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A two-stage safety evaluation model for the red light running behaviour of pedestrians using the game theory

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Abstract: Red light running behaviour of pedestrians at the signalized crosswalks has been one of the major causes of pedestrian-vehicle crashes. Prior studies have identified the personal, environmental and traffic factors that affect the tendency of pedestrian to violate the pedestrian signal. However, it is rare that the safety consequences of red light running behavior of pedestrians are assessed. This paper aims to estimate the risk of pedestrian-vehicle conflicts attributed to the red light running behaviour of pedestrians using a two-stage modeling framework. In the first stage, interference of the decisions between driver and pedestrian at the crosswalks is modeled as a simultaneous two-player game, with which the errors of players' perceptions are incorporated using the quantal response equilibrium method. Then, the anticipations of pedestrian (to cross) and driver (to yield) in the game are estimated using the expected utility theory. In the second stage, risk of pedestrian-vehicle conflicts is modeled using the bivariate ordered Probit regression method, based on post encroachment time. Results indicate that both the pedestrian (i.e., gender and walking speed) and vehicle (i.e., speed, distance, and vehicle type) characteristics would affect the anticipations of driver and pedestrian, and therefore the risk of potential conflicts. For example, male and fast walking pedestrians have the higher expectations to cross. In contrast, vehicle speed increases with the anticipations of both pedestrian and driver to yield. Additionally, male have a higher risk of more severe conflicts. However, risk of more severe conflicts reduces when the walking speed and vehicle speed increase. Findings are indicative to the implementation of appropriate remedial measures including traffic management and targeted enforcement that can deter against the red light running behaviour of pedestrians. Hence, overall pedestrian safety can be improved in the long run.

Keywords: Pedestrian safety; Red light running behaviour; Game theoretical model; Safety surrogate measure; bivariate ordered model

1. INTRODUCTION

Recently, there has been increasing interest in pedestrian safety round the world. Non-motorized transportation constitutes to over one-third of total road deaths (World Health Organization, 2018). This is a particularly alarming problem in the metropolitan areas where pedestrian-vehicle interactions are frequent. In Hong Kong, 51% of road deaths were pedestrians in 2019 (Transport Department, 2019). Also, red light running violation of pedestrians is one of the key contributory factors to pedestrian-vehicle crashes (Wang et al., 2020). This constitutes a quarter of pedestrian-involved crashes at the signal intersections (Zhu et al., 2021a). Studies have examined the roles of road environment, traffic control, traffic condition, and personal characteristics in the propensity of red light running violation of pedestrians through field observation (Mukherjee and Mitra, 2020; Zhu et al., 2021a) and questionnaire survey (Zhu et al., 2021b). For instance, it is possible to measure the association between pedestrians' safety attitudes, social influences, conformity tendency, and intentions to run the red light using a psychological framework like theory of planned behavior (TPB) (Evans and Norman, 1998; Yagil, 2000; Zhou and Horrey, 2010; Zhou et al., 2016). Despite that some previous studies have investigated the yield behaviours of drivers and pedestrians in the pedestrian-vehicle interactions using a gap acceptance model, it is rare that the safety risk attributed to the red light running behaviour of pedestrians is investigated. Additionally, effects of vehicle dynamics and pedestrians' decisions in the pedestrian-vehicle interactions in the crossing process should be considered in the pedestrian-vehicle conflict risk prediction model. Findings should help improve the understanding of policy makers on the safety implication of red light running behaviour of pedestrians and possible explanatory factors. Therefore, optimal engineering design and policy strategies can be implemented to deter against red light running behaviour of pedestrians and mitigate the associated crash risk. For instance, interventions like remedial road design, optimized signal timing plan, automated enforcement system, and targeted safety campaign can be implemented to increase the safety awareness, promote the compliance with traffic rules, and protect the pedestrians from being hit at the signalized crosswalks.

1.1 The current paper

In this study, a two-stage framework is proposed to predict the safety risk attributed to the red light running behaviour of pedestrians, with which the effects of pedestrian characteristics, traffic conditions, vehicle dynamics, and pedestrian-vehicle interactions are considered. In the first stage, a game theoretical model is proposed to model the yield behaviours of pedestrians and drivers in the pedestrian-vehicle interactions, using the Quantal Response Equilibrium (QRE) approach, at two different moments in the crossing process of pedestrian who violates the red light. In the second stage, association between conflict risk and possible explanatory factors of the pedestrian-vehicle interactions is modeled using a bivariate ordered Probit model.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 describes the data collection and analysis methods. Section 4 presents the modeling results of yield behaviours of pedestrian and driver, and associated conflict risk. Section 5 discusses the implications of the results. Section 6 provides the concluding remarks and future research directions.

2. LITERATURE REVIEW

2.1 Risk of pedestrian-vehicle conflicts

Studies have attempted to examine the factors including road environment, traffic condition, and personal characteristics that affect the risk of pedestrian-vehicle conflicts (Vogel, 2002; Tarko et al., 2009; Ismail et al., 2009; Almodfer et al., 2016; Fu et al., 2018; Khosravi et al., 2018; Zhang et al., 2020), based on different surrogate safety measures (SSMs) including time-to-collision (TTC) (Hayward, 1972) and post-encroachment time (PET) (Varhelyi, 1998). For instance, risk of older pedestrian is higher than that of normal adult, considering the physical capability and walking speed of elderly (Liu and Tung, 2014). Additionally, safety awareness and risk perception of male are lower than that of female when crossing the roads (Yagil, 2000). For the effect of traffic condition, increases in traffic volume and vehicular speed are associated with the increase in the risk of severe pedestrian-vehicle conflicts, especially when the pedestrians are annoyed because of the long waiting time (Cheng, 2013). Furthermore, absence of central refuge and increase in the size of pedestrian platoon are associated with the increase in the risk of pedestrian-vehicle conflicts (Zhang et al., 2017).

A few studies have assessed the risk of pedestrian-vehicle conflicts using emerging analytic approaches. For instance, an automated video analysis method is proposed to extract the trajectories of pedestrians and vehicles for the modeling of pedestrian-vehicle conflicts (Ismail et al., 2009). Additionally, a mathematical simulation platform is proposed to predict the pedestrian-vehicle conflicts for the safety assessment of road geometry and traffic operation characteristics in the design stage (P. Chen et al., 2019). Furthermore, machine learning approach is adopted to predict the pedestrian-vehicle conflicts (Zhang et al., 2020; Pustokhina et al., 2021).

Above studies shed light on the analytic methods and possible explanatory factors for pedestrian-vehicle conflicts. However, it is rare that the interactions between pedestrians and vehicles (drivers) are considered in the safety risk assessment, except an empirical survey based on manual tracking (Ni et al., 2016). Nevertheless, it is crucial to account for the yield behaviours of driver and pedestrian when modeling the pedestrian-vehicle interactions.

2.2 Interactions between driver and pedestrian

Numerous studies have examined the factors including road geometry, traffic operation and signal time plan, pedestrians' characteristics and behaviours that affect the crossing decision of pedestrians (de Lavalette et al., 2009; Koh et al., 2014; Li, 2013; Liu and Tung, 2014). Different microscopic traffic simulation models are proposed to model the dynamic interactions between pedestrian and vehicle. For example, cellular automata (CA) approach is adopted to simulate the movements of pedestrians, with which the interferences among pedestrian, vehicle and other obstacles are considered, when crossing the roads (Zhang et al., 2004). In addition, effects of vehicular and pedestrian flows, arrival rates, waiting time and sensitivity of pedestrians on the pedestrian-vehicle interactions can be accommodated in the decision rules of CA model (Sun et al., 2012; Xin et al., 2014). However, these studies primarily focus on the decision of pedestrians only and do not consider the drivers' responses. This may in turn under- or over-estimate the risk of pedestrian-vehicle conflicts.

Studies also investigated the yield behaviour of drivers at the uncontrolled crosswalks. For example, driver had a higher likelihood to give way to the pedestrian who appeared to behave confidently (Schroeder and Rouphail, 2011). In addition, yield behaviour of drivers could be moderated by the factors including pedestrian characteristics, road geometry, and distance to the crosswalks (Fricker and Zhang, 2019). Furthermore, factors that affected the yield behaviour of drivers were examined using the microscopic traffic simulation model (Amado et al., 2020). Nevertheless, it is rare that the choice behaviours of driver and pedestrian, which are interdependent, are modeled simultaneously.

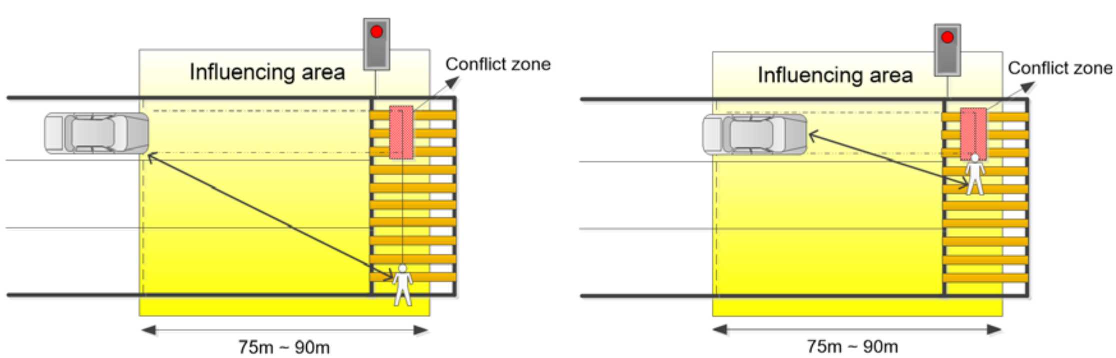
Indeed, it is possible to model the decisions of more than one parties simultaneously in the interactions (i.e., vehicle-vehicle, vehicle-bicycle, and vehicle-pedestrian) using the game theoretical model (Arbis and Dixit, 2019; Meng et al., 2016; Talebpour et al., 2015; Wang et al., 2015). While the game theoretical model is widely applied for the interactions between vehicles, a few studies have adopted it for the interactions between pedestrian (or bicycle) and vehicle at the uncontrolled and semi-controlled crosswalks (Chen et al., 2016; Bjørnskau, 2017). In the game model, a solution - Nash equilibrium refers to a combination of strategies (i.e., yield versus not yield) of individuals that can give the best outcome. However, basic assumptions of conventional game model are perfect information and rational expectation of all individuals. To this end, Quantal Response Equilibrium (QRE) is proposed to relax such assumptions, given which errors of individual choice behaviours are allowed (McKelvey and Palfrey, 1995). For instance, it is possible to accommodate the heterogeneity of individual behaviours by incorporating the bounded rationality in an evolutionary game framework (Bjørnskau, 2017; Arbis and Dixit, 2019).

To sum up, it is viable to model the interactions between pedestrian and vehicle (driver) at the crosswalks using the game theoretical model. To step forward, it is crucial to estimate the safety risk attributed to the red light running behaviour of pedestrians, with which the dynamic interferences of the behaviours between pedestrian and driver are considered.

3. METHOD

3.1 Game theoretical model

This study aims to examine the factors that affect the risk of pedestrian-vehicle conflicts related to the red light running behaviour of pedestrians at the signalized crosswalks. The interaction between pedestrian and driver is modeled as a simultaneous two-player game. In other word, choice decisions of one pedestrian and one driver in an interaction are made at the same time. For instance, an effective interaction is established when (1) the pedestrian signal is red, (2) there is one pedestrian who violates the pedestrian signal and crosses the road, and (3) there is one vehicle approaching the crosswalk. **Figure 1** depicts the "influencing area" and "conflict zone" for the pedestrian-vehicle interactions. The former refers to the area in which the decision of one player would interfere with that of another player. The latter refers to the intersecting area of the maneuvers of pedestrian and vehicle. The longitudinal distance (75 to 90 meters) of influencing area is set out in accordance with the acceptable time gaps of pedestrians (e.g., 6 seconds) (Koh and Wong, 2014; Pawar and Patil, 2016) and prevailing speed limit. In this study, all crosswalks under investigation are in the urban area, and the prevailing speed limits are 50 km/hour.



(a) First interaction **(b) Second interaction**

Figure 1. Illustrations for the interactions between vehicle and pedestrian

As shown in **Figure 1**, interactions between vehicle (driver) and pedestrian at two different moments: (a) when the pedestrian is at the kerbside, and (b) when the pedestrian is near the conflict zone, are considered[1]. In the game model, each of the two players can have two choices. For example, the driver can choose 'to yield' or 'not to yield', and the pedestrian can choose 'to cross' or 'not to cross', respectively. Let S denotes the strategy set of the players, with $S_{driver} = \{yield, not\ yield\}$ and $S_{pedestrian} = \{cross, not\ cross\}$. Then, the resultant strategy set of $S = S_{driver} \times S_{pedestrian}$ is {(*yield, cross*), (*yield, not cross*), (*not yield, cross*), (*not yield, not cross*)}. Both players are assumed to choose the strategies that have the highest perceived return.

In Quantal Response Equilibrium (QRE), perceptions of the players are subject to errors. Therefore, choice decisions of pedestrian and driver, who are boundedly rational, are stochastic. Such decisions are modeled using Expected Utility Theory, with which the utilities of a player are dependent on the anticipations of the strategies of another player. In this study, utilities of pedestrian and driver are given by,

Pedestrians' utilities:

$$EU_{cross} = p_{yield} \times a\boldsymbol{U} + \boldsymbol{c}_1 \quad \text{(Eq. 1)}$$

$$EU_{not\ cross} = b\boldsymbol{V} \quad \text{(Eq. 2)}$$

Drivers' utilities:

$$EU_{yield} = d\boldsymbol{M} \quad \text{(Eq. 3)}$$

$$EU_{not\ yield} = (1 - p_{cross}) \times e\boldsymbol{W} + \boldsymbol{c}_2 \quad \text{(Eq. 4)}$$

where $\boldsymbol{U}$ and $\boldsymbol{V}$ are the vectors of explanatory variables for pedestrian, $\boldsymbol{M}$ and $\boldsymbol{W}$ are the vectors of explanatory variables for driver, c_1 and c_2 are constant terms, a, b, d and e are the vectors of

[1] Despite that it is possible to have multiple interactions between a pedestrian and a driver in the crossing process, only the interactions at these two moments are considered for illustrative purpose. For instance, the pedestrian would usually look around for a suitable time gap when he or she is intended to cross (i.e., making violation decision). In contrast, the driver would decide to yield and decelerate when a pedestrian is near the conflict area. Hence, (a) and (b) are considered as the safety-critical moments.

coefficients, $0 \leq p_{yield} \leq 1$ is the anticipation of pedestrian that the driver will yield, and $0 \leq p_{cross} \leq 1$ is the anticipation of driver that the pedestrian will cross, respectively.

As shown in Equation 1-4, payoffs are linear combinations of explanatory factors that affect the choice behaviour of pedestrians and drivers. The explanatory factors must satisfy two criteria. First, they should be independent, with Pearson correlation of every pair of variables being less than 0.5 Second, they should be statistically significant at the 5% level.

Table 1. Payoff matrix for the game between pedestrian and driver

$\boldsymbol{S_{pedestrian}}$	$\boldsymbol{S_{driver}}$			
	Yield		**Do not yield**	
	Pedestrian payoff	Driver payoff	Pedestrian payoff	Driver payoff
Cross	$p_{yield} \times a\boldsymbol{U} + \boldsymbol{c}_1$	$d\boldsymbol{M}$	$\boldsymbol{c}_1$	$\boldsymbol{c}_2$
Not cross	$b\boldsymbol{V}$	$d\boldsymbol{M}$	$b\boldsymbol{V}$	$(1 - p_{cross}) \times e\boldsymbol{W} + \boldsymbol{c}_2$

Table 1 illustrates the payoff matrix for the game between pedestrian and driver. The payoff functions of pedestrian and driver are interdependent. Additionally, it is assumed that strategies with less time delay are preferred, given that the vehicle-pedestrian conflict risks are minimal. Probabilities for the strategies of driver and pedestrian are estimated using the logit functions given as follows,

Choice probability of driver:

$$p_{yield} = \frac{exp[EU_{yield}(1-p_{cross})]}{exp[EU_{yield}(1-p_{cross})]+exp[EU_{notyield}]} \qquad \text{(Eq. 5)}$$

Choice probability of pedestrian:

$$p_{cross} = \frac{exp[EU_{cross}(p_{yield})]}{exp[EU_{cross}(p_{yield})]+exp[EU_{notcross}]} \qquad \text{(Eq. 6)}$$

In accordance with QRE, on average, choice probabilities of the players in the above logit functions (Eq. (5) and Eq. (6)) are equal to the perceived probabilities, which are subject to errors, of another player in Eq. (1) and Eq. (4) (Watling, 2006).

Then, it is a fixed point problem to solve $p_{yield} = \boldsymbol{F}(p_{cross})$ and $p_{cross} = \boldsymbol{H}(p_{yield})$, The probabilities p_{yield} and p_{cross} are solved iteratively using a logit QRE, with which the errors in the players' perceptions follow an extreme value distribution (McKelvey and Palfrey, 1995).

The coefficients *a* and *b* are estimated using the maximum likelihood approach, with the latent expected utility indices (ΔEU) of the driver and pedestrian given by,

Pedestrian:

$$\Delta EU_{cross} = (EU_{cross} - EU_{notcross}) \quad \text{(Eq. 7)}$$

Driver:

$$\Delta EU_{yield} = (EU_{yield} - EU_{notyield}) \quad \text{(Eq. 8)}$$

Hence, the log-likelihood functions for the decisions are given by,

Pedestrian:

$$LL_{pedestrian}(a: S, V) = \sum_i \{ ln[\varphi(\Delta EU_{cross})] \times I\{y_i = 1\} + ln[1 - \varphi(\Delta EU_{cross})] \times I\{y_i = 0\}\} \quad \text{(Eq. 9)}$$

Driver:

$$LL_{driver}(b: S, W) = \sum_j \{ ln[\varphi(\Delta EU_{yield})] \times I\{y_j = 1\} + ln[1 - \varphi(\Delta EU_{yield})] \times I\{y_j = 0\}\} \quad \text{(Eq. 10)}$$

where y_i and y_j denote the choice decisions of pedestrian and driver, with 1 indicating 'yes' and 0 otherwise, and φ (.) is the cumulative distribution function of logistic distribution.

Lastly, the resultant log-likelihood function for the maximization is given by (Dixit and Denant-Boemont, 2014),

$$LL = LL_{pedestrian}(a: S, V) + LL_{driver}(b: S, W) \quad \text{(Eq. 11)}$$

Convergence of solution algorithm - expectation maximization (EM) – of logit QRE was testified in a recent study. For details of the algorithm, readers may refer to (Zhang and Fricker, 2021). For instance, the logit QRE usually converges within 200 iterations.

3.2 Modeling of pedestrian-vehicle conflicts

In the preceding part, the interaction between pedestrian and driver is modeled as a simultaneous game using QRE approach. The choice probabilities of pedestrian and driver are then incorporated into a joint probability function to estimate the likelihood of potential conflict, $p_{conflict}$ as,

$$p_{conflict} = p_{cross} \times (1 - p_{yield}) \tag{Eq. 12}$$

In addition, a surrogate safety measure – post encroachment time (PET) is considered to estimate the safety consequence of red light running behaviour of pedestrians at the signalized crosswalks. For instance, PET can be given by,

$$PET = \Delta TTA$$
$$= |TTA_{veh} - TTA_{ped}| = |\frac{d_{veh}}{v_{veh}} - \frac{d_{ped}}{v_{ped}}| \tag{Eq. 13}$$

where TTA_{veh} and TTA_{ped} are the times to arrival (at the conflict area) of vehicle and pedestrian, d_{veh} and d_{ped} are the distances from the conflict area of vehicle and pedestrian, and v_{veh} and v_{ped} are the vehicular speed and pedestrian's walking speed, respectively. It should be noted that the PET used could be regarded as anticipated "safety margin", which is defined as the difference between the time a pedestrian crossed the conflict point and the time the next vehicle arrived at the same conflict point (Avinash et al., 2019).

It is considered that the pedestrian-vehicle conflicts are more plausible when PET is smaller. Therefore, the conflict risk is estimated using,

$$p'_{conflict} = kp_{conflict} = kp_{cross} \times \left(1 - p_{yield}\right) \tag{Eq. 14}$$

Where $k = 0$ when $PET > 6$ seconds, $k = 1$ when $2.5 \leq PET \leq 6$ seconds, and $k = 2$ when $PET < 2.5$ seconds respectively.

Then, as shown in **Table 2**, risk of pedestrian-vehicle conflict is considered as negligible (zero) when PET is greater than 6 seconds. In contrast, the risk is considered as 'major' when PET is less than 2.5 seconds and $p'_{conflict}$ is greater than 15%. Then, the ordered Probit regression approach is adopted to measure the association between conflict risk and possible explanatory factors as the dependent variable (risk level) is ordinal.

Table 2. Risk of pedestrian-vehicle conflicts

Risk level	Description
0 (Negligible)	$PET > 6$ seconds
1 (Minor)	$2.5 \leq PET \leq 6$ seconds
2 (Major)	$PET < 2.5$ seconds, and $p'_{conflict} > 15\%$

In this study, interactions between pedestrian and driver at two instances ((a) when the pedestrian is at the kerbside, and (b) when the pedestrian is near the conflict area) are considered. It is possible that the conflict risks of these two interactions are correlated. To address the problem of possible correlation, the bivariate ordered Probit (BOP) regression model is adopted (Greene and Hensher, 2009; Anastasopoulos et al.,2012). For the details of the bivariate ordered Probit regression model, readers may refer to Russo et al. (2014)'s study.

4. DATA

The video observation surveys were conducted at four signalized crosswalks in Hong Kong during the period from January 2021 to March 2021. In conventional observation studies that focused on the prevalence of traffic rule violations, map-based random sampling approach was used to avoid location bias (Porter, 2011). However, the key issue of this study is how to model the choice behaviour of pedestrians and drivers when they interact at the signalized crosswalks contingent upon red light running violation of pedestrians. Hence, there should be adequate sample of pedestrian-vehicle interactions and red light running violation events. To this end, selection criteria of video observation sites were: (1) pedestrian volume should not be too low, and traffic volume should neither be too low nor too high respectively, (2) sight distance for both pedestrian and driver should be adequate, (3) signalized crosswalk should not be too long (i.e., number of traffic lanes should not be too high). Therefore, pedestrians would be tempted to violate the pedestrian signal and result in "effective" interactions with approaching traffic. We have selected the four video observation sites, that satisfied all the above criteria, based on road network design plan, transport planning data, field observations, and pilot surveys. In addition, to capture a wider coverage of built environment, four sites that are of different land use, e.g., residential, commercial, government utility, and mixed land use, are considered. **Figure 2** illustrates the aerial views of the four observation sites. A total of 8-hour video was captured for each site. For instance, surveys were conducted at weekday peak, weekday non-peak, and weekend, considering the effect of the variation in traffic condition. Furthermore, weather and lighting conditions were fine in all surveys. Nevertheless, the green time, red time, and cycle time of almost all signalized junctions in Hong Kong are not fixed. They are responsive to the real-time traffic flow.

(a) Fung Tak Road

(b) Hung Hom Road junction with Tak Man Street

(c) Yee Wo Street near Peterson Street

(d) Tokin Street junction with Lai Chi Kok Road

Figure 2. Aerial view of the survey sites

Among the four sites, number of traffic lanes is either 2 or 3. In the surveys, 1,051 pedestrians were found violating the red pedestrian signal. For instance, 349 x 2 = 698 pedestrian-vehicle interactions were observed. In this study, trajectories of pedestrians and vehicles are extracted using the image processing and recognition algorithm including YOLO (you only look once) Version 5.0 (https://github.com/ultralytics/yolov5) and Deep Sort Version 4.0. For instance, efficacies of YOLO (Redmon et al., 2016; Jana et al., 2018; Lin and Sun, 2018) and Deep Sort (Hou et al., 2019; Zhang et al., 2020) for trajectory tracking were verified. **Figure 3** illustrates the snapshot of object detection and tracking using YOLO and Deep Sort. Then, the displacement, speed and acceleration of pedestrian and vehicle are estimated based on the trajectory data. Nevertheless, attributes including red time, green time, vehicle type, and gender of pedestrian are recorded manually. **Table 3** summarizes the variables considered in this study.

Figure 3. Trajectory tracking of pedestrian and vehicle

Table 3. Variables considered in this study

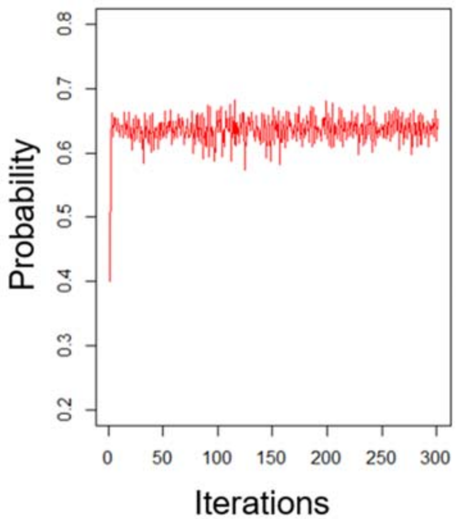
Variable	**Description**	**Type**	**Range**	**Mean**	**Standard deviation**
Choice decision					
Pedestrian's decision	Crossing behaviour of pedestrian	Indicator	Cross: 1; Otherwise: 0	0.47	0.41
Driver's decision	Yield behavior of driver	Indicator	Yield: 1; Otherwise: 0	0.59	0.49
Pedestrian					
Pedestrian gender	Gender of pedestrian	Indicator	Male: 1; Female: 0	0.52	0.50
Pedestrian distance	Distance of pedestrian from the conflict area	Continuous	0 – 11.0 (metre)	4.76	3.12
Walking speed	Walking speed of pedestrian	Continuous	0 – 2.3 (metre/second)	1.38	0.36
Red time	Time of red pedestrian signal	Continuous	0 – 98 (second)	62.15	29.14
Anticipated waiting time	Time to green pedestrian signal	Continuous	0 – 85 (second)	50.25	25.61
Actual waiting time	Time between the arrival of pedestrian and the start of crossing	Continuous	0 – 45 (second)	15.41	10.15
Presence of another violator	Presence of another pedestrian who violates the red light	Indicator	Yes: 1; No: 0	0.50	0.48
Driver					
Vehicle distance	Distance of approaching vehicle from the conflict zone	Continuous	0 – 85 (metre)	59.42	17.84
Vehicle speed	Speed of approaching vehicle	Continuous	0 – 18.1 (metre/second)	11.23	3.87

5. RESULTS

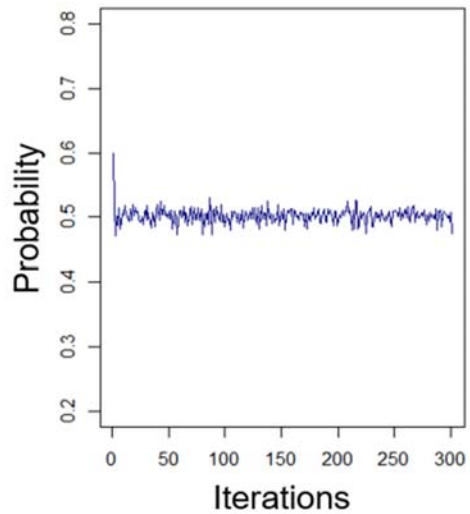
5.1 Interactions between vehicle and pedestrian

In the logit QRE for pedestrian-driver interaction, initial values of p_{cross} and p_{yield} are set as 0.6

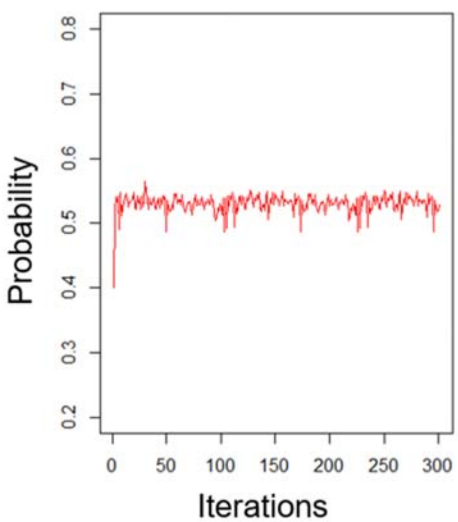
and 0.6, and the step size of iteration is 0.001, respectively. **Figure 4** illustrates the trace plots of p_{cross} and p_{yield} with 200 iterations. The solution is converged within 300 iterations for both interactions. As shown in **Figure 4**, p_{cross} = 0.35 and p_{yield} = 0.48 for the first interaction, and p_{cross} = 0.47 and p_{yield} = 0.51 for the second interaction, respectively.



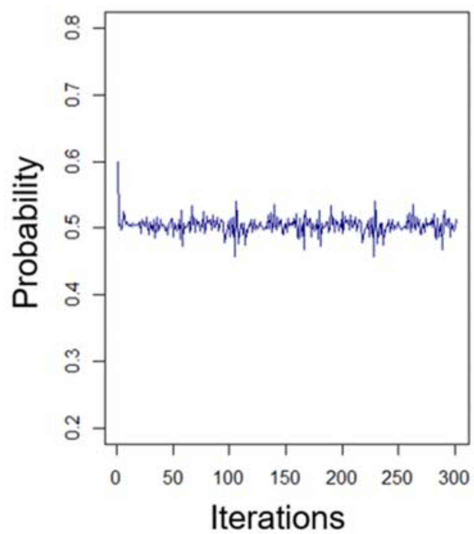
(a) First interaction – pedestrian (not cross)



(b) First interaction – driver (yield)



(c) Second interaction – pedestrian (not cross)



(d) Second interaction – driver (yield)

Figure 4. Trace plots for convergence of the EM Algorithm of yielding probability

Results of parameter estimation for the game between pedestrian and driver are shown in **Table 4**. For instance, empirical distribution of parameters using bootstrap simulation can be given

(Train, 2009; Zhang et al., 2021). As shown in **Table 4**, pedestrian gender, actual waiting time and walking speed, and vehicle speed significantly affect the decision of pedestrian, all at the 5% level. For instance, male pedestrian (Coefficient = 0.58 for the first interaction; coefficient = 1.15 for the second interaction) has a higher utility to cross. Additionally, walking speed (1.13; 0.48) is positively associated with the pedestrian's utility to cross. However, vehicle speed (-0.02; -0.03) and pedestrian's actual waiting time (-0.05; -0.07) are negatively associated with the pedestrian's utility to cross.

As also shown in **Table 4**, vehicle type, distance and speed significantly affect the decision of driver, all at the 5% level. For instance, vehicle speed (0.14; 0.08) and walking speed (0.03; 0.05) are positively associated with the driver's utility to yield. In contrast, vehicle distance (-0.02; -0.03) is negatively associated with the driver's utility to yield. Also, utility to yield of driver of heavy vehicle is lower (-0.24; -0.58) than that of other vehicle type. **Figure 5** illustrates the probability distribution of potential conflicts for the first and second pedestrian-driver interactions. As shown in **Figure 5**, mean probability of potential conflict in the first interaction (10.7 ± 5.0%) is lower than that of the second interaction (11.6 ± 6.3%).

Table 4. Results of parameter estimation of game theoretical model

Factor	First interaction		Second interaction	
	Coefficient	z	Coefficient	z
Expected utility of pedestrian to cross				
Constant	-0.57*	-2.42	-1.52**	-3.35
Male pedestrian	0.58**	3.72	1.15**	3.27
Walking speed	1.13**	3.96	0.48**	5.14
Vehicle speed	-0.02**	-7.69	-0.02**	-4.67
Actual waiting time	-0.04**	-4.29	-0.07**	-7.05
Expected utility of driver to yield				
Constant	-1.42**	-4.22	-1.77**	-5.48
Vehicle distance	-0.02**	-4.12	-0.03**	-3.84
Vehicle speed	0.14**	9.87	0.08**	4.12
Heavy vehicle	-0.24**	-4.08	-0.58*	-2.52
Walking speed	0.03**	3.81	0.05**	3.92

** Statistically significant at the 5% level; **Statistically significant at the 1% level*

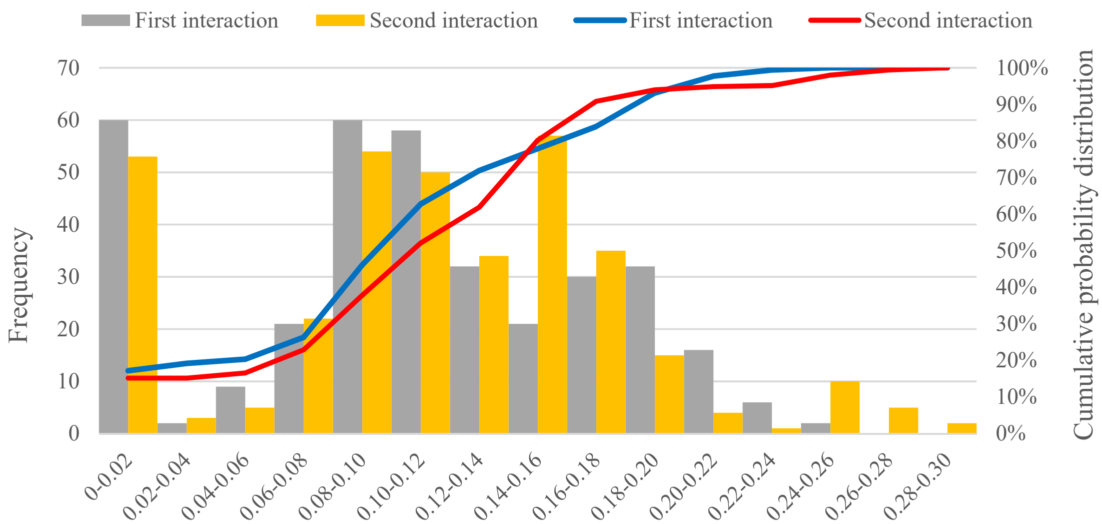


Figure 5. Distribution of the probabilities of potential conflicts

5.2 Pedestrian-vehicle conflict risk

Table 5 presents the results of bivariate ordered Probit model for the risk of pedestrian-vehicle conflicts. Overall, goodness-of-fit of the model is satisfactory, with significant likelihood ratio test statistic. In addition, the correlation parameter is significant. This justifies the use of bivariate model. As shown in **Table 5**, pedestrian gender, walking speed and actual waiting time, anticipation of pedestrian to cross, vehicle type, distance and speed, and anticipation of driver to yield significantly affect the risk of pedestrian-vehicle conflicts, all at the 5% level. For instance, likelihood of male pedestrian (coefficient = 0.31 for the first interaction; coefficient = 0.24 for the second interaction) for more severe pedestrian-vehicle conflicts is higher. Additionally, vehicle speed (0.33; 0.22) is positively associated with the likelihood of more severe pedestrian-vehicle conflicts. Furthermore, walking speed (-0.61; -0.38), anticipation of pedestrian to cross (-1.69 for the second interaction), actual waiting time (-0.15; -0.39), vehicle distance (-0.96; -1.24), anticipation of driver to yield (-1.46; -2.12) are negatively associated with the likelihood of more severe pedestrian-vehicle conflicts. Nevertheless, likelihood of heavy vehicle (-0.40 for the second interaction) for more severe pedestrian-vehicle conflicts is lower.

Table 5. Results of parameter estimation of bivariate ordered Probit model

Factor	First interaction		Second interaction	
	Coefficient	(*t*-statistic)	Coefficient	(*t*-statistic)
Constant	0.26**	(3.21)	IS	
Male pedestrian	0.31**	(4.72)	0.24**	(2.89)
Walking speed	-0.61*	(-2.30)	-0.38*	(-2.19)
Anticipation of pedestrian to cross	IS		-1.69*	(2.01)
Actual waiting time of pedestrian	-0.15**	(7.88)	-0.39**	(2.75)
Vehicle distance	-0.96**	(-8.31)	-1.24**	(-7.25)
Vehicle speed	0.33**	(4.47)	0.22**	(3.98)
Anticipation of driver to yield	-1.46*	(1.96)	-2.12**	(3.12)
Heavy vehicle	IS		-0.40*	(1.96)
Threshold parameter	2.16**	(14.32)	2.40**	(7.34)
Correlation parameter	0.210**			
Restricted loglikelihood	-712.65			
Unrestricted loglikelihood	-347.20			
McFadden Pseudo R^2	0.40			
AIC	630.7			

*IS: Not significant; * Statistically significant at the 5% level; ** Statistically significant at the 1% level*

6. DISCUSSION

6.1 Interactions between vehicle and pedestrian

Pedestrian demographics significantly affect the utility of pedestrian and driver. For example, utility to cross of male pedestrian is higher than that of female, in both two interactions. This is consistent with the findings of previous studies that males are usually more aggressive when crossing (Rosenbloom, 2009). On the other hand, walking speed and actual waiting time of pedestrian significantly affect the utilities of pedestrian and driver. For instance, walking speed of pedestrian is positively associated with the utility to cross, in both two interactions. This could be because more aggressive pedestrians tend to walk faster. Hence, the likelihood to cross would increase (Yang et al., 2015; Zhu et al., 2021a; b). Additionally, walking speed of pedestrian is positively associated with the utility of driver to yield. This could be attributed to the anticipation of driver that a fast walking pedestrian is usually less cautious (Alhajyaseen and Iryo-Asano, 2017). Therefore, he or she must yield to avoid the crash. However, actual waiting time of pedestrian is negatively associated with the utility to cross. This could be because the perceived disutility (of additional time loss) is incremental for a pedestrian who has already waited for long at the kerbside. He or she tends to be more cautious when crossing the road. This is consistent to the finding of previous study that pedestrians who have longer waiting time in the first stage tend to be more obedience in the subsequent stage, at the multi-stage crosswalks (Zhu and Sze, 2021).

For the vehicle characteristics, vehicle speed, vehicle distance and vehicle type significant affect the utilities of driver and pedestrian. For example, vehicle speed is negatively associated with the utility of pedestrian to cross. This could be because of the anticipation of pedestrian that safety margin (available time gap) would reduce when the vehicle speed increases (Avinash et al., 2019). Such speculation is also applicable for the increase in the utility of driver to yield, despite that the driver should have the right of way. Therefore, vehicle distance is negatively associated with the utility of driver to yield since the safety margin for a vehicle that is further away from the crosswalk is high (Alhajyaseen et al., 2013). Despite that, it is worth investigating the drivers' perception of safety margin, of different vehicle speed and distance to the crosswalk, when the driving performance data in the driving simulator experiments and naturalistic driving studies are available. Nevertheless, it is alarming that driver of heavy vehicle has a lower utility to yield, even that the consequence of potential crash involving heavy vehicle is remarkably undesirable.

6.2 Pedestrian-vehicle conflict risk

It is rare that the safety consequences of red light running behaviour of pedestrians are estimated, with which the interferences between the decisions of pedestrian (who violates the red light) and driver are considered, using the trajectory data of pedestrian and vehicle (Iryo-Asano and Alhajyaseen, 2017; Zhuang et al., 2020; Shen et al., 2020; Zhang and Fricker, 2021). Results of this study indicate that gender and walking speed of pedestrian significantly affect the pedestrian-vehicle conflict risk attributed to the red light running behaviour of pedestrians. For example, likelihood of more severe conflict of male pedestrian is higher than that of female.

This is again because males are usually more aggressive when crossing. Additionally, walking speed of pedestrian is negatively associated with the risk of more severe conflict. This could be attributed to the increase in driver awareness and reduction in crash exposure when a pedestrian is walking faster (Pei et al., 2012). Furthermore, actual waiting time of pedestrian is negatively associated with the risk of more severe conflict. It may be because pedestrians who have already waited for a while at the kerbside tend to be more cautious. Nevertheless, driver of approaching vehicle can have more time to recognize and predict the behaviour of pedestrian (W. Chen et al., 2019).

For the vehicle characteristics, speed, distance and type of vehicle approaching the crosswalk both affect the risk of more severe pedestrian-vehicle conflicts attributed to the red light running behaviours of pedestrians. For example, consistent with previous studies, vehicle speed is positively associated with the risk of more severe conflicts (Gårder et al., 2004; Fu et al., 2018; Guo et al., 2020). Despite that increase in vehicle speed can increase the utility of pedestrian to not cross and utility of driver to yield, crash severity is directly related to the momentum and energy dissipation in the collision (that are affected by the mass and speed of vehicle). Such finding is indicative to the implementation of appropriate remedial measures, i.e., reduced speed limit and automated speed enforcement camera, at the hot spots of red light running violations of pedestrians. In addition, distance of vehicle from the conflict zone is negatively associated with the risk of more severe conflict. This could be attributed to the ease of defensive driving behaviour when a driver who is further away from the crosswalk can recognize the behaviours of pedestrians at the crossing. Yet, it is worth investigating the desirable sight distances for driver and pedestrian that can mitigate the potential collision risk in the simulated experiments. Furthermore, risk of more severe conflict of heavy vehicle is higher. This may be because any defensive maneuver of heavy vehicle is implausible (Zhang et al., 2014).

7. CONCLUSION

The aim of this paper is to evaluate the safety consequence of red light running behaviours of pedestrians using a two-stage modeling framework. Choice behaviour of pedestrians and drivers when they interact at the signalized crosswalks contingent upon red light running violation of pedestrians were modeled using the game theoretical model. Then, prevalence and severity of pedestrian-vehicle conflicts were estimated. Furthermore, factors that affect the choice behaviour of drivers and pedestrians in the interaction and therefore the risk of pedestrian-vehicle conflicts were identified.

Results indicate that the proposed QRE model can predict the anticipations of pedestrian (to cross) and driver (to yield) in the interaction game. Additionally, pedestrian and vehicle characteristics that affect the anticipations, and the risk of potential conflicts are identified. For example, male and fast walking pedestrians have a higher utility to cross, pedestrians waited for a while have a lower utility to cross, and faster vehicles can reduce the utility of pedestrian to cross but increase the utility of driver to yield. Additionally, male pedestrians have a higher risk of more severe conflicts, vehicle speed increases with the risk of more severe conflicts. However, walking speed of pedestrians would decrease with the risk of more severe conflicts. Findings are indicative to the remedial engineering measures and policy strategies including local area traffic management, speed limit, and targeted enforcement that could deter against the red light running behaviour of pedestrians. For example, pedestrian-actuated warning signs can be deployed to increase the awareness of drivers when they are approaching the crosswalks. In addition, optimized signal timing plan considering the real-time pedestrian and vehicular traffic flow can be implemented to minimize the waiting time of pedestrians. Hence, tendencies to violate the red signal of pedestrians would be reduced. Therefore, overall pedestrian safety at the signalized crosswalk could be enhanced.

Even that precise trajectory data of pedestrians and vehicles can be extracted using the advanced image processing and recognition algorithm, some personal characteristics that may affect the anticipations of drivers (i.e., driver demographics, socio-economics, driving experience) and pedestrians (i.e., trip purpose, physical health and fitness) in the game are unknown. In the future study, it is worth investigating the effects of experience, belief and attitudes on the utilities of the players when more personal data is available in the attitudinal survey. Nevertheless, interactions between driver and pedestrian at two instances only are considered in the proposed model. It is anticipated this study can be extended to model the dynamics of pedestrian-driver interference using the multivariate model or deep learning approach when the interactions at multiple moments are considered.

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