and risky driver behavior may have a higher likelihood of KSI, but those occurring when the footpath was overcrowded had a lower likelihood of KSI. This could be attributed to reductions in visibility and surface friction in the presence of rain, and a corresponding increase in the sensitivities of risky driver and pedestrian crossing behaviors to crash and injury risk. Indeed, a longer braking distance and response time would be required when visibility is reduced and the pavement surface condition is poor (Theofilatos and Yannis, 2014; Mondal et al., 2011). Also, cognitive performance with respect to road signs, road environment, car-following, and approaching traffic and/or pedestrians has been found to be impaired when visibility is reduced, based on the results of a driving simulator experiment and eye tracking (Chapman and Crundall, 2010). The authors reported an expectation that driver and pedestrian awareness in undesirable weather conditions could be enhanced by the use of variable messages and warning signs, thereby enhancing pedestrian safety. Last but not least, under rainy condition, crashes that occurred when the footpath was overcrowded had a lower likelihood of KSI. This finding is consistent with that of a previous study (Xu et al., 2016), and could be because a protective barrier was often provided when pedestrian volume was high.

Nevertheless, rarely has the association between crash severity, possible risk factors, and weather conditions been measured using real-time weather data. Therefore, the remedial measures proposed to date have been relatively inelastic and unresponsive to the weather conditions. As revealed in this study, the interaction effects of weather conditions on the association between crash severity and risky driver and pedestrian behaviors (e.g., jaywalking, driving under the influence) are significant. Therefore, real-time weather data must be incorporated with traffic data in any proactive traffic management system. For instance, messages presented by variable message signs and in-vehicle driver assistance systems could both be responsive to real-time weather conditions, especially in extreme hot weather and heavy rainstorms. This would enhance the safety awareness of drivers and pedestrians, and reduce the corresponding crash and injury risks in adverse weather conditions. Also, targeted road-user education and road-safety publicity could be implemented during the summer period, in which extreme hot weather, typhoons, and rainstorms are prevalent.

6. Conclusions

Pedestrians are vulnerable to severe injury and mortality in road crashes, and pedestrian behavior and injury risk are sensitive to the weather conditions. In this era of climate change, occurrences of extreme weather events including heat waves and rainstorms are more frequent. It is essential to identify the factors contributing to high injury risk on roads and the moderating effects of weather condition on this association. In this study, we integrated high-resolution weather data, and the corresponding temporal and spatial distributions, with crash and traffic data. In particular, we obtained information on wind speed, gust speed, air temperature, humidity, and rainfall at 1-minute intervals from eighteen automatic weather stations across Hong Kong (a compact city with land area of 1,100 sq. kilometer). We then established a mixed logit regression model, allowing for variation in parameters across observations. Our results indicate that hot weather and the presence of rain both contributed to a higher likelihood of more severe crashes. Also, we examined the interaction effects of weather on the association between crash severity and driver and pedestrian behaviors to identify risky behaviors under adverse weather conditions. For instance, we found the effects of jaywalking and risky driver behavior on crash severity to be more prevalent in rainy conditions. In addition, we found the effects of driver inattention and reckless crossing on crash severity to be more significant in hot weather conditions. This indicates a need to develop and implement a proactive traffic management system that integrates both real-time weather and traffic data. By doing so, the safety awareness of drivers and pedestrians can be enhanced in adverse weather conditions.

In this study, we obtained information about driver and pedestrian behaviors and crash circumstance from police crash records. These records are subject to the judgment of and details provided by the attending police officer at the crash. Also, it is crucial to understand the relationship between weather condition, pedestrian and driver behaviors, and personal characteristics, including demographics and socio-economic characteristics. In future research, it will be worthwhile to explore the association between real-time weather condition (e.g., storm and fog), traffic conditions, personal characteristics, and driver and pedestrian behaviors when comprehensive information is available for an empirical survey and a pedestrian/driving simulator experiment.

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