RED LIGHT RUNNING BEHAVIOUR AND SAFETY OF PEDESTRIANS AT SIGNALIZED CROSSINGS

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Red Light Running Behaviour and Safety of Pedestrians at Signalized Crossings

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CERTIFICATE OF ORIGINALITY

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Abstract

Walking is increasingly promoted as a sustainable transport mode. However, pedestrians are vulnerable to fatality and severe injury in road crashes. In Hong Kong, 62% of road fatalities are pedestrians. Red light running violation of pedestrians is the leading cause of pedestrian-vehicle crashes at the signalized intersections. Therefore, it is of high importance to examine the factors that affect the propensities of red light running of pedestrians and the risk of related crashes. Then, appropriate engineering measures, traffic management, and enforcement strategies can be implemented to deter against the red light running behaviour of pedestrians. In this study, red light running behaviour of pedestrians and related safety outcomes are attempted from three perspectives.

First, pedestrians' intentions to run the red light are investigated using an attitudinal survey. Factors including individual demographics, socioeconomics, personality trait, and situational features are considered. Additionally, trade-off between perceived safety and waiting time is gauged using a stated preference approach. Then, a regret-based model is established to measure the association between possible factors and propensities of red light running of pedestrians. Furthermore, effects of unobserved heterogeneity and correlation in the choices between different scenarios of the same individual are considered using a panel mixed approach. Results indicate that the choice decision of pedestrians are more sensitive to the reduction in waiting time, as compared to the equivalent increase in perceived safety risk. Such trade-off could vary with pedestrian group. Nevertheless, presence and characteristics of another violator can also affect the propensities of red light running of pedestrians.

Second, actual red light running behaviours of pedestrians at the signalized crossings are examined using the observational surveys. Both personal (i.e., demographics and walking behaviours) and environmental (presence and behaviours of other pedestrians, signal time, and traffic conditions) factors that affect the likelihood of red light running violation are considered. Results of random parameter binary logit models indicate that gender and age group of pedestrians, presence of a companion, number of pedestrians around, presence of other violators, time to green, red time, traffic volume, and percentage of heavy vehicles all affect the propensities of red light running of pedestrians. In addition, there are significant interactions between gender and age of pedestrians, presence of other violators, presence of a companion, traffic volume and propensities of red light running. On the other hand, propensities of red light running of pedestrians at two-stage crossings with split (pedestrian) phasing are also investigated. Results indicate that, in addition to personal characteristics and traffic conditions, pedestrian signal of the second stage can affect the propensities of red light running of pedestrians in the first stage. Furthermore, waiting time before crossing the first stage also affects the propensities of red light running in the second stage.

Third, a two-stage framework is established to model the interactions between vehicles and pedestrians (who run the red light) and the associated safety outcomes. In the first stage, a game theoretical model is adopted to model the yielding behaviours of drivers and pedestrians at two specific time points. In the second stage, surrogate safety measures including post-encroachment time (PET) are used to estimate the risk of potential pedestrian-vehicle conflicts. For instance, a bivariate ordered probit model is adopted to measure the association between possible factors, yielding behaviours of pedestrians and drivers, and potential pedestrian-vehicle conflicts.

Overall, findings are indicative to effective countermeasures and innovations including adaptive signal time plan, dynamic warning signs, automated enforcement system, sliding scale penalties, and targeted safety education that can combat the red light running behaviours of pedestrians. Therefore, pedestrian safety at the signalized intersections can be improved in the long run.

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Chapter 1 Introduction

1.1 Background of this study

Walking is being increasingly promoted as a sustainable mode of transport. The Hong Kong Transport Department has been undertaking various policy initiatives to enhance the walkability of Hong Kong. An official report explored walking environments in four Hong Kong districts and concluded that there are good individual examples of walkability in Hong Kong, notably in Central, and summarized the benefits of good walkability from several aspects, including public health, property prices and rents, greater accessibility, increased economic opportunities, environmental benefits and social benefits (Ng et al., 2016). Additionally, inspired by a three-criterion framework articulated by the Danish urban designer Jan Gehl et al. (2006), i.e., protection, comfort, and enjoyment, the Hong Kong government modified Gehl's framework to better fit Hong Kong's environment as a four-criterion framework for good walkability. The proposed framework consists of four issues: possible to walk, i.e., the requisite level of pedestrian facilities and conditions necessary for everyone to be able to walk (important where there are pedestrians); efficient to walk, i.e., the conditions required for pedestrians to get from origin to destination efficiently and easily; comfortable to walk, the qualities required for pedestrians to feel comfortable and at ease; and interesting to walk, i.e., the qualities required for pedestrians to stay in the space and use it for recreational and social activities. This framework can be regarded as a set of standards for public area design. The places that meet the required standards are likely to allow people to enjoy walking and spending time in streets and other public areas.

Given the increasing attention given to walkability, safety is one of the most important related attributes. For instance, Speck (2013) defined four assessment criteria of walkability: usefulness, comfort, attractiveness and safety. However, the issue of pedestrian safety is rising worldwide since pedestrians are vulnerable to fatalities and severe injuries in road crashes. It has been reported that pedestrian and cyclist road traffic fatalities account for over one-third of road traffic deaths (World Health Organisation, 2018). This issue is of particular interest in densely populated cities such as Hong Kong.

As shown in Figure 1.1, during a five-year period (2015-2019), the total number of pedestrian injuries was reduced by a 3.5% rate per year, which appears to be a good trend. However, the proportion/number of serious and fatal injuries remained relatively high (approximately 22.5%). In 2019, 51% of road fatalities were pedestrians (Transport Department, 2020). Violations in which pedestrians run red lights are one of the key contributory factors to pedestrian-vehicle crashes (Wang et al., 2020); this factor is related to a quarter of pedestrian-involved crashes at signal intersections (Zhu et al., 2021a). On the one hand, pedestrians are vulnerable road users due to the absence of physical protection. On the other hand, when pedestrians make illegal/violation crossings, drivers may not be able to respond to the violation crossing behaviour of pedestrians in time, which may result in the high speed of the vehicle when collisions occur. Therefore, a comprehensive study of pedestrian red light running behaviour and safety should be conducted to enhance the knowledge of human decision-making and behaviour, provide insights for potential policy-making and develop safety countermeasures. The findings are indicative of the development of effective engineering, enforcement and educational initiatives that combat the red light running violation behaviour of pedestrians, for different types of crossings (i.e., one-stage and multi-stage with split signal phase). Hence, overall pedestrian safety can be improved in the long run.

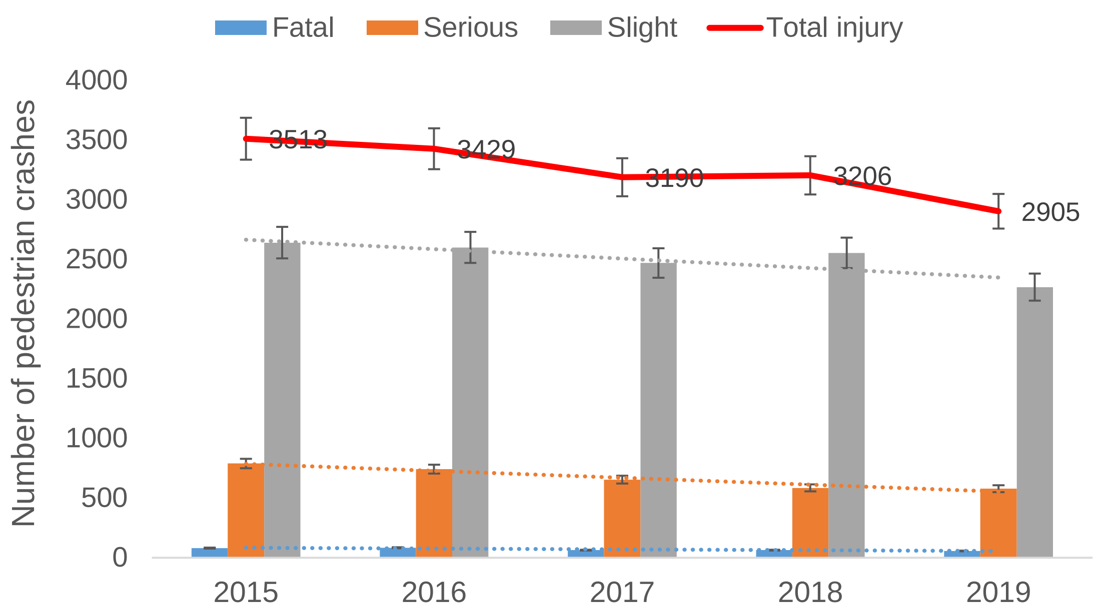


Figure 1. 1 Pedestrian casualties by degree of injury from 2015 to 2019

1.1.1 Problem statement

This study attempts to assess the red light running behaviour and safety of pedestrians from a comprehensive view. Several research questions are therefore proposed herein:

- First, what is the role of the trade-off between cost and benefit in the decision-making process of red light running intention for pedestrians? Would the personality traits (e.g., risk-taking tendency) or other personal characteristics affect the valuation of trade-offs?
- Second, what are the contributory factors that affect the propensity of pedestrian red light running at one-stage crossings? Do the interaction effects between personal characteristics and environmental factors matter?
- Third, for two-stage crossings, what are the differences in the explanatory factors of the propensities of pedestrians to run red light in the first and second stages? What are the effects of the presence and behaviours of other pedestrians on the propensity of red light running in the first and second stages?
- Last but not the least, what happens during the process of pedestrian red light running? How can safety risk be quantified, particularly when incorporating pedestrian-vehicle interactions?

1.2 Research aims and objectives

This study aims to assess the red light running behaviour and safety of pedestrians in Hong Kong. It is of great importance to investigate the red light running behaviour of pedestrians, to evaluate their trade-off between cost (safety risk) and benefit (time saving) before making the crossing decision, to investigate the contributory factors that affect the revealed behaviours in both one-stage and two-stage crossings, and to quantify the risk level during the red light running process by incorporating pedestrian-vehicle interactions. Two observation studies, a perception survey and a two-stage safety evaluation model are employed to achieve this aim. The specific objectives of this study are as follows:

1) Roles of trade-off between time and safety in the red light running behaviour

- To examine the roles of personal characteristics, social influences and road environments in the intentions of red light running behaviour of pedestrians based on the situational decision for the trade-off between safety and time, using a stated preference method. The effects of three situational features, namely, weather conditions, the presence (and type) of other pedestrians who violate, and the presence of a warning sign, on the trade-offs, are investigated. Information on personal characteristics, including demographic and socioeconomic characteristics, travel habits, and personality traits, is also considered.

2) Contributory factors affecting the propensity of pedestrian red light running behaviour

- To examine both the personal (gender, age, pedestrian behaviour) and environmental (signal time and traffic condition) factors affecting the individual decision of red light running violation using a video observation survey at hot spots of pedestrian crashes. The effects of the presence and behaviour of other pedestrians in the same cycle on the propensity are considered. Moreover, interaction effects by personal and environmental factors on the propensity are considered.

- To investigate the red light running behaviours of pedestrians at the two-stage crossings, with which the green pedestrian signal phases in the two stages are split, based on video observation surveys at six urban intersections in Hong Kong. Not only the influences of pedestrian demographics, behavioural characteristics, geometric design, pedestrian signal time and traffic condition but also the interaction effects between personal characteristics and situational features on the propensities are considered.

3) Safety evaluation of pedestrian red light running by incorporating pedestrian-vehicle interactions

- To evaluate the safety consequences of red light running behaviours of pedestrians using a two-stage modelling framework. Interactions between driver and pedestrian at the crosswalk are modeled as a simultaneous two-player game using the quantal response equilibrium (QRE), in which errors in the anticipations of pedestrian and driver are considered. The association between the risk of pedestrian-vehicle conflicts and relevant explanatory factors is modeled, based on post-encroachment time (PET), using a bivariate ordered probit regression model.

It is expected that the findings from this study will support the decision making of transport operators regarding the management of pedestrians, enhance the current understanding of the pedestrian decision-making process and the effectiveness of penalties and educational strategies, and provide useful insights into relevant countermeasures that can enhance the safety culture and awareness of pedestrians and combat the non-compliance behaviour). Therefore, the safety of pedestrians (particularly at intersections) can be improved in the long run.

1.3 Thesis organisation

Chapter 2 reviews the literature on various aspects of red light running behaviour and the safety of pedestrians, including influencing factors, methodological issues and safety evaluations.

Chapter 3 assesses the perceptions and intentions of pedestrians regarding red light running behaviour by using a stated preference method. The trade-offs between safety and time are quantified among different user groups. Additionally, the effects of factors including demographic, socioeconomic, travel experience and personality traits are considered.

Chapter 4 focuses on the roles of personal and environmental factors, as well as interaction effects on the propensity of pedestrian red light running behaviour at one-stage crossings. The crossing behaviours of 6320 pedestrians during the red (pedestrian) signal at six signalized crosswalks in both peak (i.e., 8:00 am~9:00 am; 5:00 pm~6:00 pm) and non-peak periods (10:00 am~11:00 am; 3:00 pm~5:00 pm) of the daytime are captured.

Moreover, the effects of social influences as indicated by the presence, number and behaviours of other pedestrians around on the red light running propensity are considered.

Chapter 5 identifies the personal characteristics, traffic attributes and environmental factors that affect the red light running propensities of pedestrians at two-stage crossings, in which the green pedestrian signal phases in the two stages are split, based on video observation surveys at six urban signal intersections in Hong Kong. Notably, interferences in the crossing behaviours and situational features between the two stages are considered.

Chapter 6 estimates the risk of pedestrian-vehicle conflicts attributed to the red light running behaviour of pedestrians using a two-stage modelling framework. In the first stage, interference in the decisions between drivers and pedestrians at the crosswalks is modeled as a simultaneous two-player game, in which the errors of players' perceptions are incorporated using the quantal response equilibrium method. Then, the anticipations of pedestrians (to cross) and drivers (to yield) in the game are estimated using expected utility theory. In the second stage, the risk of pedestrian-vehicle conflicts is modeled using the bivariate ordered probit regression method, based on post-encroachment time.

Chapter 7 concludes the study with a summary of the findings, implications, limitations, and future research directions.

Chapter 2 Literature review

This chapter reviews the literature on red light running behaviour and safety of pedestrian from several aspects. Section 2.1 summarized the factors affecting the propensity of pedestrian red light running behaviour as well as the studies on multi-stage crossings. Section 2.2 presented the method of data collection first. Then, modelling issues for pedestrian red light running behaviour are illustrated. Lastly, Section 2.3 reviews the works on safety evaluation of pedestrians at intersections.

2.1 Factors affecting the propensity of pedestrian red light running behaviour

2.1.1 Demographics and socioeconomic characteristics of pedestrian

For the demographics, majority of studies indicated that propensity of red light running of male pedestrians was higher than that of females (Rosenbloom, 2009; Guo et al.,2011; Xie et al., 2017). However, the gender effect on red light running violation depends on the traffic condition. Propensity of red light running of female pedestrians could be higher when the available gap time of approaching traffic increases (Ren et al., 2011). Yet, a national survey indicated that no evidence could be established for remarkable difference in red light running propensity between male and female pedestrians (Dommes et al., 2015). For the age effect, studies indicate that crossing behaviours of older pedestrians are different from that of the younger counterpart (Gorrini et al., 2016, 2018). For example, propensities of red light running of the former tend to be lower (Kim et al., 2008; Wang et al., 2011). Older pedestrians are more willing to wait at the crosswalks and obey the traffic rules (Guo et al., 2011; Diependaele, 2018; Zhang et al., 2018). However, risk of mortality and severe injury in the road crashes of older pedestrians are remarkably higher than that of normal adults (Asher et al., 2012). It is attributed to the reduction of locomotion (Oxley et al., 1997, Winogrond, 1981) and degradation of perception and cognitive skills by age (Dommes et al., 2013).

For the socioeconomic characteristics, Wu et al. (2014)'s study indicates that the educational background of pedestrian can affect the crossing behaviour. An attitudinal model indicates that both the education level and income of a pedestrian can affect the red light running propensity (Zhang et al., 2016). However, it is rare that the roles of personal factors in pedestrian's crossing decision under different environmental conditions are examined. Indeed, the attitudinal survey that focuses on the contributions of personal factors to the safety awareness and pedestrian decision should have considered the effects of traffic condition and road environment factors.

2.1.2 Other personal characteristics

Lam (2001) found that the pedestrian's bi-directional flow and crossing speed also have a significant impact on their crossing behaviour. The authors found that pedestrian's risk-taking attitude positively and significantly increases with the crossing speed of a pedestrian. Guo et al. (2012) identified that in Beijing, China pedestrian's signal violation behaviour substantially increases when a pedestrian is going for the work trip. Evidence from existing researches also suggests that distraction from electronic devices increase the likelihood of illegal crossing behaviour of the pedestrian (Zegeer and Bushell, 2012, Stavrinos et al., 2011, Nasar et al., 2008). Further, Xu et al., (2013) commented that previous experience of successful violations at the same location increases the likelihood of violating tendencies. Additionally, a few studies examined the effects of safety awareness and attitude, social norms, and conformity tendency on the intentions of red light running violation of pedestrians using attitudinal surveys based on different psychological frameworks, i.e., theory of planned behaviour (TPB) (Evans and Norman, 1998; Yagil, 2000; Zhou et al., 2010; Zhou et al., 2016). The results show that altitude and conformity tendency play important roles in the decision making process of pedestrians with respect to red light running behaviour.

2.1.3 Traffic control and road environments

For the effect of traffic control, presence of an exclusive pedestrian signal (Cambon de Lavalette et al., 2009) and the pedestrian signal countdown (countdown to green) device (Markowitz et al., 2006) are negatively correlated with the red light running frequency. On the other hand, increase in (maximum) waiting time is correlated with the increase in red light running rate of pedestrians at the midblock crosswalks (Van Houten et al., 2007; Wang et al.,2011; Brosseau et al., 2013). For instance, Wang et al. (2011) concluded that the likelihood of compliance decreases with longer waiting time and that almost 50% of the pedestrian would not wait more than 40 seconds.

For the effect of geometric design, both the number of traffic lanes and length of pedestrian crossing affect the red light running rate of pedestrians. For instance, increases in the number of traffic lane and crosswalk length are correlated with the reduction of red light running violation rate (Van Houten et al., 2007; Cambon de Lavalette et al., 2009; Diependaele, 2018). Additionally, other geometric design and traffic attributes, including the presence of central refugee (Cambon de Lavalette et al., 2009; Yan et al.,2016), speed of approaching vehicle (Lobjois et al., 2013; Sun et al., 2015), volume of conflicting vehicle stream (Koh et al., 2014; Wang et al., 2011), available gap time (Koh and Wong, 2014) can all affect the red light running violation rate of pedestrians. For instance, increases in the volume of conflicting vehicle stream and speed of approaching vehicle are correlated with the reduction of red light running rate.

The abovementioned studies focus on the effects of environmental factors at the intersection level (micro-level). Indeed, environmental factors including land use, weather and lighting condition at the macro-level can also affect the red light running propensity of pedestrians. Guo et al. (2011) conducted an observation survey to examine the effect of land use, e.g., commercial, industrial and residential, on the red light running propensity of pedestrians. Results indicated that the red light running rate was lower at the crosswalks near the schools. Weather, lighting condition and visibility also affect the red light running frequency of pedestrians. Li and Fernie (2010) indicated that the pedestrian walking speed and red light running rate under the cold and snowy conditions were higher than that under the warm weather and when the pavement surface was dry. Liu and Tung (2014) indicated that the pedestrian could be more cautious and have a lower propensity of red light running when crossing under the dark and poor visibility conditions. Yet, it is necessary to examine the interaction effects by pedestrian demographics and socioeconomic characteristics on the association between road environment, traffic control and red light running propensity.

2.1.4 Social influences and presence of other pedestrians

Presence and behaviours of other pedestrians can affect the red light running propensity of an individual. It is attributed to the effect of social norms. Faria et al. (2010) suggests that pedestrians tend to follow the behaviours of others for the traffic gap judgment. This is the possible cause of unsafe crossing behaviour. Pedestrians tend to be more inattentive when they are alone, as compared to being part of a large group. Studies also indicate that red light running propensity decreases when number of other pedestrians (crossing or waiting) around increases (Rosenbloom, 2009; Russo et al., 2018; Zhang et al., 2018). Furthermore, Rosenbloom (2009) suggested that pedestrian age could modify the association between red light running propensity and number of pedestrians around. For example, adolescents are more risk-taking. Such risk-taking behaviour is more prevalent when the pedestrian group size increases. On the other hand, study also suggests that female pedestrians are more sensitive to the effect of social norms (Sorenson and Taylor, 2005). Therefore, it is worth exploring the interactions between (presence and size of) pedestrian group, demographics and red light running propensity of pedestrians.

2.1.5 Multi-stage pedestrian crossings

A few studies have examined the perception and behaviour of pedestrians at the multi-stage unsignalized crossings (Hamed, 2001; Rosenbloom and Pereg, 2012; Ma and Lu, 2011). Hamed (2001) indicated that the pedestrian’s waiting time before crossing the first stage was negatively correlated to that before crossing the second stage at the divided street. It implied that the behaviours were different when a pedestrian was crossing from one side of the road to the central island and from the central island to another side. Rosenbloom and Pereg (2012) extended the research by examining the pedestrian behaviours at the three-stage unsignalized crossings. Results indicated that waiting time before crossing the first stage was positively correlated to that of second stage when there was a wide central island, but there was no correlation when the central island was narrow. Also, there was a positive correlation between the waiting times in the second and third stages, regardless of the island width. Finding was indicative to the innovative design (e.g. road signs) that can affect the pedestrian’s level of patience and decision to stop and wait between two crossings.

Majority of studies focused on the pedestrian flow capacity and time delay of two-stage signalized crossings. A microscopic traffic simulation study indicates that the pedestrian signal time plan of a two-stage crossing (i.e., whether split or not split) would affect the number of pedestrians waiting (both at the kerbside and central island), and therefore determine the minimum area required for the central island (Ma and Lu, 2011). Pedestrian delays at the two-stage crossing are sensitive to the signal time plan and compliance of pedestrians (i.e., crossing during the green pedestrian signal phase). Some innovative measures like overlap phases can significantly reduce the pedestrian delays (Wang et al., 2009; Wang and Tian, 2010).

A few studies have attempted the safety of two-stage signalized crossing. An empirical study investigated the behaviour and compliance of pedestrians when crossing an eight-lane two-stage crossing in Toronto under the cold weather condition. Results indicated that the non-compliance rate of pedestrians under adverse weather condition was higher than that under favorable weather condition (Li and Fernie, 2010). On the other hand, a perception survey indicated that the propensity of red light running of older pedestrians was higher (Cao et al., 2017). However, these studies did not consider the correlation in the pedestrian behaviours between the first and second stages. Also, effects of social influences (i.e., presence and behaviours of other pedestrians) and traffic flow conditions were not considered.

2.2 Methodological issues

2.2.1 Method of data collection

The most common approach to collect pedestrian crossing behaviour data is video recording (Mukherjee and Mitra, 2020; Yannis et al., 2013; Zhao et al., 2019; Zhu et al., 2021a). A recent study by Sheykhfard and Haghighi (2020) extended the previous methods by using two approaches, namely, fixed videography (FV) and in-motion videography (IMV). Amado et al. (2020) conducted an extensive review of pedestrian and vehicle interactions at unsignalized crosswalks. The authors mentioned the ability to enhance video recording, as well as the ability to use several of the most advanced robust tools for subsequent analysis; however, they also noticed that there is a lack of modelling of human vehicle interaction in commercial simulation software tools. These insights can also be reasonably translated into observations of all types of intermediate block intersections. However, the observation study can only collect the revealed behaviour of pedestrians, which is not adequately representative. Even for the same individual, he or she might make different crossing decisions before entering the road. Additionally, observation studies could not provide insights into the decision-making process of pedestrians. Another widely used approach is questionnaire surveys (Dommes et al., 2015; Deb et al., 2017; Zhang. W et al., 2016; Zhou et al., 2016). Generally, researchers have designed questionnaires to collect the crossing intention of respondents, as well as their personal information and personality traits, based on the framework of the theory of planned behaviour (Ajzen, 1991). Recently, another advanced data collection method is Virtual Reality technology. By applying VR technology, experimental study could not only reveal potential realistic behavior, but also investigate underlying preference of respondents by showing different designed scenarios (Calvi et al., 2020, Chung et al., 2020, Schwebel et al., 2017).

2.2.2 Modelling pedestrian red light running behaviour

From the methodological perspective, a single factor and multi-factor analysis of variance (ANOVA) approach can be applied to compare the crossing behaviour of different pedestrian groups (Li and Ferinie, 2010, Ren, et al., 2011). Alternately, it is possible to model pedestrian crossing behaviour by estimating the expected time duration until the occurrence of an event, i.e., red light running violation, using survival analysis (Hamed, 2001; Tiwari et al., 2007). In addition, as pedestrians do not necessarily wait until there is no traffic in any lane, a rolling gap approach has been proposed to model gap acceptance behaviour, and thus the red light running propensity of pedestrians (Koh et al., 2014). Furthermore, to model the effects of real-time traffic flow, signal time, and pedestrian position and motion on the crossing decision, a probabilistic approach, namely, the dynamic Bayesian network model, has been proposed (Hashimoto et al., 2016). To model the red light running propensity of pedestrians while the confounding effects of all possible factors are considered, regression models for dichotomous data, including binary logit and probit models, are commonly used (Kim et al., 2008; Rosenbloom, 2009;

Brosseau et al., 2013). To account for unobserved heterogeneity in pedestrian crossing decisions, the random parameter approach should be applied (Wang et al., 2019; Bai and Sze, 2020). A few studies have used more advanced methods, such as multilevel models (Chung, 2019) and neural networks (Kadali et al., 2015).

To model the (discrete) choice decision, the prevalent estimation method is the random utility maximization (RUM) approach. The RUM-based approach assumes that a decision maker prefers a choice that can provide the highest level of satisfaction (Train, 2009). However, the RUM-based approach may also allow for self-compensation between underperforming and outperforming attributes (Chorus et al., 2008). In behavioural science, alternative modelling approaches based on the decision rules, including relative advantage maximization (Leong and Hensher, 2015), contextual concavity (Kivetz et al., 2004), fully compensatory decision making (Arentze and Timmermans, 2007), and random regret minimization (RRM) (Chorus et al., 2008, Chorus, 2010), have been proposed. Among them, RRM is a promising alternative due to its mathematical simplicity (Iraganaboina et al., 2021).

2.3 Evaluation of pedestrian safety at intersections

2.3.1 Pedestrian-vehicle crash at intersections

Although macro- or meso-level analyses are meaningful to investigate the effects of area-wide variables on the frequency of pedestrian-vehicle crashes, pedestrian safety is actually a microscopic concern (Huang et al., 2016) because pedestrian-vehicle crashes are usually caused by micro-level factors related to specific road locations and interactions between pedestrians and motorists (Retting et al., 2013; Zegeer and Bushell, 2012; Stoker et al., 2015; Yue et al., 2020). The existing studies of pedestrian-vehicle crash analysis have primarily focused on the neighbourhood level; however, relatively limited research efforts have been devoted to investigating the relationship between the frequency of pedestrian-vehicle crashes and the potential risk factors at intersections, particularly at traffic-signalized intersections in densely populated cities (Leden, 2002; Lyon and Persaud, 2002; Torbic et al., 2010; Strauss et al., 2014; Stipancic et al., 2020). As vehicle and pedestrian volumes increase, the absolute number of pedestrian-vehicle crashes at intersections also increases. A nonlinear relationship has consistently been reported, which indicates that as the number of crossing pedestrians increases, the risk of individual pedestrians being involved in a collision with a vehicle decreases (Leden, 2002; Lyon and Persaud, 2002; Schneider et al., 2010; Torbic et al., 2010; Miranda-Moreno et al., 2011; Elvik et al., 2013; Strauss et al., 2014; Elvik, 2016; Xie et al., 2018; Stipancic et al., 2020). This is referred to as the “safety-in-numbers” effect (Jacobsen, 2003; Elvik and Bjørnskau, 2017; Elvik and Goel, 2019; Xu et al., 2019). However, this conclusion based on a cross-sectional research design should be interpreted with great caution because it is impossible to determine whether this safety-in-numbers effect is a causal relationship or merely a statistical association (Bhatia and Wier, 2011; Xu et al., 2019).

However, although pedestrian volume is indispensable for determining pedestrian-vehicle crash incidences at intersections, few transportation agencies regularly collect these data on a large scale due to limited resources. The volume of pedestrians is thus mostly estimated based on a short period of field observations (Leden 2002; Lyon and Persaud, 2002; Schneider et al., 2010; Torbic et al., 2010; Miranda-Moreno et al., 2011; Pulugurtha and Sambhara, 2011; Elvik et al., 2013; Strauss et al., 2014; Quistberg et al., 2015; Elvik et al., 2016; Kröyer, 2016; Mooney et al., 2016; Stipancic et al., 2020), predicted by pedestrian-activity models (Thomas et al., 2017), or surrogated as surrounding land-use and demographic characteristics (Quistberg et al., 2015; Wang et al. 2017). However, either the absence or improper representation of pedestrian exposure likely leads to inconsistent results (Steinbach et al., 2014), and the measurement errors inherent to this process may also bias the parameter estimates (Kröyer, 2016). Therefore, the microscopic analysis of pedestrian-vehicle interactions and related conflicts should be focused on providing insightful information on precrash events (i.e., unsafe interactions).

2.3.2 Pedestrian-vehicle interactions and conflicts

2.3.2.1 Risk of pedestrian-vehicle conflicts

Previous studies have attempted to examine the factors, including road environment, traffic condition, and personal characteristics, which 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, the risk of harm to older pedestrians is higher than that of normal adults, considering the physical capability and walking speed of elderly people (Liu and Tung, 2014). Additionally, the safety awareness and risk perception of males are lower than those of females when crossing roads (Yagil, 2000). For the effect of traffic conditions, increases in traffic volume and vehicular speed are associated with an increase in the risk of severe pedestrian-vehicle conflicts, especially when pedestrians are annoyed because of the long waiting time (Cheng, 2013). Furthermore, the absence of a central refuge and an increase in the size of pedestrian groups are associated with an 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 has been proposed to extract the trajectories of pedestrians and vehicles for the modelling of pedestrian-vehicle conflicts (Ismail et al., 2009). Additionally, a mathematical simulation platform is proposed to predict pedestrian-vehicle conflicts for the safety assessment of road geometry and traffic operation characteristics in the design stage (P. Chen et al., 2019). Furthermore, a machine learning approach has been adopted to predict pedestrian-vehicle conflicts (Zhang et al., 2020).

The 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 safety risk assessments, except for an empirical survey based on manual tracking (Ni et al., 2016). Nevertheless, it is crucial to account for the yield behaviours of drivers and pedestrians when modelling the pedestrian-vehicle interactions.

2.3.2.2 Interactions between driver and pedestrian

Numerous studies have examined factors, including road geometry, traffic operation and signal time plans, pedestrians' characteristics and behaviours, which 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 have been proposed to model the dynamic interactions between pedestrians and vehicles. For example, the cellular automata (CA) approach has been adopted to simulate the movements of pedestrians, in which the interferences among pedestrians, vehicles and other obstacles are considered when crossing roads (Zhang et al., 2004). In addition, the effects of vehicular and pedestrian flows, arrival rates, waiting time and sensitivity of pedestrians on pedestrian-vehicle interactions can be accommodated in the decision rules of the 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 drivers' responses. This may in turn either under- or overestimate the risk of pedestrian-vehicle conflicts.

Indeed, it is possible to model the decisions of more than one party simultaneously in such 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 has been widely applied to the interactions between vehicles, few studies have adopted it for the interactions between pedestrians (or bicycles) and vehicles at 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 who can give the best outcome. However, the basic assumptions of the conventional game model are the perfect information and rational expectations of all individuals. To this end, the 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 bounded rationality in an evolutionary game framework (Bjørnskau, 2017; Arbis and Dixit, 2019).

In summary, it is viable to model the interactions between pedestrians and vehicles (drivers) at crosswalks using the game theoretical model. To move forward, it is crucial to estimate the safety risk attributed to the red light running behaviour of pedestrians, in which the dynamic interferences of the behaviours between pedestrians and drivers are considered.

2.4 Concluding remarks

This chapter demonstrates the results of the literature survey on pedestrian red light running behaviour and safety studies. There are several research gaps identified in the literature, which are listed as follows:

(1) Studies have revealed the effects of personal characteristics, traffic attributes and road environments on the red light running propensity of pedestrians in separate models. Some studies have focused on the effects of personal factors on individual decisions, while others have focused on the effects of traffic and road environment factors on the overall red light running violation rates. However, it is rare that the roles of personal (individual level) factors of pedestrians and environmental (cycle level) factors in the prevalence of red light running behaviour of pedestrians are both investigated. Particularly, to the best of our knowledge, not many studies have considered the effects of the behaviours of other pedestrians when evaluating the propensity of red light running. Additionally, the interaction effects between personal characteristics, social influences, and environmental features on the propensity of red light running violation have not been revealed.

(2) Studies that investigate the propensity of red light running of pedestrians at the two-stage crossings (with split pedestrian signal phases) are rare. Particularly, the main effects and interaction effects of factors including pedestrian demographics, social influences, built environment, traffic condition and traffic control on the red light running propensities in different stages should be considered. Compared to studies focusing on one-stage crossings, the relationship between influencing factors and the red light running behaviours of pedestrians at the multi-stage crossings could be different. For example, the waiting time before crossing the first stage may affect the crossing decision of pedestrians in the subsequent stages. Additionally, the pedestrian signal in the subsequent stage can affect the decisions of pedestrians in the first stage. Thus, it is necessary to

assess the differences in the effects of possible factors on the red light running propensities of pedestrians between different stages of crossing.

(3) Numerous studies have contributed to the literature by measuring the relationship between the red light running behaviours of pedestrians and possible explanatory factors, including personal characteristics. However, to the best of our knowledge, it is rare that the intentions of red light running are evaluated based on the situational decision of individuals with respect to the trade-off between safety risk (i.e., road injuries) and time. In addition, moderation effects by situational features and personal characteristics on individuals' decisions should be considered. The stated preference (SP) approach, which gauges the choice decisions of individuals in different scenarios in which the attribute levels of more than one factor vary in the analyses of choice, could be applied to examine pedestrians' red light running intention under hypothetical scenarios. Moreover, by combining SP survey data and a regret-based MNL model, the roles of personal characteristics, social influences and road environments in the intentions of red light running behaviour of pedestrians based on the situational decision for the trade-off between safety and time could be examined.

(4) Although some previous studies have investigated the yield behaviours of drivers and pedestrians in 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, the effects of vehicle dynamics and pedestrians' decisions in pedestrian-vehicle interactions in the crossing process should be considered in the pedestrian-vehicle conflict risk prediction model.

Chapter 3 The trade-off between safety and time in the red light running behaviours of pedestrians

3.1 Introduction

Pedestrian safety has been of major concern in road safety research as pedestrians are more vulnerable to fatality and severe injury in the road crashes, as compared to car occupants. Red light running violation of pedestrians is one of the key contributory factors that affect the risk of pedestrian-vehicle crashes (Wang et al., 2020a). It constitutes a quarter of pedestrian-involved crashes at the signal intersections (Zhu et al., 2021). In Hong Kong, pedestrians who are found committing red light running offences would be liable to a monetary fine of 2,000 HKD (equivalent to 258 USD) (Department of Justice, 2020). Unlike the enforcements against speeding and red light running offences of drivers (using automated enforcement system), enforcement against red light running offence of pedestrians relies heavily on manual enforcement. This could reduce the perceived probability of being caught and punished of pedestrians for any violation offence. Hence, the deterrent effect of any penalty against red light running violation of pedestrians could be diminished (Chen et al., 2020; Zhu et al., 2020). It would be crucial to improve the understanding on the personal characteristics (e.g., demographics, socioeconomics, and personality) and situational features (e.g., traffic conditions, weather conditions, and traffic control) that may affect the intentions of red light running of pedestrians (Zhu et al., 2021; Zhu and Sze, 2021). Therefore, effective traffic control measures and enforcement strategies can be implemented to deter against the red light running offence of pedestrians.

Numerous studies have contributed to the literature by measuring the relationship between the red light running behaviours of pedestrians and possible explanatory factors including personal characteristics, road environments (e.g., geometric design, pavement surface condition, and weather conditions), social influences (e.g., number and behaviours of other pedestrians around), traffic conditions (e.g., traffic volume, traffic composition, and vehicular speed), and signal time phase based on observational surveys

(Kim et al., 2008; Rosenbloom, 2009; Brosseau et al., 2013; Russo et al.,2018; Wang et al., 2019b; Mukherjee and Mitra, 2020; Zhu et al., 2021). Alternately, it is possible to examine the effects of safety awareness and attitude, social norms, and conformity tendency on the intentions of red light running violation of pedestrians using attitudinal surveys based on different psychological frameworks, i.e., theory of planned behaviour (TPB) (Evans and Norman, 1998; Yagil, 2000; Zhou et al., 2010; Zhou et al., 2016). However, to the best of our knowledge, it is rare that the intentions of red light running behaviour are evaluated based on the situational decision of individuals with respect to the trade-off between safety risk (i.e., road injuries) and time. In addition, moderation effects by the situational features and personal characteristics on individual's decision should be considered.

Stated preference (SP) approach is an efficient survey method to gauge the choice decision of individual in different scenarios with which the attribute levels of more than one factors are varying, in the analyses of transport mode choice (Loo et al., 2006; Ho et al., 2020), travel behaviour (Anciaes and Jones, 2020; Zhao et al., 2021), and traffic safety (Steinbakk et al., 2019; Li et al., 2020). SP method has been applied to investigate the perception and attitudes towards the enforcement strategies and penalties against traffic offences including red light running and speeding violations of occupational drivers (Wong et al., 2008; Chen et al., 2020). In addition, trade-off between different penalties including monetary fine, driver demerit points, and driving disqualifications deterring against different extents of drink driving offence, in terms of frequency of conviction and alcohol concentration, were investigated (Li et al., 2014). Compared to observational survey and revealed preference (RP) survey, SP method is capable of evaluating the effectiveness of policy strategies that have not yet been implemented (while being realistic and consistent to the actual environment) (Loo et al., 2006). This should shed light on the effective enforcement strategies that can deter against different traffic offences.

However, there could be considerable variations in the intentions among individuals who share the same demographic and socioeconomic characteristics under identical situation (Chen et al., 2020). Intentions of traffic violation behaviour are sensitive to risk perception, subjective norms, and perceived behavioural control of individuals, in accordance with TPB (Wang et al., 2019a; Zhou et al., 2016). Risk perception refers to the rational or irrational beliefs of a person regarding the likelihood of any negative consequence associated with a hazard event. For the red light running violations, negative consequences are injuries and material loss resulting from potential pedestrian-vehicle conflicts and collisions (Chambers, 2004). Subjective norms are the normative expectations of what a person believes that other peoples, including his or her family members, friends, peers and other members in the society, think he or she ought to do (i.e., comply with the traffic signal or not). Perceived behavioural control indicates the perceived capability (i.e., confidence) of a person to execute an act (i.e., violate the traffic signal and cross the road) (Ajzen, 1991; Evans and Norman, 1998). It is necessary to account for the moderation effects of personality trait and safety attitudes on the association between demographic and socioeconomic characteristics, situational features, and propensities of red light running violation of pedestrians (Rosenbloom, 2009; Zhu et al., 2021). In addition, interference by the presence of another pedestrian who violates the signal (and whether that pedestrian is an adolescent, normal adult or elderly) on the intentions of red light running violation should be investigated (Rosenbloom, 2009; Zhu et al., 2020). This would be useful for the development and implementation of targeted road safety education for vulnerable pedestrian groups.

Red light running behaviours of pedestrians can be stratified into two: (1) cross immediately once arriving at the crosswalk; and (2) wait until there is a suitable gap and cross. They are usually modeled separately in preceding studies. For instance, discrete outcome methods, e.g., logit and probit models, are applied to model the likelihood of whether a pedestrian would violate the red light or not (Wang et al., 2019; Zhu and Sze, 2021). On the other hand, survival methods are applied to model the (waiting) time-to-violate of pedestrians based on the gap acceptance theory (Hamed, 2001; Koh and Wong, 2014; Zhang and Fricker, 2020). From the methodological perspective, it is capable to model the choice among three alternatives: (i) comply with pedestrian signal; (ii) not comply but wait for a suitable gap; and (iii) not comply and cross immediately, in a single framework. It is expected that risk-taking pedestrians tend to cross immediately for the higher anticipated benefit (i.e., time saving), and risk-averse pedestrians are willing to sacrifice some benefit and comply with the signal (or wait for a suitable gap). Results of the willingness of pedestrians to trade-off between anticipated time saving and perceived risk of road injuries should be indicative to efficient signal time plan and initiatives including flashing warning signs and pedestrian signal countdown devices that could improve the pedestrian safety at the signal intersections (Zhu et al., 2020).

In this study, we attempt to examine the roles of personal characteristics, social influences and road environments in the intentions of red light running behaviour of pedestrians based on the situational decision for the trade-off between safety and time, using the SP method (Zhou et al., 2009; Elvik, 2019; Zhu et al., 2021). In addition, effects of three situational features including weather condition, presence (and type) of other pedestrian who violates, and presence of a warning sign on the trade-off are also considered (Mukherjee and Mitra, 2020; Zhu and Sze, 2021). Furthermore, information on personal characteristics including demographic and socioeconomic characteristics (i.e., gender, age, educational level, and income), travel habit (i.e., frequency of walking travel, number of trips making days per week, and possession of driving license), and personality traits (i.e., safety perception, subjective norms, perceived behavioural control, and legal awareness) are collected in the survey. To model the (discrete) choice decision, prevalent estimation method is the random utility maximization (RUM) approach. RUM-based approach assumes that a decision maker prefers choice that can provide the highest level of satisfaction (Train, 2009). However, RUM-based approach may also allow for self-compensation between underperforming and outperforming attributes (Chorus et al., 2008). In behavioural science, alternative modelling approaches based on the decision rules including relative advantage maximization (Leong and Hensher, 2015), contextual concavity (Kivetz et al., 2004), fully-compensatory decision making (Arentze and Timmermans, 2007), and random regret minimization (RRM) (Chorus et al., 2008, Chorus, 2010) have been proposed. Among them, RRM is a promising alternative for its mathematical simplicity (Iraganaboina et al., 2021). In this study, a regret-based multinomial logit model is adopted to estimate the effects of possible explanatory factors on the propensities of red light running violation of pedestrians. It is expected that the personality traits would moderate the association between anticipated waiting time, perceived safety risk, situational features, and intentions of red light running violation. Nonetheless, effect of unobserved heterogeneity on the association would be considered using a mixed logit approach (Mannering et al., 2016).

The remainder of this chapter is structured as follows. Section 3.2 describes the methods of data collection and analysis. Section 3.3 summarizes the data used in the analysis. Section 3.4 and Section 3.5 present the results of mixed multinomial logit regression model and interpretations. Section 3.6 concludes the study with a summary of findings, policy implications, and future research directions.

3.2 Method

3.2.1 Study design

Intentions of red light running violation of pedestrians were investigated using an online survey in the period from September to November in 2020. The questionnaires were distributed through social media posts and QR code on the smartphones or tablets (at the locations including the entrances of schools, shopping malls and public transport stations) with the help of several part-time research assistants. It is to avoid the questionnaires from reaching a restricted range of participants only and increase the sample diversity with respect to demographics and socio-economics. To increase the response rate, a snowball sampling method was also applied.

The questionnaire has four parts: (1) SP experiments on the intentions of red light running violation; (2) personality traits; (3) travel habit (e.g., trip frequency, and frequency of walking travel); and (4) demographics and socio-economics (e.g., gender, age, educational level, and income). In the second part, attributes including subjective norms, perceived behavioural control, risk perception and legal awareness will be gauged using the five-point Likert scale (Jiang et al., 2017a). For instance, four questions, e.g. “Do you think your family members will agree with the act of violating the pedestrian signal?”, “Do you have any difficulty when making the choice decision of crossing the roads?”, “Do you think you are risk-taking?”, and “Do you think obeying the traffic rules is important?” are adopted.

Table 3.1 illustrates the choice alternatives and factor attributes considered in the SP design. As shown in Table 1, trade-offs between anticipated waiting time and perceived relative safety risk for three choice alternatives: (i) comply with the pedestrian signal; (ii) not comply but wait for a suitable gap to cross; and (iii) not comply and cross immediately, are measured. There are two attribute levels for both anticipated waiting time (i.e., 30, 20, and 0 second versus 50, 35, and 0 second) and perceived relative safety risk (i.e., 0%, 20%, and 50% versus 0%, 30%, and 60%). Since the common cycle length in Hong Kong is 120 seconds, the waiting times adopted in the SP design are commonly experienced. For situational features, there are two levels for the weather condition (i.e., fine weather versus raining condition), four levels for the presence and type of other pedestrian who violates the red light (i.e., no, adolescent, normal adult, and elderly), and two levels for the presence of warning sign (i.e., yes and no). To provide realistic choice scenarios, illustrations were developed based on an actual pedestrian crossing in the urban area of Hong Kong. In addition, variations in the attributes including weather condition, presence and type of other pedestrian who violates, and presence of warning sign can be revealed in the illustrations (For details, readers may refer to a typical illustration shown in **Figure A1** of the **Appendix**).

Since there are five factors (with the number of attribute levels ranging from two to four) in the SP design, there would be (4 x 2 x 2 x 2 x 2 =) 64 combinations of factor attributes if the full factorial design were adopted. It is however not efficient and practical to gauge the respondents' decision when all the 64 choice scenarios are considered. Hence, an orthogonal fractional factorial design is adopted, and the number of scenarios is reduced to eight (Bhat and Sardesai, 2006; Hössinger and Berger, 2012; Li et al., 2014; Chen et al., 2020). In addition, the eight choice scenarios are stratified into two sub-sets using a randomized block design approach. Therefore, there are only four scenarios presented to each respondent to avoid overwhelming information.

Table 3. 1 Factors and attributes considered in the SP design

Factor		**Attribute**		
		Choice 1: Comply with pedestrian signal	**Choice 2: Not comply but wait for a suitable gap**	**Choice 3: Not comply and cross immediately**
Anticipated waiting time	Level 1	30 second	20 second	0 second
	Level 2	50 second	35 second	0 second
Perceived relative risk	Level 1	0%	20%	50%
	Level 2	0%	30%	60%
Weather condition	Level 1	Fine weather		
	Level 2	Raining condition		
Presence and type of violator	Level 1	No violator		

	Level 2	Adolescent
	Level 3	Normal adult
	Level 4	Elderly
Presence of warning sign	Level 1	No
	Level 2	Yes

3.2.2 Statistical model

In conventional studies, multinomial logit model has been applied to model the discrete outcome, e.g., choice between more than two unordered alternatives. To account for the effect of unobserved heterogeneity among different individuals, a mixed logit approach is adopted. In addition, to resolve the problem of correlation in the choices between different observations of the same individual in the panel data, a simulation approach using the Halton draw method is applied to estimate the parameters of proposed model (Train, 2001, 2009; Chen et al., 2020).

In the formulation of proposed regret-based model, i (i = 1, 2, …, I) is the indicator variable of individual, j (j = 1, 2, …, J, and J = 4) is the indicator variable of choice scenario, k (k = 1, 2, …, K, and K = 3) is the indicator variable of choice alternative, s denotes other viable alternative, and m (m = 1, 2, …, M) is the indicator variable of factor attribute. Then, the random regret RR_{ijk} of alternative k in scenario j of individual i can be given by,

$$RR_{ijk} = \sum_{s \neq k} \sum_{\forall m} ln\{1 + \exp[(\alpha' + \rho_i')(z_{ismj} - z_{ikmj})]\}\varepsilon_{ijk} \quad (3\text{-}1)$$

where z_{ikmj} denotes the vector of factor attributes of chosen alternative k and z_{ismj} denotes that of other alternative s, α' is the vector of coefficients that reflects the mean effects, ρ_i' is the vector of coefficients that reflects the effect of unobserved heterogeneity of individual i (assumed to be normally distributed), and ε_{ijk} is the error term (assumed to be identically and independently Gumbel distributed).

Then, the probability of choosing alternative k can be written (McFadden, 1978) as,

$$P_{ijk} = \frac{e^{-RR_{ijk}}}{\sum_{k=1}^{K} e^{-RR_{ijk}}} \quad (3\text{-}2)$$

The unconditional probability can then be computed as,

$$P_{ik} = \int_{\rho_i^{'}} (P_{ijk} \mid \rho_i^{'}) dF(\rho_i^{'} \mid \sigma) \tag{3-3}$$

where $\boldsymbol{F}$ is the multivariate cumulative normal distribution.

Conditional on ρ_i, the likelihood function of observed sequence of choices of individual *i* is given by,

$$L_i(\alpha \mid \rho_i) = \prod_{j=1}^{J} [\prod_{k=1}^{K} \{P_{ijk} \mid \rho_i\}^{\delta_{ijk}}] \tag{3-4}$$

where δ_{ijk} is an indicator variable that takes the value of 1 when individual *i* chooses alternative *k* in scenario *j*, and 0 otherwise.

Eventually, the unconditional likelihood function is given by,

$$L_i(\alpha, \sigma) = \int_{\rho_i} L_i(\alpha \mid \rho_i) dF(\rho_i \mid \sigma) \tag{3-5}$$

where the log-likelihood function is $L(\alpha,\sigma) = \sum_i lnL_i(\alpha \mid \sigma)$.

A simulation approach is applied to estimate the integrals of the likelihood function and maximize the simulated likelihood function across all individuals with respect to the parameters. Under the weak regularity conditions, the maximum (log) simulated likelihood (MSL) estimator is consistent, asymptotically efficient, and asymptotically normal (see Hajivassiliou and Ruud, 1994; Lee and Carter, 1992; McFadden and Train, 2000). Furthermore, Halton sequences are used to draw the realizations for ρ_i from the prevailing normal distributions. For the details of Halton sequence, readers may refer to Bhat (2001, 2003) and McFadden and Train (2000). With the Halton sequence, the draws from a single observation can fill all the empty spaces. Therefore, the simulated probabilities would be negatively correlated. Such negative correlation can reduce the variance of the log-likelihood function. It should be noted that the negative correlation still exists in the simulated probabilities between observations, even when some attributes of different observations are identical for the panel data (Train, 2001).

3.3 Data

A total of 1,007 respondents completed the questionnaire survey. As four choice scenarios were presented to each respondent, there were 1,007 × 4 = 4,028 observations in the dataset. **Table 3.2** illustrates the distribution of choice decisions. Of the 4,028 observations, 2,105 (52.3%) comply with pedestrian signal, 1,399 (34.7%) not comply but wait for a suitable gap, and 524 (13.0%) not comply and cross immediately respectively. Distributions of choice decision in different scenarios are shown in **Table 3.2**. As shown in Table 2, proportion of "comply with pedestrian signal" tends to increase when relative risk level is higher, anticipated waiting time is shorter, it is under raining condition, there is no other violator, and there is a warning sign. In this study, effects of the trade-off between perceived relative risk and anticipated waiting time, as well as the interactions by situational features and personal characteristics, on the intentions of red light running violation of pedestrians would be gauged.

Table 3. 2 Distributions of choice decision in different scenarios

Scenario	SP attribute					Choice decision		
	Waiting time	**Perceived relative risk**	**Weather condition**	**Presence and type of violator**	**Presence of warning sign**	**Choice 1: Comply with pedestrian signal**	**Choice 2: Not comply but wait for a suitable gap**	**Choice 3: Not comply and cross immediately**
1	(30 sec, 20 sec, 0 sec)	(0, 20%, 50%)	Fine weather	No	No	185 (39.7%)	197 (42.3%)	84 (18.0%)
2	(50 sec, 35 sec, 0 sec)	(0, 30%, 60%)	Fine weather	Adolescent	No	157 (33.7%)	203 (43.5%)	106 (22.8%)
3	(50 sec, 35 sec, 0 sec)	(0, 20%, 50%)	Raining condition	Normal adult	No	284 (60.9%)	139 (29.8%)	43 (9.0%)
4	(50 sec, 35 sec, 0 sec)	(0, 20%, 50%)	Fine weather	Elderly	Yes	285 (61.2%)	131 (28.1%)	50 (10.7%)
5	(30 sec, 20 sec, 0 sec)	(0, 30%, 60%)	Raining condition	Elderly	No	272 (50.3%)	218 (40.3%)	51 (9.4%)
6	(50 sec, 35 sec, 0 sec)	(0, 30%, 60%)	Raining condition	No	Yes	353 (65.2%)	134 (24.8%)	54 (10.0%)
7	(30 sec, 20 sec, 0 sec)	(0, 20%, 50%)	Raining condition	Adolescent	Yes	322 (59.5%)	172 (31.8%)	47 (8.7%)
8	(30 sec, 20 sec, 0 sec)	(0, 30%, 60%)	Fine weather	Normal adult	Yes	247 (45.7%)	205 (37.9%)	89 (16.4%)

3.3.1 Demographics, socio-economics and travel habit

Table 3 summarizes the demographics and socio-economics of the respondents. Overall, ratio of male to female is 780 to 1,000. It is consistent to that of Hong Kong population (male to female equal to 830 to 1,000) (Census and Statistic Department, 2018a). For the age distribution, proportion of the respondents between the age of 18 and 24 is relatively high, and that of over 55 years is 10.2% only. For the educational level, 86.5% of respondents have attained secondary education or above. For the marital status, 39.2% of respondents are married (50.1% for Hong Kong population) (Census and Statistic Department, 2018b). Furthermore, monthly incomes of 37.9% of respondents are less than HK$10,000, and that of 18.2% of respondents are more than HK$30,000 respectively (where the median monthly income in Hong Kong was about HK$15,000 (Census and Statistic Department, 2018b). For the travel habit, 36.4% of respondents have a driving license. In addition, half of the respondents (50.1%) travel almost every day, and 39.2% of respondents walk more than six times a day. This could be attributed to the promotion of walkability and improvement in walking environments in Hong Kong. Despite that the sample may be skewed, there should not be any adverse impact on the interpretation since all segments in terms of gender, age, income, and education level are adequately represented. Additionally, there is no significant discrepancy between the stated choices in this study and revealed behaviours in preceding observational survey (Zhu and Sze, 2021).

3.3.2 Attitude and personality traits

Four variables that characterize the personality of respondents are measured. For the subjective norms, 37.4% of respondents consider that their family members would not agree with the violation behaviours, while 34.3% would agree. For the perceived behavioural control, majority of respondents (68.0%) consider themselves as having low behavioural control. For the risk perception, 35.7% of respondents are risk-taking, and 33.1% are risk-averse respectively. For the legal awareness, majority of respondents (59.3%) consider themselves as having high awareness. Despite that these four variables are commonly adopted in other TPB-based studies, whether the attitude and personality traits of respondents can represent that of Hong Kong population should be assessed when comprehensive empirical data were available.

Table 3. 3 Distributions of the sample

Category	Factor	Attribute	Count	%
Demographics	Gender	Male	444	44.1
		Female	563	55.9
	Age	18 to 24 years old	428	42.5
		25 to 54 years old	470	46.7
		55 years old or above	109	10.8
Socio-economics	Educational level	Primary or below	135	13.5
		Secondary	217	21.5
		Tertiary or above	655	65.0
	Marital status	Unmarried	612	60.8
		Married with no children	157	15.5
		Married with children	238	23.7
	Monthly income	Less than 10,000 HKD	382	37.9
		10,000 – 19,000 HKD	251	24.9
		20,000 – 29,000 HKD	191	19.0
		30,000 HKD or above	183	18.2
Travel habit	Possession of driving license	No	638	63.4
		Yes	369	36.4
	Walking trip frequency per day	None	30	3
		1 – 2 times	206	20.5
		3 – 5 times	376	37.3
		6 times or more	395	39.2
	Number of trip making day per week	0 day	9	0.9
		1 – 2 days	91	9.0
		3 – 5 days	403	40.0
		6 – 7 days	505	50.1
Attitude and personality traits	Family norms towards the violation behaviour	Agree	343	34.1
		Neutral	287	28.5
		Disagree	377	37.4
	Perceived behavioural control	High	117	11.6
		Medium	205	20.4
		Low	685	68.0
	Risk perception	Risk-taking	360	35.7
		Risk-neutral	314	31.2
		Risk-averse	333	33.1
	Legal awareness	High	597	59.3
		Medium	256	25.4
		Low	154	15.3

3.4 Results

In this study, a regret-based panel mixed multinomial logit model is adopted to measure the association between possible explanatory factors and intentions of red light running violation of pedestrians. For the random components of coefficients, typical distributions including normal, Gumbel and log-normal are considered. Specifically, mixed model based on normal distribution provides the best fit. Table 3.4 summarizes the results of parameter estimation for: (i) Choice 2: not comply but wait for a suitable gap; and (ii) Choice 3: not comply and cross immediately.

3.4.1 Waiting time and safety risk

Variables including anticipated waiting time and perceived relative risk are alternative-specific. Hence, their parameter estimates are the same for Choice 2 - "not comply but wait for a suitable gap" and Choice 3 – "not comply and cross immediately". As shown in **Table 3.4**, anticipated waiting time is positively associated with the propensity of red light running violation (β = 0.02), at the 1% level of significance. This indicates that pedestrians tend to have less regret for running the red light when anticipated waiting time increases. In contrast, perceived relative risk is negatively associated with the propensity of red light running violation (β = -1.42), at the 1% level of significance. This implies that pedestrians tend to have greater regret for running the red light when the perceived safety risk increases.

3.4.2 Situational features

As shown in Table 3.4, propensities of red light running violation in the raining condition are significantly lower (Choice 2, -0.86; Choice 3, -1.26) than that in the fine weather condition, at the 1% level. In addition, propensities of red light running violation (Choice 2, -0.32; Choice 3, -0.26) are significantly lower when there is a warning sign, at the 1% level. Furthermore, propensities of red light running violation are significantly higher (Choice 2, 0.23; Choice 3, 0.21) when an adolescent violator is present, at the 5% level. However, propensity of "not comply and cross immediately" (Choice 3) is significantly lower (-0.25) when an elderly violator is present, at the 5% level.

3.4.3 Demographics, socio-economics, and travel habit

For the effects of personal characteristics including demographics, socio-economics and travel characteristics, as also shown in Table 3.4, propensities of red light running violation of males are significantly higher (Choice 2: 0.53; Choice 3: 0.36) than that of females, at the 1% level. In addition, propensities of red light running violation of respondents who are 18 to 24 years old are significantly higher (Choice 2: 0.42; Choice 3: 1.29) than that who are 25 to 55 years old, at the 5% level. Also, propensities of red light running violation of respondents who have attained tertiary education or above are significantly lower (Choice 2: -0.12; Choice 3: -0.29), at the 5% level. Furthermore, propensities of red light running violation of respondents who have higher salaries (i.e., 20,000 HKD per month or above, Choice 2: 0.17; Choice 3: 0.58) are significantly higher, at the 5% level. Nevertheless, propensities of red light running violation of respondents who have a driving license are significantly lower (Choice 2: -0.16; Choice 3: -0.15), at the 5% level. However, propensities of “not comply and cross immediately” (Choice 3) of respondents who walk three to five times a day (0.18), and travel on three to five days a week (0.31) are marginally higher, as compared to those who walk less than three times a day and travel less than three days a week, at the 10% level.

3.4.4 Attitude and personality traits

For the effect of pedestrians’ perception, propensities of red light running violation of respondents whom their family members tend to agree with (Choice 2: 0.25; Choice3: 0.22) or neutral to (Choice 2: 0.32) the violation behaviours are higher, at the 1% level of significance. In addition, propensities of red light running violation of respondents who have medium (Choice 2: 0.46; Choice 3: 1.14) and high perceived behavioural control (Choice 2: 0.20; Choice 3: 0.81), and are risk-neutral (Choice 2: 0.52; Choice 3: 0.64) and risk-taking (Choice 2: 0.46; Choice 3: 0.76) are significantly higher, at the 1% level. However, propensities of red light running violation of respondents who have medium (Choice 2: -0.32; Choice 3: -0.51) and high legal awareness (Choice 2: -1.05; Choice 3: -1.35) are significantly lower, at the 1% level.

3.4.5 Interaction effects

Interaction effects between personal attributes and perception on the propensities of red light running violations are also investigated. For example, “18 to 24 years old x family members agree with violation behaviour” (Choice 2: 0.17) are positively associated with the propensities of red light running violation, at the 10% level. Also, “high perceived behavioural control x risk-taking” (Choice 2: 0.37; Choice 3: 0.10) are positively associated with the propensities of red light running violation, at the 5% level of significance. However, “18 to 24 years old x perceived relative risk” and “tertiary education or above x presence of warning sign” are negatively associated with the propensity of “not comply and cross immediately” (Choice 3), at the 5% level of significance.

Table 3. 4 Results of parameter estimation of regret-based panel mixed multinomial logit model

Category	Factor	Attribute		Choice 2: Not comply but wait		Choice 3: Not comply and cross immediately	
				Coefficient	**S.E.**	**Coefficient**	**S.E.**
	Constant			IS		-1.36**	0.33
SP attribute	Waiting time		Mean	0.02**	0.01	0.02**	0.01
			SD	0.03**	0.01	0.03**	0.01
	Perceived relative risk			-1.42**	0.51	-1.42**	0.51
	Weather condition (Control: Fine)	Raining	Mean	-0.86**	0.14	-1.26**	0.31
			SD	0.57*	0.30	0.69**	0.24
	Presence of warning sign (Control: No)	Yes		-0.32**	0.11	-0.26**	0.07
	Presence of violator (Control: No)	Adolescent		0.23**	0.03	0.21*	0.10
		Normal adult		IS		IS	
		Elderly		IS		-0.25*	0.12
Demographics	Gender (Control: Female)	Male	Mean	0.53**	0.21	0.36**	0.15
			SD	0.45**	0.19	0.23**	0.09
	Age (Control: 24-55 years old)	18-24 years old		0.42*	0.22	1.29*	0.61
		55 years old or above		IS		IS	
	Educational level (Control: Secondary or below)	Tertiary or above		-0.12*	0.06	-0.29*	0.14
	Monthly income (Control: Less than 10000 HKD)	10000-19999 HKD		IS		0.31**	0.10
		20000 HKD or above		0.17*	0.09	0.58**	0.12
Travel habit	Holding a driving license (Control: No)	Yes		-0.16**	0.05	-0.15*	0.07
		3-5 times		IS		0.18*	0.08

	Walking trip frequency per day (Control: Twice or less)	6 times or more	0.12*	0.05	IS	
	Number of trips making day per week (Control: 2 days or less)	3-5 days	IS		0.31^	0.16
		6-7 days	IS		IS	
Attitude and personality trait	Family norms towards violation behaviour (Control: Disagree)	Neutral	0.32**	0.12	IS	
		Agree	0.25**	0.11	0.22**	0.07
	Perceived behavioural control (Control: Low)	Medium	0.46**	0.08	1.14**	0.31
		High	0.20*	0.09	0.81**	0.30
	Risk perception (Control: Risk-averse)	Risk-neutral	0.52**	0.14	0.64**	0.24
		Risk-taking	0.46**	0.12	0.76**	0.18
	Legal awareness (Control: Low)	Medium	-0.32**	0.10	-0.51**	0.19
		High	-1.05**	0.06	-1.35**	0.11
Interaction term	18-24 years old x perceived relative risk		IS		-2.28*	0.98
	18-24 years old x family members agree with violation behaviour		0.17^	0.10	IS	
	High perceived behavioural control x risk-taking		0.37**	0.13	0.10*	0.04
	Tertiary education or above x presence of warning sign		IS		-0.27*	0.13
Number of parameters			62			
Restricted log likelihood			-4226.50			
Unrestricted log likelihood			-3247.72			
McFadden Pseudo R-square			0.27			
AIC			6,612			

*** Statistical significance at the 1% level*

** Statistical significance at the 5% level*

3.5 Discussion

Table 3. 5 summarizes and compares the results between current and previous studies. As shown in Table 3. 5, findings of current study are generally consistent with that of the literature, particularly the effects of anticipated waiting time, weather condition, presence of the first violator, education level, monthly income, social influences, perceived behaviour control, and risk-taking attitude on the propensities of red light running of pedestrians. However, it is rare that the effects of perceived risk, presence of warning sign, travel habit and legal awareness are investigated. Implications of current findings and recommendations of remedial measures that can deter against the red light running behaviour of pedestrians are given in subsequent Section 3.6.1-3.6.4.

Table 3. 5 Comparison between current and previous studies

Factor attribute	**Current study**	**Previous studies**	
Anticipated waiting time	↑	↑	van Houten et al., 2007; Brosseau et al., 2013; Zhu et al., 2021
Perceived safety risk	↓	Rarely attempted	
Raining condition	↓	↓	Li & Fernie, 2010; Liu & Tung, 2014
Presence of violator	↑	↑	Rosenbloom, 2009; Zhu et al., 2021
Presence of warning sign	↓	Rarely attempted	
Male	↑	↑	Guo et al., 2011
		↓	Ren et al., 2011
Young adult	↑	↓	Zhu et al., 2021
Educational level	↓	↓	Wu et al., 2014; Zhang et al., 2016
Monthly income	↑	↑	Zhang et al., 2016
Holding a driving license	↓	Rarely attempted	
Walking trip frequency per day	↑	Rarely attempted	
Family norms towards violation behaviour	↑	↑	Zhou et al., 2016
Perceived behavioural control	↑	↑	Zhou et al., 2016
Risk-taking attitude	↑	↑	Zhou and Horrey, 2009
Legal awareness	↓	Rarely attempted	

Notes: ↑ *Positively associated with the propensities of red light running violation of pedestrians*

↓ *Negatively associated with the propensities of red light running violation of pedestrians*

3.5.1 Trade-off between waiting time and perceived risk

The positive association between anticipated waiting time and propensities of red light running violation, and negative association between perceived risk and propensities are expected. Also, effects of anticipated waiting time on the propensities are normally distributed (with standard deviation of 0.03). This implies that 75% of respondents would have higher tendency to violate the red light when waiting time increases. **Table 6** presents the results of sensitivity analysis of anticipated waiting time and perceived risk on the propensities. As shown in **Table 6**, 10% increase in anticipated waiting time is associated with 8.7% reduction in the likelihood of "comply with pedestrian signal". In contrast, 10% increase in perceived risk is associated with 1.1% increase in the likelihood of "comply with pedestrian signal". Apparently, compliance of pedestrian signal is less sensitive to the increase in perceived risk. This is because peoples tend to be loss-averse, as suggested by the prospect theory (Levy, 1992; Wakker, 2010; Andersson et al., 2019). For example, peoples usually hate losses more than the same extent of gains. To this end, travellers are more willing to take risk to avoid a loss, i.e., time delay (Jou and Chen, 2013; Wang and Zhao, 2019; Flügel et al., 2019; Hu et al., 2019).

To this end, risk-return rate can be estimated to indicate the trade-off between safety (risk) and time (return) using the formulation given by (Iraganaboina, 2021),

$$RR = \frac{\sum_{s \neq k} -\beta_t (1 + \frac{1}{exp[\beta_t (t_k - t_s)]})}{\sum_{s \neq k} -\beta_r (1 + \frac{1}{exp[\beta_r (r_k - r_s)]})} \tag{3-6}$$

where β_t and β_r are parameter estimates of anticipated waiting time and perceived safety risk respectively, t_k and t_s are waiting times for alternative k and s respectively, and r_k and r_s are perceived safety risks for alternative k and s respectively.

Figure 3.1 illustrates the changes in the risk-return rate with respect to perceived safety risk and waiting time. As shown in **Figure 3.1**, risk-return rate ranges from 0.5 to 1.5 (%

per second). In other word, pedestrians are willing to accept 15 to 44% increase in safety risk for the saving of 30 seconds.

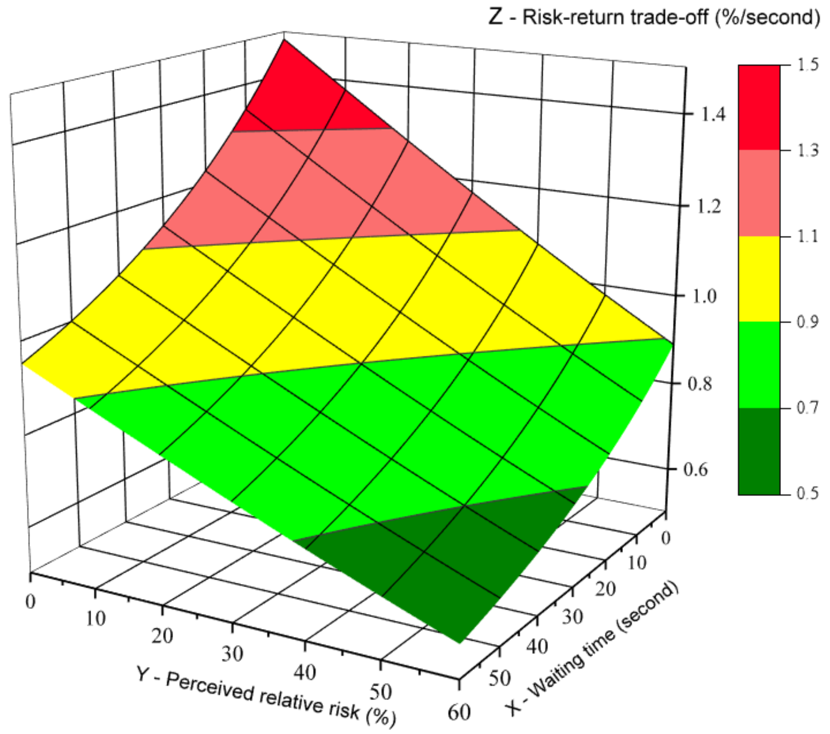


Figure 3. 2 Risk-return rate, perceived safety risk and waiting time

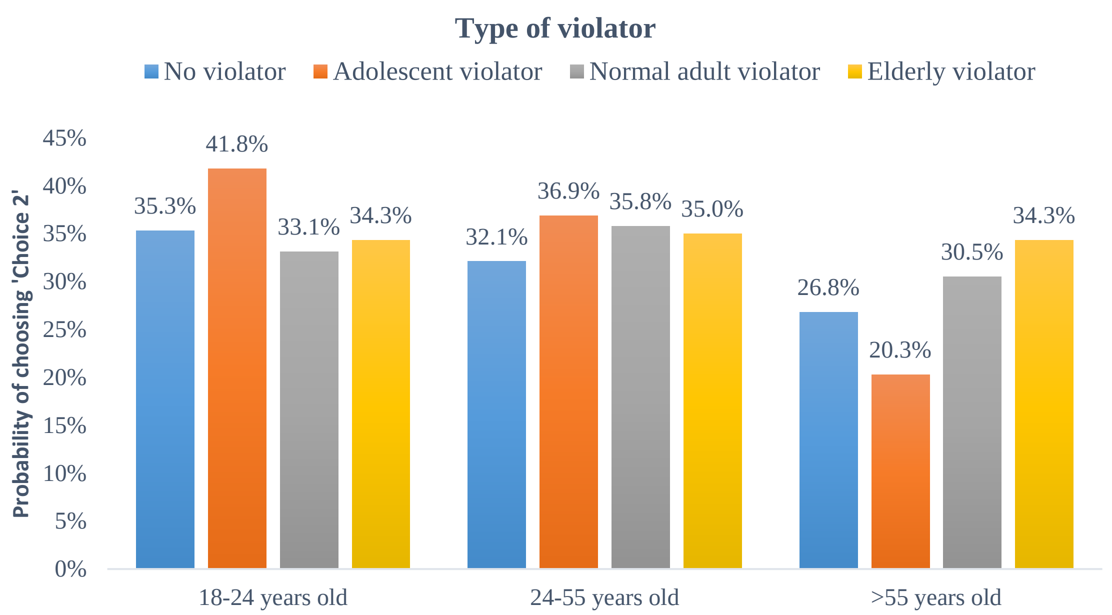
Table 3. 6 Marginal effect of SP attributes

SP attribute	Choice 1: Comply with pedestrian signal	Choice 2: Not comply but wait	Choice 3: Not comply and cross immediately
10% increase in anticipated waiting time for Choice 1	-8.7%	10.0%	0.8%
10% increase in perceived relative risk for Choice 3	1.1%	2.6%	-7.2%

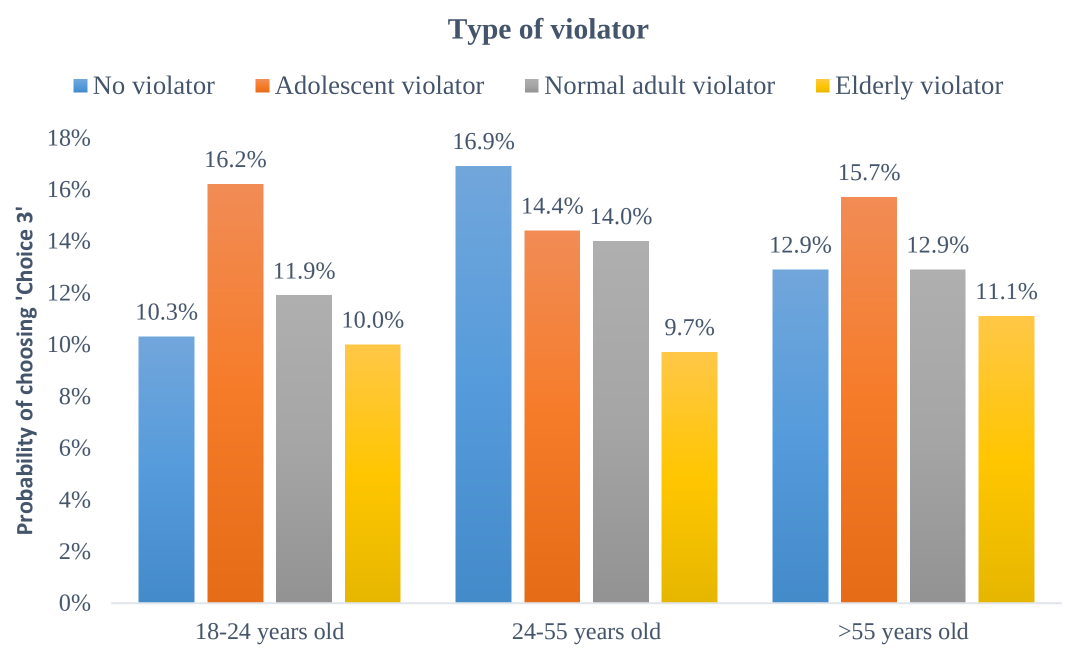
3.5.2 Situational features

Presence of a violator affects the propensities of red light running violation. For instance, propensities are positively associated with the presence of an adolescent violator. This could be attributed to the vicarious experience of punishment avoidance as suggested by the deterrence theory (Ellis, 2003). As revealed in previous studies, peoples are more motivated to violate the traffic rules when they see there is another violator (Rosenbloom et al., 2009; Zhu et al., 2021). However, propensities are negatively associated with the presence of an elderly violator. This is because peoples often perceive the red light running violations of elderly as prevalent, regardless of the road environment and traffic conditions. Therefore, the red light running behaviours of elderly could be less instructive (Oxley et al., 1997; Dommes et al., 2013).

Figure 3.2 depicts the distributions of red light running rates with respect to the age group of respondents and age group of violators (if any). As shown in **Figure 3.2**(a), for the respondents who are 18 to 24 years old, red light running rate (Choice 2: not comply but wait for a suitable gap) is the highest when there is an adolescent violator. In addition, for the respondents who are 55 years old or above, red light running rate is the highest when there is an elderly violator. As also shown in **Figure 3.2**(b), for the respondents who are 18 to 24 years old, red light running rate (Choice 3: not comply and cross immediately) is the highest when there is an adolescent violator. These could be attributed to the effect of social influence. Peoples tend to follow the behaviour of a person who shares the same characteristics, e.g., age (Rosenbloom, 2009; Jay et al., 2020; Kok et al., 2020). However, for the respondents who are 25 to 54 years old, there is no obvious difference in the red light running rate. Nevertheless, such finding indicates that targeted enforcement measures against red light running violation of pedestrians should be imposed at the strategic locations, e.g., schools and elderly homes, where peoples who share the same characteristics may gather.



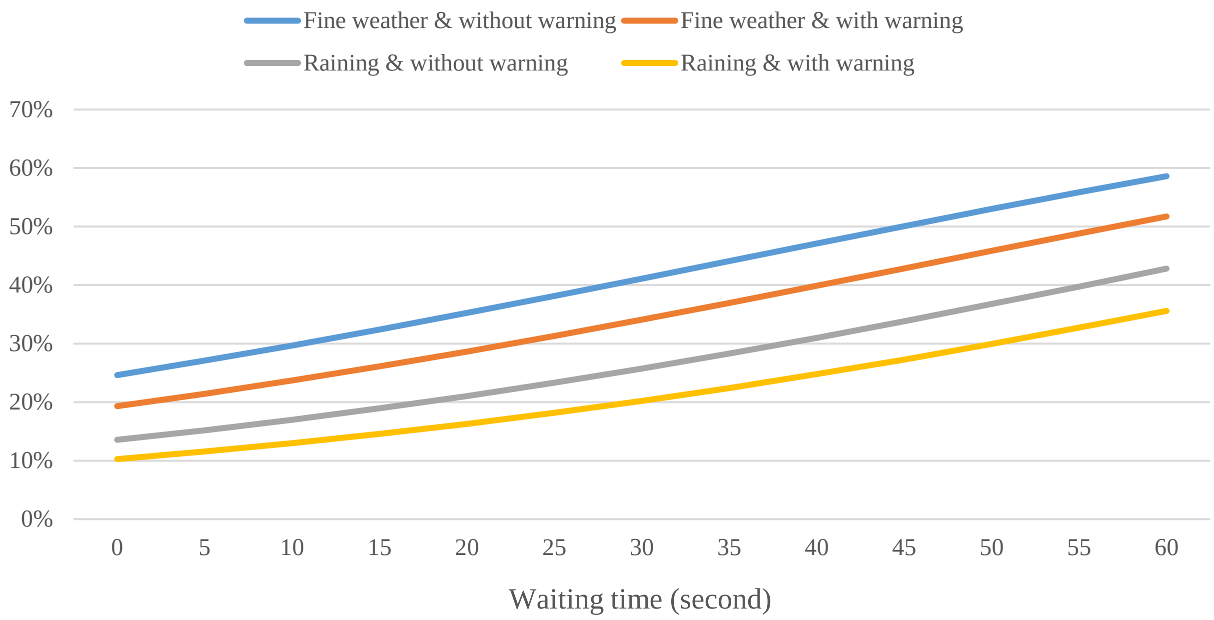
(a) Not comply but wait for a suitable gap



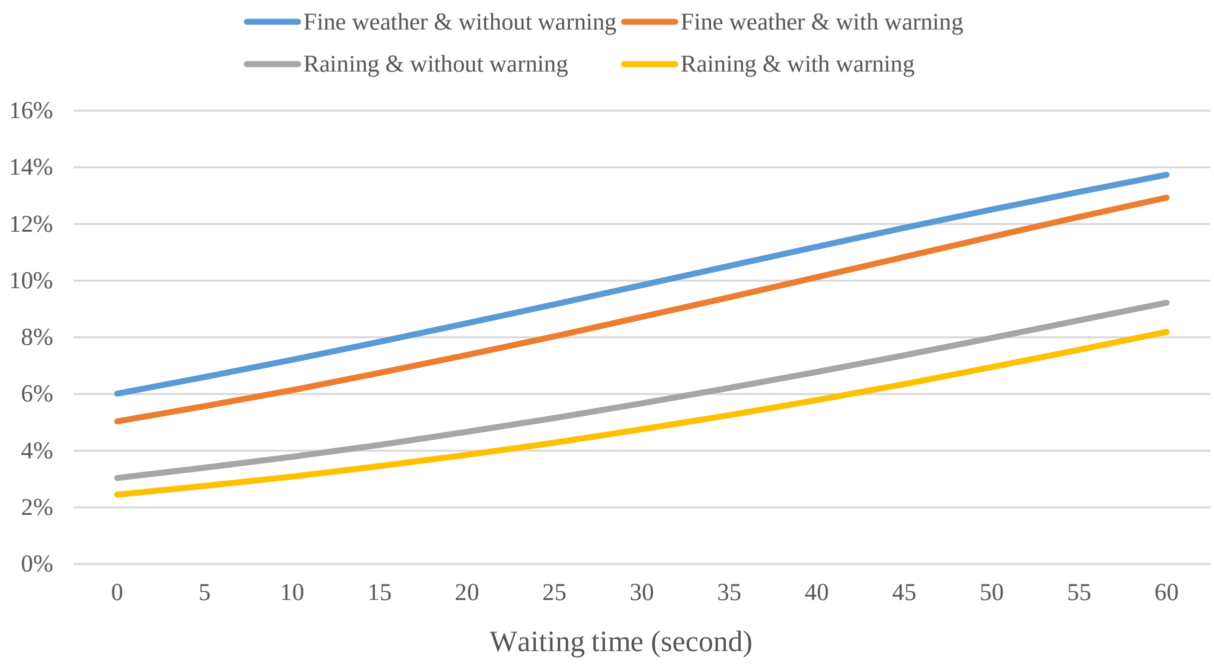
(b) Not comply and cross immediately

Figure 3. 3 Propensities of red light running violation with respect to presence and type of violator

Figure 3.3 illustrates the changes in the propensities of red light running violation with respect to waiting time under different scenarios (i.e., raining and presence of warning sign). As shown in **Figure 3.3**, propensities of red light running violation of pedestrians are lower when there is a warning sign and in the raining condition. Effects of weather condition on the propensities are normally distributed (with standard deviation of 0.57 for Choice 2 and 0.69 for Choice 3 respectively). This implies that only 6.5% (Choice 2) and 3.3% (Choice 3) of respondents would violate the red light in the raining condition. This could be because peoples tend to be risk averse when travelling in the inclement weather conditions (Li and Fernie, 2010). Furthermore, educational level can modify the effect of the presence of warning sign on the propensities. For instance, favorable effect of the presence of warning sign can be magnified for the respondents who have attained the tertiary education or above. This could be attributed to better cognitive performance and safety awareness of peoples who have attained the higher education (Zhang et al.,2016; Liu et al., 2019). Despite that warning signs are installed at the hot spots of pedestrian crashes (i.e., more than five pedestrian injuries per year) in Hong Kong (Transport Department, 2020), it is worth investigating the effectiveness of any innovative solutions, e.g., variable message sign and real-time traffic-actuated signal, in improving the safety awareness of pedestrians in the future study (Liu et al., 2019; Zhao et al., 2020).



(a) Choice 2

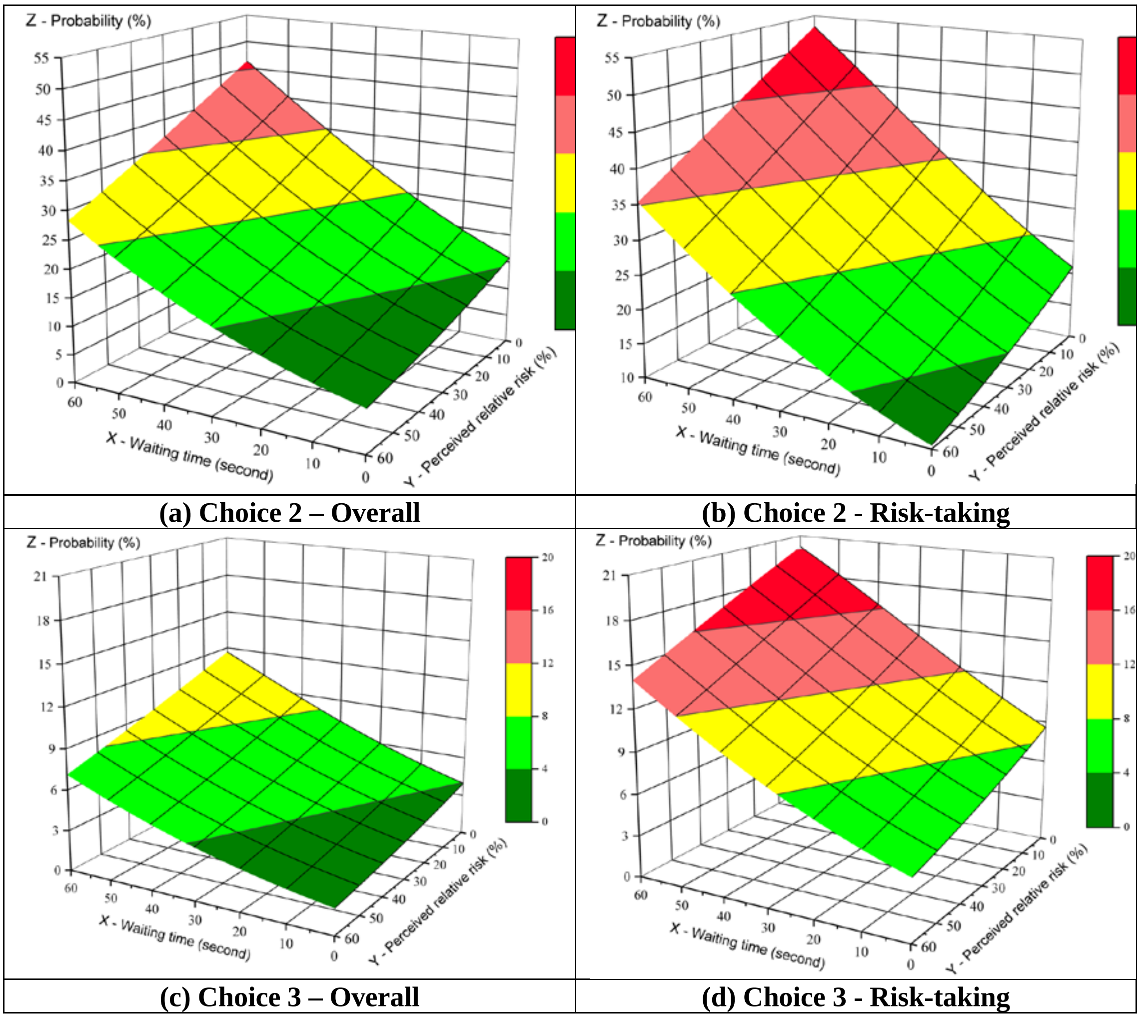


(b) Choice 3

Figure 3. 4 Propensities of red light running violation under different scenarios

3.5.3 Attitude and personality traits

As suggested by the theory of planned behaviour, subjective norms and perceived behavioural control can affect the behavioural intention of individuals (Jiang et al, 2017b; Borhan et al, 2019). As revealed in this study, expectation of family members can affect the propensities of red light running violation of pedestrians (Schwanen and Ettema, 2009). For instance, propensities of red light running violation would increase when one expects that his or her family members also agree with the violation behaviour. Such unfavorable effect could be more profound for the respondents who are 18 to 24 years old. On the other hand, propensities of red light running violation are higher for the respondents who have higher perceived behavioural control, lower legal awareness, and are more risk-taking. Moreover, the compound effect (i.e., behavioural control x risk-taking) could be magnified. Such findings are consistent to that of previous studies (Zhou et al., 2016; Wang et al, 2020b). Nevertheless, it is worth investigating the effectiveness of targeted road safety education for the vulnerable road user groups, i.e., adolescents, in improving the safety awareness. **Figure 3.4** depicts the changes in the propensities with respect to perceived safety risk and waiting time of different pedestrian groups (i.e., risk-taking or not). As shown in **Figure 3.4(b)** and **3.4(d)**, propensities of red light running violation of risk-taking pedestrians are higher in general.



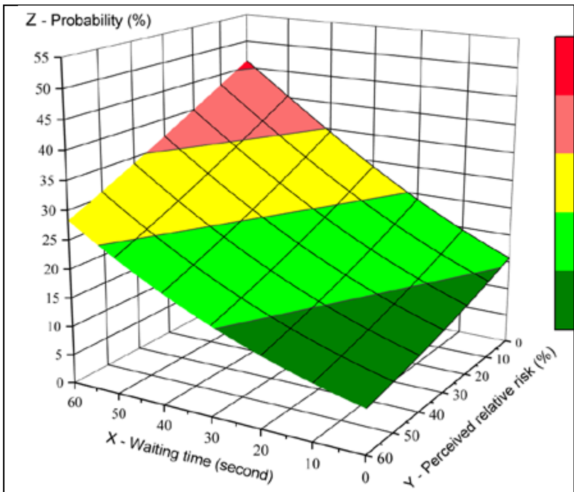
(a) Choice 2 – Overall
(b) Choice 2 - Risk-taking
(c) Choice 3 – Overall
(d) Choice 3 - Risk-taking

Figure 3. 5 Propensities of red light running violation of different pedestrian groups

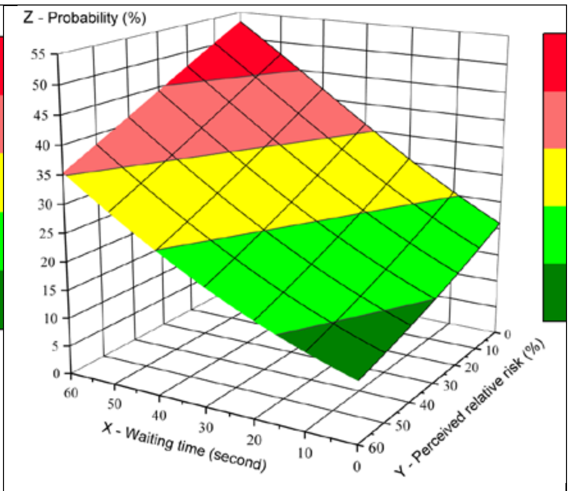
3.5.4 Demographics and socioeconomics

Males and respondents who are 18 to 24 years old have a higher likelihood to violate the red light. However, respondents who have attained higher education have a lower likelihood to violate the red light. Such findings are consistent to that of previous studies (Rosenbloom, 2009; Guo et al., 2011; Brosseau et al., 2013; Zhang et al., 2016; Zhu et al., 2021; Rod et al., 2021). As abovementioned, effects of personality traits and situational features on the red light running propensity can be modified by personal characteristics including age and educational level. This is indicative to the targeted road safety education and promotion strategies. **Figure 3.5** depicts the changes in the propensities with respect to perceived safety risk and waiting time of different age groups. As shown in **Figure 3.5(b)** and **3.5(d)**, propensities of red light running violation of pedestrians who are 18 to 24 years old are higher in general.

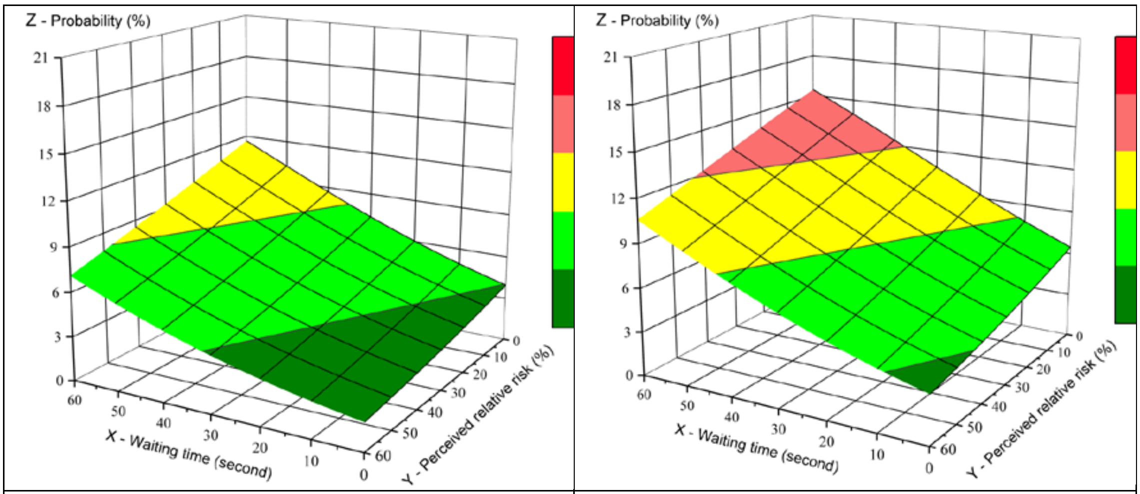
In addition, propensities of red light running violation of respondents who have higher monthly income are higher, but that of respondents who possess a driving license are lower. Apparently, peoples are less sensitive to the monetary fine against red light running violations (i.e., HK$ 2,000), as compared to other penalties including driving disqualification (Wong et al., 2008; Li et al., 2014). As suggested by the deterrence theory, individuals' perceptions of sanction are determined by the severity, certainty and celerity of a punishment (Gibbs, 1985; Kergoat et al., 2017). Above findings imply that it is necessary to increase the certainty of enforcement against red light running violation of pedestrians, particularly at the strategic locations and hot spots of pedestrian crashes (Chen et al., 2020).



(a) Choice 2 – Overall



(b) Choice 2 – 18 to 24 years old



(c) Choice 3 – Overall	(d) Choice 3 – 18 to 24 years old

Figure 3. 6 Propensities of red light running violation of different age groups

3.6 Concluding remarks

In this study, effects of perceived risk, anticipated waiting time, weather condition, presence of violators, and other personal characteristics on the red light running behaviours of pedestrians are investigated using a questionnaire survey. Then, a regret-based multinomial logit model is adopted to analyse the choices between (i) comply with pedestrian signal, (ii) not comply but wait for a suitable gap, and (iii) not comply and cross immediately of pedestrians. Contribution of this study is twofold: First, effects of the trade-off between safety and time, as well as the situational features and personality traits, on the propensities of red light running violation of pedestrians are gauged using a stated preference method. Second, effects of unobserved heterogeneity and correlation between the choices in different scenarios of the same individual are considered using a panel mixed approach.

Results indicate that propensities of red light running violation of pedestrians are positively associated with anticipated waiting time, but negatively associated with perceived relative risk. The safety versus time trade-off of individual can be gauged using the regret-based model. For instance, compliance of pedestrian signal is more sensitive to the change in waiting time than that in safety risk. In addition, situational features including weather condition, presence and type of violator, and presence of warning sign all affect the propensities of red light running violation of pedestrians. Peoples have a higher tendency to run the red light when they see another violator, especially when the violator is an adolescent. Furthermore, males and peoples who are 18 to 24 years old and risk-taking have a higher tendency to run the red light. Such findings should enhance the understanding on the relationship between personal characteristics, choice decision, and red light running behaviours of pedestrians. They are indicative to remedial traffic control measures (i.e., variable message sign and flashing warning sign), enforcement strategies, and targeted road safety education against the red light running behaviour of vulnerable pedestrian group.

Chapter 4 Roles of personal and environmental factors in the red light running propensity of pedestrian

4.1 Introduction

Non-compliance with traffic signals of pedestrians is the leading cause of pedestrian crashes. It constitutes about 25% of pedestrian crashes at the signalized intersections (Transport Department, 2017). Therefore, it is of high importance to identify the factors that affect the occurrence of red-light running violations of pedestrians, particularly at the locations that are prone to vehicle-pedestrian conflicts and associated crashes. Then, effective engineering, enforcement and educational initiatives can be developed to deter against red light running violations.

Factors affecting the propensity of traffic violation and road crash are usually categorized into three types: human, traffic and road environment. Human factors refer to the demographics and socioeconomic characteristics of an individual. For the traffic condition, effects of traffic volume, vehicular speed and traffic composition are considered. Likewise, the road environment is characterized by the factors including geometric design, pavement condition, lighting condition and traffic control. In the conventional studies, discrete choice approaches (i.e. binary logit and probit) are applied to examine the effects of explanatory factors on the individual decision of red light running violation (Kim et al., 2008; Rosenbloom, 2009; Brosseau et al., 2013; Koh et al., 2014; Russo et al.,2018; Zhang et al.,2018; Wang et al., 2019). The propensities of illegal behaviour are different among the pedestrians who have the same demographics and socioeconomic characteristics. For example, adolescents tend to be more risk-taking, and are more likely to commit red light running violation offence. However, the propensities even of the same person could be lower under adverse weather condition. Effect of the latter is often not measured. To control for the effect of unobserved heterogeneity on the individual decision, random parameter logit or probit model can be applied (Xie et al., 2017). On the other hand, behaviours of the pedestrians arriving at the signal crosswalk in the same cycle tend to be similar. Red light running propensities of the pedestrians in the same cycle are more likely affected by the environmental factors including road environment, pedestrian volume, traffic condition and signal time. To this end, linear modelling approaches can be applied to evaluate the effects of traffic and road environment attributes on the red light running violation rate of pedestrians in the same cycle (Diependaele, 2018).

However, it is rare that the roles of personal (individual level) factors of pedestrian and environmental (cycle level) factors in the prevalence of red light running behaviour of pedestrian are investigated. Particularly, to the best of our knowledge, not many studies have considered the effects of the behaviours of other pedestrians when evaluating the propensity of red light running. Additionally, the interaction effects between personal characteristics, social influences, and environmental features on the propensity of red light running violation have not been revealed. In this study, we aim to identify the factors including personal characteristics of pedestrian, behaviours of other pedestrians, traffic condition, signal time and road environment that affect the decision of red light running violation of pedestrian based on the video observation survey in the urban area of Hong Kong. Both the individual level (pedestrian demographics and behavioural attributes) and cycle level (pedestrian arrival pattern, traffic volume, traffic composition and signal time plan) factors are incorporated into the same model.

In Hong Kong, a typical pedestrian signal cycle has three phases: steady green signal; flashing green signal; and steady red signal. It is illegal for a pedestrian to cross during the steady red time, and to start crossing during the flashing green time. There is no pedestrian signal countdown display at the pedestrian crosswalks in Hong Kong. In this study, crossing behaviours of 6320 pedestrians during the red (pedestrian) signal at six signalized crosswalks in both the peak and non-peak periods of the daytime are captured. Then, a random parameter logit model is developed to measure the association between the propensity of red light running violation and possible explanatory factors. Moreover, effects of social influences as indicated by the presence, number and behaviours of other pedestrians around on the red light running propensity are considered. Results should be indicative to the development of future policy initiatives that can combat the red light running behaviour of pedestrians, and therefore, reduce the pedestrian crash and injury risk.

Remainder of this chapter is organised as follows. Section 4.2 illustrates the details of video observation survey. Study design and method of data collection are described in Section 4.3. Section 4.4 presents the statistical method. Section 4.5 and Section 4.6 presents the analysis results and policy implications respectively. Finally, concluding remarks and study limitations are summarized in Section 4.7.

4.2 Method

4.2.1 Study design

To capture the information on the crossing behaviour, pedestrian personal factor, traffic attributes, road environments and signal time plan, the video observation surveys were conducted at six signalized crosswalks in the urban area of Hong Kong on the weekdays. The sites under investigation were all hot spots of pedestrian crashes (each had more than ten pedestrian crashes in the preceding five years). About half of the crashes involving pedestrians occurred when the pedestrian signals were ‘steady red’. This implies the red light running behaviours of pedestrians could be of great concern. At each site, the duration of observation was five hours (2 hours in the morning and 3 hours in the afternoon). The weather, lighting, visibility and pavement surface conditions were fine during the survey.

Figure 4.1 and **Table 4.1** present the locations and characteristics of the six sites under investigation. The pedestrian and vehicular traffic volumes were high during the survey. Additionally, one should note that the cycle time and green time of all intersections in Hong Kong are not fixed. The signal time plans are responsive to the real-time traffic volume.

Table 4. 1 Descriptions of the sites investigated

No.	**Location**	**Number of traffic lane**	**Crosswalk width (meter)**	**Average traffic volume (/lane/hour)**	**Average pedestrian volume (/meter/hour)**
1	Prince Edward R**oad** West **j/w** Nathan	4	5.5	275	410

	Road				
2	Argyle Street **j/w** Nathan R**oa**d	4	6.5	310	362
3	Argyle Street **j/w** Sai Yee Street	2	4	219	217
4	Tonkin Street **j**/**w** Shun Ning Road	4	5.5	165	234
5	Hung Hom South Road **j/w** Po loi Street	2	4	105	154
6	To Kwa Wan Road **j/w** Chi Kiang Street	2	4	125	258

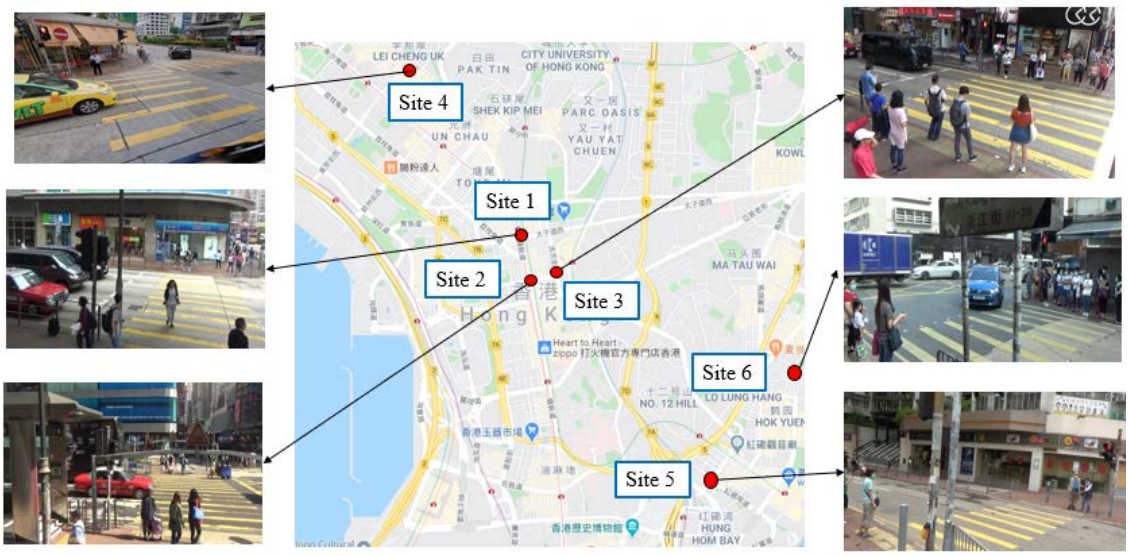


Figure 4. 1 Illustration and location of the sites investigated

4.2.2 Statistical model

Outcome variable of this study is dichotomous (run the red light versus not run), therefore, the binary logit regression approach is used to measure the association between pedestrian decision of red light running and possible risk factors. To account for the unobserved heterogeneity effect on the association, the random parameter approach will be applied (Hensher and Greene, 2003). For instance, effects of the variation in risk-taking behaviour, safety perception and attitude towards red light running violation enforcement, which are often not observed and measured, on the decision among the pedestrians of the same demographics and socioeconomic characteristics can be accommodated. Formulation of the proposed random parameter logit model is given as follows.

Y_i=1 denotes that the i^{th} pedestrian violates the red light, and Y_i=0 the otherwise. Suppose the probability of Y= 1 is p and that of Y = 0 is 1−p respectively, then we have,

$$y \sim Binomial(p)$$

$$\log it(p) = \log(\frac{p}{1-p}) = \mathbf{X}_i\boldsymbol{\beta} + \varepsilon_i \tag{4-1}$$

where $\mathbf{X}_i$ is the vector of explanatory variables, β is the vector of corresponding coefficients (i.e., β_1, β_2,…, β_l) and ε_i is the identically and independently distributed random error term respectively.

$$Normal \sim (0, \sigma^2)$$

One restriction of Equation (1) is that it assumes the effects of individual explanatory variables to be fixed across observations. This ignores the effect of unobserved heterogeneity (i.e., personality and attitude) on the association between red light running violation propensity and pedestrian characteristics. To account for the effect of unobserved heterogeneity, the coefficients are assumed to be randomly distributed with the formulation given as follows,

$$\beta_{il} = \beta_l + \varphi_i \tag{4-2}$$

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

Then, a random parameter model is established based on the conditional probability specified as follows,

$$PROB\left[y_i = 1 \middle| x_i, \beta_i\right] = F\left(\beta_i' x_i\right) \tag{4-3}$$

Parameter estimation of the proposed random parameter logit model is carried out using the maximum likelihood approach with the NLOGIT (Version 5.0) software (Greene, 2012). The parameters are assumed to be normally distributed (Christoforou et al., 2010; Milton et al., 2008). Additionally, a stepwise iterative approach is applied to evaluate whether a parameter is random or not (see Islam and Jones, 2014; Zhai et al., 2019).

To assess the prediction performance of candidate models, the Akaike Information Criterion (AIC) is used. AIC takes into account both the model fit and model complexity. AIC is specified as follows,

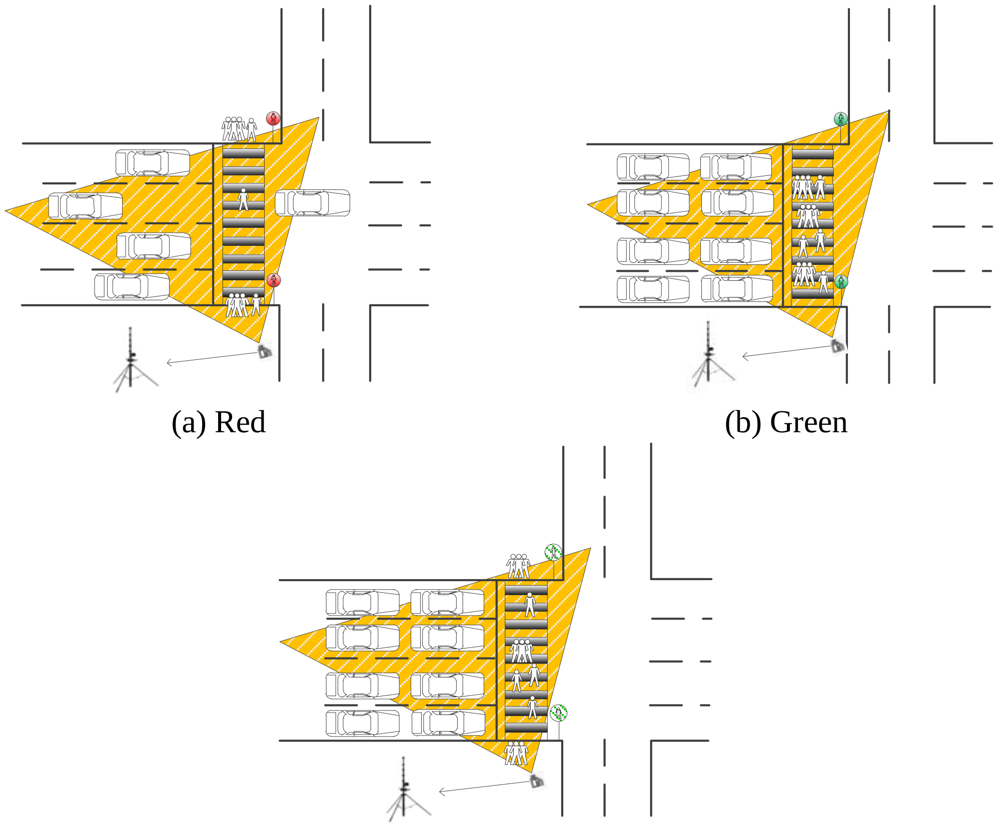
$$AIC = -2\ln(L) + 2K \quad (4\text{-}4)$$

where L refers to the maximum likelihood function and K refers to the number of parameters respectively.

To access the goodness-of-fit of proposed models, Maddala R^2 and likelihood ratio test statistics would be estimated (Maddala, 1986; Anastasopoulos et al., 2008). In this study, parameter estimations of proposed models are carried out using the software package *NLOGIT 6.0*.

4.3 Data

Figure 4.2 illustrates the sequence of pedestrian signals. As shown in Figure 4.2, there are three different (pedestrian signal) phases in a cycle: (i) green – pedestrians can cross; (ii) flash green – pedestrians can cross but cannot start to cross; and (iii) red – pedestrians cannot cross. In this study, we focus on the red light running decision of pedestrians arriving during red (pedestrian) time. In particular, effects of pedestrian demographics, other characteristics and behaviour of other pedestrians, signal time and traffic condition on the red light running propensity of pedestrians will be examined. For the pedestrian demographics, effects of gender and age (adolescent, adult and elderly) are investigated. Also, other attributes including presence of baggage, presence of children, presence of a companion are considered. Number and behaviours (violated red signal or not) of other pedestrians in the same cycle indicate the effects of social norms on individual decision. It is expected that a pedestrian who is accompanied by a friend or family member may have a lower tendency to run the red light. Also, the propensity of red light running may be lower when there are more pedestrians (not run the red light) around. However, the propensity of red light running might be higher when other pedestrians violated the red signal. For the signal time attributes, factors considered are cycle time, green time and time to green (upon the arrival of a pedestrian). It is expected that the propensity of red light running would increase when time to green (maximum waiting time) increases. For the traffic condition, effects of pedestrian arrival rate, vehicular traffic volume, average available gap time and percentage of heavy vehicles are considered.



(a) Red (b) Green

(c) Flashing green

Figure 4. 2 Illustration of the three pedestrian signal phases

Figure 4.3 provides an illustration for the estimation of pedestrian waiting time as well as time to green. As shown in Figure 3, pedestrian waiting time refers to the difference between (pedestrian) arrival time and entry time (start to cross). Time to green refers to the difference between (pedestrian) arrival time and the start of green. In this study, we focus on the decision of pedestrians arrived during the red time. Pedestrians of concern (who violate pedestrian red signal) are shaded in solid red in **Figure 4.3**.

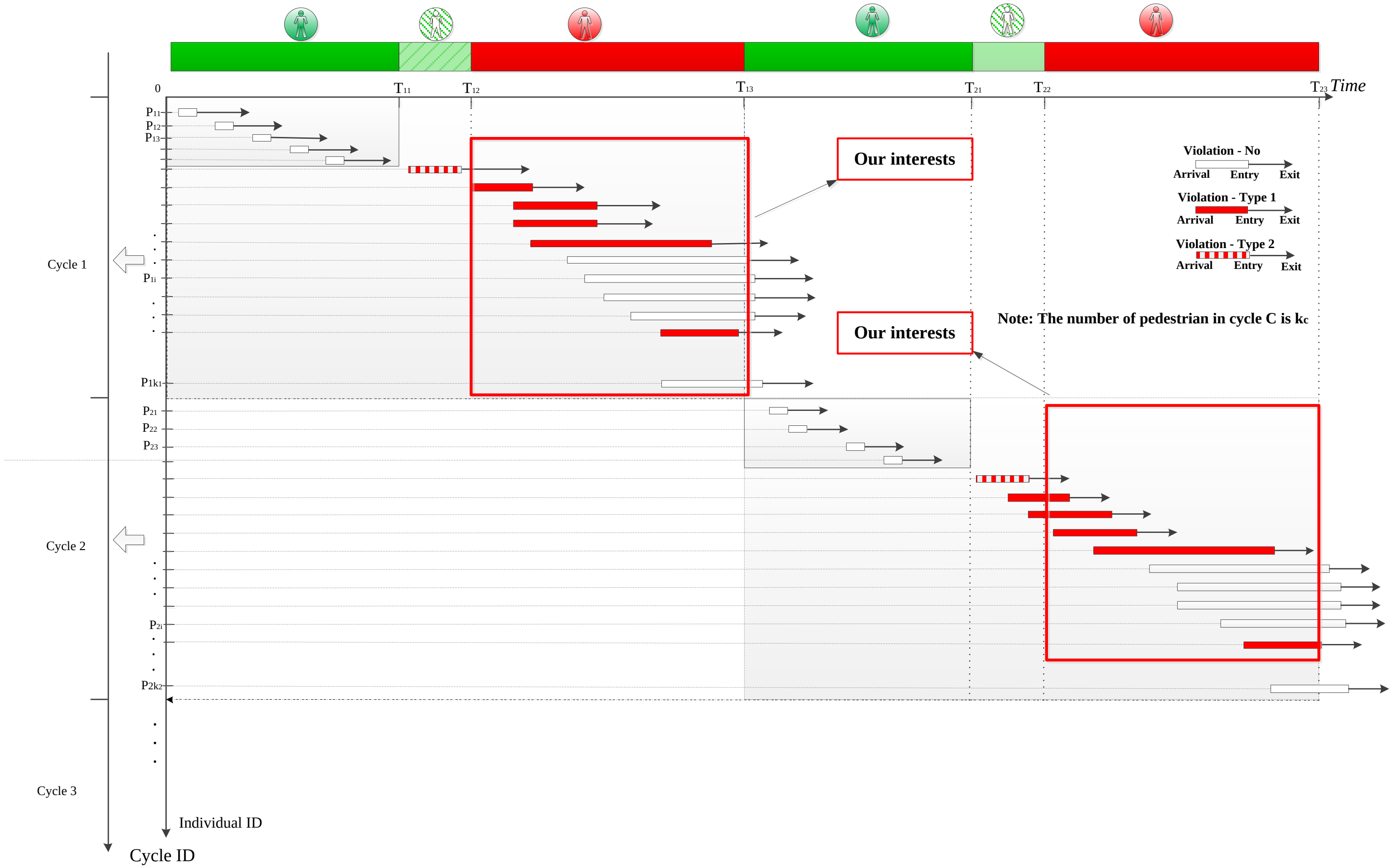


Figure 4. 3 Illustration of method of data collection and coding

In the survey, characteristics and behaviour of 6,320 pedestrians which arrived at the six crosswalks under investigation during the red time of 652 cycles are recorded. **Table 3** summarizes the characteristics of the 6,320 pedestrians. Of the 6,320 pedestrians, 1,169 (18.5%) ran the red light. For the cycle level factors, pedestrian and vehicular traffic attributes in 652 cycles were captured. As shown in Table 3, the average cycle time is 151.8 seconds and the average red time is 72.5 seconds respectively. Also, variations in pedestrian and vehicular traffic volumes of the sample are considerable.

Table 4. 2. Descriptive statistics of the sample

Category	**Factor**	**Level**	**Attribute**	**Count**	**Mean**	**%**	**Std. dev.**
Outcome	Red light running violation	Individual	No	5151		81.5%	
			Yes	1169		18.5%	
Demographics	Gender	Individual	Male	3103		49.1%	
			Female	3217		50.9%	
	Age	Individual	Adolescent	1630		25.8%	
			Adult	2965		46.9%	
			Elderly	1725		27.3%	
Other personal characteristics	With baggage	Individual	No	5493		86.9%	
			Yes	827		13.1%	
	With children	Individual	No	6155		97.4%	
			Yes	165		2.6%	
	With a companion	Individual	No	4746		75.1%	
			Yes	1574		24.9%	
Behaviour of other pedestrians	Other pedestrians in the cycle violated red light	Individual	No	4431		70.1%	
			Yes	1889		29.9%	
	Number of people waiting upon arrival	Individual	Min = 0; Max = 40		7.7		7.4
Signal time	Time to green	Individual	Min = 0; Max = 130		35.48		24.4
	Waiting time	Individual	Min = 0; Max = 131		30.99		6.5
	Red time	Cycle	Min = 37; Max = 144		72.5		23.7
Traffic condition	Pedestrian arrival rate (per minute)	Cycle	Min = 1.5; Max = 41.6		18.4		8.4
	Traffic volume	Cycle	Min = 2.4; Max = 49.6		26.7		11.9
	Percentage of heavy vehicles	Cycle	Min = 0; Max = 90		28.6		12.8

Number of pedestrians = 6320; Number of cycles = 652

4.4 Results

In this study, both the models with and without considering the possible interaction effects (between personal and environmental factors) were developed. Prior to the association measure, a multi-collinearity test was carried out to ensure that the variables included were not highly correlated. In particular, results of multi-collinearity test indicate that there is a remarkable correlation between time to green and waiting time, therefore, only the ‘time to green’ is included in the confined model. No evidence can be established for possible multi-collinearity for other factors of concern.

4.4.1 Model with no interaction effect

Table 3 presents the parameter estimation results. Table 3 (Model 1) illustrates the results of model with no interaction effect. Taking into account the possible confounding factors, some factors including presence of baggage, presence of children and pedestrian arrival rate are included in the proposed model, even they are not statistically significant.

For the pedestrian demographics, gender significantly affects the propensity of red light running at the 1% level. For instance, propensity of red light running of female pedestrians is lower (β = -0.405, *odds ratio* = 0.667) than that of males. Pedestrian age group is correlated with the propensity of red light running at the 5% level of significance. For example, adolescents have the lower propensity (β = -0.181, *odds ratio* =0.834) and older pedestrians (β = 0.189, *odds ratio* = 1.208) have the higher propensity, as compared to normal adults.

For the effect of other pedestrians, presence of a companion is correlated with the reduction in red light running violation propensity at the 1% level (β = -0.546, *odds ratio* = 0.579). Also, increase in the number of pedestrians around is correlated with the reduction in red light running propensity at the 1% level (β = -0.379, *odds ratio = 0*.685). In addition, presence of other pedestrians’ violation is correlated with the increase in the propensity at the 1% level (β = 1.392, *odds ratio* = 4.023). However, no evidence can be established for the association between presence of baggage, children and red light running violation.

For the signal time, increase in time to green (β = 0.072) and red time (β = 0.061) are significantly correlated with the increase in red light running propensity at the 5% level. For the traffic condition, increase in traffic volume (β = -0.025) and the percentage of heavy vehicles (β = -0.016) are correlated with the reduction in the propensity of red light running at the 5% and 1% level respectively. Additionally, increase in the number of lanes is significantly correlated with the decrease in the propensity of red light running at the 1% level (β = -0.803).

4.4.2 Model with interaction effects

To examine the interactions between personal and environmental factors, and their interventions on the association between red light running propensity and possible factors, interaction terms (i.e. "gender x traffic volume", "gender x other pedestrians violated red light", "elderly x with a companion", "elderly x other pedestrians violated red light" and "other pedestrians violated red light x with a companion") are added. Table 3 also shows the results of parameter estimation of the model with interaction terms (Model 2). As shown in Table 3, performance of model with interaction terms (Model 2) is superior to that with no interaction (Model 1). Results of parameter estimations among Model 1 and Model 2 are similar except that there are interaction terms in the latter.

As also shown in Table 3 (Model 2), interaction effects between gender and traffic volume (β = -0.021) and between gender and violation of other pedestrians (β = 0.515, odds ratio = 1.674), on the propensity of red light running are significant at the 1% level. Also, interaction effects between elderly and presence of a companion (β = -0.221, odds ratio = 0.802) is significant at the 5% level and that between elderly and violation of other pedestrians (β = 1.126, odds ratio = 3.083) is marginal at the 10% level respectively. Additionally, interaction effect between violation of other pedestrians and presence of a companion (β = 0.996, odds ratio = 2.707), on the propensity of red light running violation, is significant at the 1% level.

Table 4. 3 Estimation results of random parameter models

Category	**Factor**		**Model 1**		**Model 2**	
			Coefficients	Z-value	Coefficients	Z-value
Constant			-1.390**	6.96	-1.511**	6.85
Demographics	Gender (Control: male)	Mean	-0.405**	-5.71	-0.433*	-3.59
		S.D.	*(0.372**)*	4.82	*(1.163**)*	8.62
	Adolescent (Control: adult)		-0.181*	-2.17	-0.228*	-2.31
	Elderly (Control: adult)		0.189*	2.18	0.174*	2.02
Other personal characteristics	With baggage		n.s.		n.s.	
	With children		n.s.		n.s.	
	With a companion		-0.546**	-5.41	-0.984*	-5.27
Behaviour of other pedestrians	Others in the cycle violated red light		1.392**	18.29	1.029**	8.74
	Number of people waiting upon arrival	Mean	-0.379**	-9.68	-0.394**	-9.48
		S.D.	*(0.214*)*	3.88	*(0.253*)*	3.64
Signal time	Time to green		0.072**	4.41	0.090**	4.84
	Red time		0.061*	2.16	0.060**	2.12
Geometric design	Number of lanes		-0.803**	-7.13	-0.827**	-7.15
Traffic condition	Pedestrian arrival rate		n.s.		n.s.	
	Traffic volume		-0.025*	-3.12	-0.021*	-2.73
	Percentage of heavy vehicles		-0.016**	-4.76	-0.018**	-5.12
Interaction term	Gender x Traffic volume		-		-0.021**	-2.97
	Gender x Others violated red light		-		0.515**	3.30
	Elderly x With a companion				-0.221*	-2.03
	Elderly x Others violated red light				0.126^	1.89
	Others violated red light x With a companion		-		0.996**	4.47
Goodness-of-fit	AIC		2776.6		2750.1	
	Restricted loglikelihood		-1373.52		-1357.43	
	Unrestricted loglikelihood		-1365.42		-1350.12	
	Chi-square statistics		24.20		14.31	

** Statistical significance at the 5% level*

*** Statistical significance at the 1% level*

4.5 Discussion

In this study, the roles of pedestrian personal factors, social influences (presence of companion, presence and number of other pedestrians, and violation of other pedestrians), and environmental factors in the individual decision of red light running violation are examined. Also, the possible interaction effects by pedestrian demographics, signal time and traffic condition on the propensity are considered. To measure the sensitivity of the red light running propensity, the marginal effects (i.e. percentage change in propensity in response to per unit change of explanatory variable) are also estimated. Discussions mainly focus on the model with interaction terms included (which has better model fit).

4.5.1 Presence and behaviours of other pedestrians

Presence of a companion and increase in the number of pedestrians around both reduce the red light running propensity of pedestrians with the elasticities of -0.228 and -0.942 respectively. More specifically, probability of red light running reduces by 0.94% when the number of pedestrians around increases by 1%. This finding is consistent with that of previous studies. Such phenomenon can be attributed to the influence of social norms (Rosenbloom, 2009; Zhang et al., 2016; Russo et al., 2018). Yet, effect of the number of pedestrians around on the individual decision varies remarkably. It is possible that the effects of pedestrian gender and age are sensitive to the social norms (Sorenson and Taylor, 2005).

Additionally, red light running propensity increased when at least one other pedestrian violated the red light. This implies that other pedestrians would be motivated (e.g. encouraged to violate the traffic rules) after the first violator appeared. Such phenomenon can be attributed to the vicarious experience of punishment avoidance in accordance to the deterrence theory (Ellis, 2003). Moreover, presence of a companion could interact with the association between propensity and behaviours (red light running violation) of other pedestrians. This suggested that pedestrians who had a companion could be even more motivated (by the traffic violation of other pedestrians), as compared to the pedestrians who were alone. However, information on the safety perception and attitude of pedestrians are not available in the current observation survey. It is worth exploring the trade-off between the perceived benefit (e.g. time saving) and anticipated cost (e.g. higher crash and injury risk) of the pedestrians when making the crossing decision, when more comprehensive data on the demographics, socioeconomics, safety perception and anticipated crossing behaviour are available in the questionnaire survey. Moreover, since the presence of the first violator could have an adverse impact on the red light propensity of other pedestrians, increases in the certainty (i.e. enforcement level) and severity (i.e. penalty level) of penalties may be of essence to deter against the red light running violation of pedestrians (Chen et al., 2020).

4.5.2 Personal factors

Results indicate that propensity of red light running violation of female pedestrians is lower. For instance, given that the parameter of gender is normally distributed, the chance that the propensity of red light running of females is lower than that of males is 64.3%. This finding is consistent with that of previous studies (Rosenbloom, 2009; Xie et al.,2017; Guo et al., 2011). Indeed, involvement rate of fatal crash of female pedestrians is lower than that of males (Harre et al., 1996). Additionally, the random component of gender effect is statistically significant at the 1% level. This justifies that the risk-taking attitude and safety awareness could vary remarkably among female pedestrians. Interestingly, the interaction effects by the traffic volume and presence of violation behaviour of others on the association between gender and red light running violation propensity is significant. It implies that the social influences (particularly for the leading behaviour of other pedestrians) and traffic condition can moderate the safety perception and therefore the crossing behaviour of female pedestrians. Yet, it is worth exploring the reasons for such modifications on the individual decision, if more comprehensive data on the safety awareness of pedestrian is available in the attitudinal survey (Ren et al., 2011).

For the age effect, adolescent pedestrians have a lower tendency to run the red light, as compared with normal adults. Indeed, it is rare that difference in the red light running propensities between adolescent pedestrians and normal adults is attempted. As revealed in this study, adolescents generally well behave. It could be because adolescents generally have better safety perception and cognitive capability (Evans and Norman, 2003). Also, adolescents could have better sense of law compliance with traffic rules because of the education (Lee et al., 2004). Results also indicate that older pedestrian has a high tendency to run the red light. This finding is contradictory to that of some previous works (Rosenbloom, 2009; Jiang et al., 2011; Wang et al., 2019), but consistent with that of a Chinese study (Cao et al., 2017). An earlier study in Hong Kong suggested that no evidence could be established for the relationship between age and red light running violation (Xie et al., 2017). However, as revealed in the police crash investigation record, 58% of pedestrians killed in road crash were of age above 65 years. Also, the main contributory factors to the crash involvement of older pedestrians were ignorance of pedestrian signal and reckless crossing (Transport Department, 2018). This is consistent with the finding of a previous study that risk of fatality of older pedestrians in the road crashes is significantly higher than that of normal adults (Asher et al.,2012). There are two possible reasons. First, obedience is positively associated with the education level (Bray and Lee, 1993; Zhang et al., 2016). Generally, older peoples in Hong Kong have relatively low educational attainment. Second, older peoples tend to have poor cognitive abilities. They may not be able to response to the hazard situations appropriately (Dommes et al., 2013). Yet, results also indicate that red light running propensity of older pedestrians increases when other pedestrians violate and decreases when they have a companion. This could be because older pedestrians may have poor judgment and tend to follow others' behaviour. Also, the companion of an elderly (probably caretaker) tends to comply with the traffic rules. Yet, it is worth exploring the effects of leading violation behaviour on the safety perception of pedestrians (particularly for the pedestrian groups that have lower self-identity) when more comprehensive information is available in the experimental or attitudinal models. Nevertheless, higher propensity of red light running violation of older pedestrian is an alarming issue. Same as other modern societies, Hong Kong is facing the problem of ageing population. Proportion of population older than 65 years is expected to increase from 16% in 2016 to over 25% in 2035. Elderly populations are concentrated in the early developed urban areas, which have frequent pedestrian activities and conflicts between pedestrian and vehicular traffic. More importantly, over 30% of pedestrian casualties are elderly (1,064 in year 2017) in Hong Kong (Transport Department, 2018). Therefore, it is important to develop effective enforcement, educational and publicity initiatives that can improve the safety awareness and combat the red light running violation behaviour of older pedestrians (Harkey and Zegeer, 2004).

4.5.3 Signal time and traffic condition

Propensity of red light running violation of pedestrian increases with the increase in time to green as well as the red time. It is because pedestrians tend to be annoyed and impatient when the anticipated waiting time increases. Such phenomenon occurred when the pedestrian signal countdown device was present as revealed in the previous study (Brosseau et al., 2013). However, there is no pedestrian signal countdown device in Hong Kong. It is suspected that the pedestrians can have good estimate of anticipated waiting time by observing the surrounding environment (i.e. number of pedestrians around and signal phases of other traffic streams), even if the signal countdown device is absent. It is suggested that the signal time (green time for pedestrian) should be responsive to both the pedestrian and vehicular traffic volumes. It is indeed viable since reliable pedestrian tracking technology is now readily available in the market. On the other hand, whether the application of pedestrian signal countdown (countdown to green) could be effective in improving the perception of pedestrian, and therefore, combating the red light running behaviour deserves further investigation. Nevertheless, safety perception towards pedestrian signal countdown can be gauged using an attitudinal model in the extended study.

For the effect of traffic condition, propensity of red light running rate is lower when the traffic volume and percentage of heavy vehicles increase (with the elasticity of -0.518 and -0.484 respectively). This is consistent to the findings of previous studies (Koh et al., 2014; Wang et al., 2011; Koh and Wong, 2014). This implies that the pedestrian decision is sensitive to both the approaching vehicles as well as the vehicle class (heavy vehicle), which the likelihood of more severe injury may increase when heavy vehicles are involved. Propensity will be reduced by 0.48% and 0.52% when the percentage of heavy vehicles and traffic volume increase by 1%. The propensity may vary with the gender and age of pedestrians. For instance, females are more sensitive to the traffic volume, as compared to males. However, vehicular speed, which is correlated with the risk and severity of possible crash, is not measured in this study. In the extended research, it is worth exploring the interactions between vehicular speed, pedestrian characteristics and the decision of red light running violation, when the comprehensive information on the traffic flow attributes (i.e., flow, density and speed) is available. Nevertheless, similar surveys can be carried out at the crosswalks of varying speed limits. Regardless of the above, warning signs indicating the prevalence of heavy vehicles and high traffic volume may be effective in improving the safety awareness and deterring against red light running violation of pedestrians.

4.6 Concluding remarks

Red light running behaviour of pedestrians is a significant contributory factor to pedestrian crashes, in which the pedestrians are more vulnerable to mortality and severe injury than the car occupants. This study aims to examine both the personal (gender, age, pedestrian behaviour) and environmental (signal time and traffic condition) factors affecting the individual decision of red light running violation using the video observation survey at the hot spots of pedestrian crashes. Also, effects of the presence and behaviour of other pedestrians in the same cycle on the propensity are considered. Moreover, interaction effects by personal and environmental factors on the propensity are considered. Contribution of this study is of two-fold. Firstly, both the individual-level (personal demographics and behaviour) and cycle-level (traffic condition and signal time) factors are included in the analysis of individual decision of red light running violation. Secondly, influence of social norms (presence of a companion, number of pedestrians around and violation of other pedestrians) on the individual decision is examined.

For the personal factors, it is known that female pedestrians generally have lower propensity of red light running, compared with males. This study reveals that presence of a violator and traffic volume can moderate the association between gender and propensity of red light running. For example, propensity of red light running of female pedestrians increases when other pedestrians violate the red light. Also, propensity of red light running of female pedestrians reduce when the traffic volume is high. On the other hand, previous studies suggested older pedestrians were risk-averse and had lower likelihood to violate the red light. However, this study reveals that older pedestrians have a higher likelihood to violate the red light. It could be because of the low educational attainment of older peoples in Hong Kong. Moreover, it is interesting to find that propensity of red light running of older pedestrians would reduce when there is a companion.

For the environmental features, previous studies indicate that when there is a pedestrian signal countdown device, ‘time to green’ is positively associated with the propensity of red light running. This study reveals that similar phenomenon can occur even when the pedestrian signal countdown device is absent in Hong Kong. More importantly, social norms, as reflected by the presence and behaviour of other pedestrians, has a favorable effect on the propensity. Moreover, pedestrians who have a companion can be even more motivated (by the traffic violation of other pedestrians), compared with the pedestrians who are alone. Such finding is indicative to the effective enforcement and educational strategies that could enhance the safety awareness of targeted pedestrian group and deter against the red light running violation of pedestrians. Moreover, it is worth exploring the effectiveness of advanced traffic control techniques, i.e., variable pedestrian signal time that is responsive to pedestrian volume and pedestrian signal countdown device, in combating the red light running violation of pedestrians. In the extended research, effects of social norms, safety perception and anticipated traffic condition on the propensity of red light running violation can be gauged using an attitudinal model. Therefore, understanding on the pedestrian crossing behaviour, and the interventions by the personal and environmental factors can be enhanced.

Chapter 5 Propensities of red light running of pedestrians at the two-stage crossings with split signal phases

5.1 Introduction

Two-stage pedestrian crossings are commonly found at the signalized intersections, where the pedestrian and vehicular traffic volumes are high, in Hong Kong (Transport Department, 2018), Mainland China (Wang et al., 2009; Ma and Lu, 2011), Germany (RiLSA, 1992), Canada (Li and Fernie, 2010) and Middle East (Hamed, 2001; Rosenbloom and Pereg, 2012). To reduce the vehicle delays, the pedestrians' right of ways (i.e., green pedestrian signal phases) of different stages are often split (Tian et al., 2001). Also, a wide central island is usually provided at the two-stage crossings. Pedestrians would cross to the central island and have to wait for the right of way to complete the crossing. Majority of prior research has been focusing on the intersection capacity, time delays (of pedestrians and vehicular traffic) and operation efficiency (Ma and Lu, 2011). However, it is rare that safety of two-stage crossings is studied. Red light running violation of pedestrian is of one the major causes of pedestrian-vehicle crashes at the signalized intersections (Transport Department, 2018). Studies indicate that pedestrians' demographics, social influences, environmental and traffic conditions can affect the propensities of red light running of pedestrians at the one-stage crossings (de Lavalette et al., 2009; Guo et al., 2011). However, relationship between influencing factors and red light running behaviours of pedestrians at the multi-stage crossings could be different. For example, waiting time before crossing the first stage may affect the cross decision of pedestrian in the subsequent stages (Rosenbloom and Pereg, 2012). Also, the pedestrian signal in the subsequent stage can affect the decisions of pedestrians in the first stage. It is necessary to assess the differences in the effects of possible factors on the red light running propensities of pedestrians between different stages of crossing.

This study aims to investigate the red light running behaviours of pedestrians at the two-stage crossings, with which the green pedestrian signal phases in the two stages are split.

Two research questions are addressed: First, what are the differences in the explanatory factors to the propensities of red light running of pedestrians in the first and second stages? We hypothesize that when the pedestrian signal of the second stage is green, pedestrian's propensity of red light running in the first stage is higher. In addition, if the waiting time before crossing the first stage is longer, propensity of red light running in the second stage is higher. Second, what are the effects of the presence and behaviours of other pedestrians on the propensity of red light running in the first and second stages? We hypothesize that propensity of red light running violation is lower when there are other pedestrians waiting, but such propensity would increase when other pedestrians are seen to violate the red light.

In this study, the crossing behaviours of 3,320 pedestrians at six two-stage pedestrian crossings in Hong Kong are investigated. A random parameter logit regression approach is applied to measure the association between possible factors and pedestrian's propensity of red light running. Results should be indicative to the understanding of the pedestrians' crossing behaviours at the two-stage signalized crossings, and more importantly, development of effective measures that can deter against the red light running violations of pedestrians.

Remainder of this chapter is organised as follows. Section 2 illustrates the details of video observation survey. Study design, data collection and analysis method are described in Section 3. Section 4 and Section 5 presents the results and discusses the policy implications respectively. Finally, concluding remarks and future research directions are given in Section 6.

5.2 Method

5.2.1 Study design

The video observation surveys were conducted at six two-stage signalized crossings in Hong Kong during the period from November 2019 to July 2020. **Figure 5.1** illustrates the locations of the six survey sites. All of them are in Kowloon, the most densely populated urban area (i.e., 2.2 million in 2016) in Hong Kong (Census and Statistics Department, 2018a). For each site, the survey time was four hours (two in the morning and two in the afternoon). At the times of surveys, the weather and lighting conditions were fine.

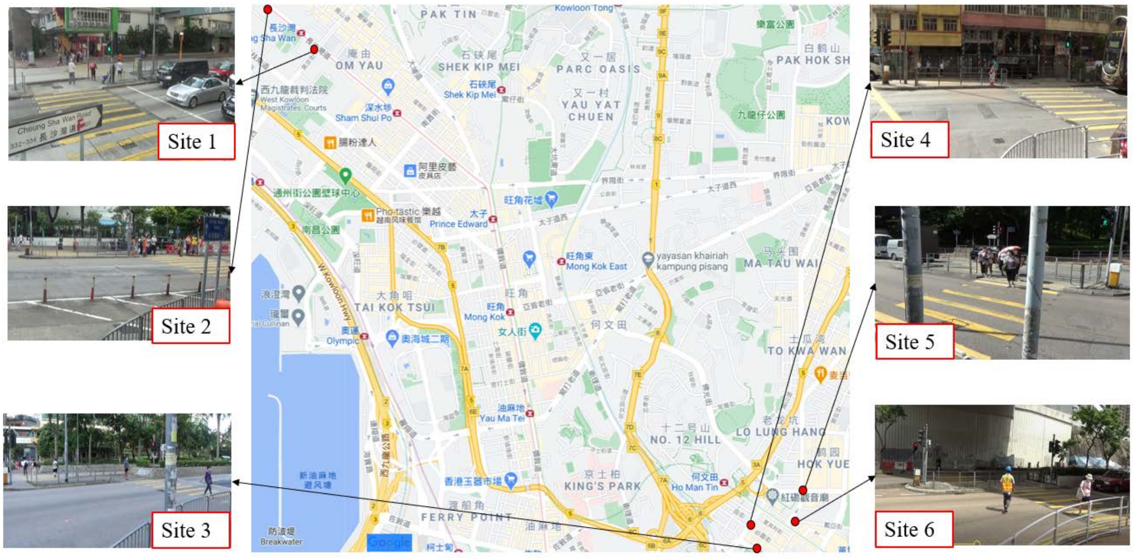


Figure 5. 1 Locations of the survey sites

Table 5.1 provides the details of the six survey sites under investigation. Number of traffic lanes of the crossings ranges from 2 to 4. Overall, crossing behaviours and compliances of 3,332 pedestrians during the solid red pedestrian signal phases were observed. As shown in Table 1, the pedestrian signal phases of different stages were split at all the sites. It should be noticed that the signal time phases at most of the signal intersections in Hong Kong are not fixed. They are adaptive to the real-time vehicular traffic flow. Cycle times, green times and red times presented in Table 5.1 are for illustrative purpose only.

As discussed earlier, the pedestrian signal phases in different stages are split at the survey sites. It is possible that when the pedestrians are waiting to cross from one side of the road (i.e., pedestrian signal of the first stage is red), the signal of another stage (i.e., crossing from the central island to other side) is green. On the other hand, after crossing from the side to the central island (i.e., pedestrian signal of the first stage is green), pedestrians have to wait at the island to complete the crossing (i.e., pedestrian signal of the second stage is red). In this study, we aim to examine the factors that affect the non-compliances of pedestrians in the first (i.e., crossing from one side of the road to the central island, Model 1) and second (i.e., crossing from the island to other side, Model 2) stages.

5.2.2 Statistical model

In this study, as the dependent variable is dichotomous (i.e., running the red light or not), the binary logit regression method is applied. To address the problem of unobserved heterogeneity, the random parameter approach is deployed (Hensher and Greene, 2003). For instances, it can account for the effects of the variations in personality, perception and safety attitude, which are often not observed and measured, on the propensity of red light running violation among the pedestrians of the same personal characteristics and under the same situation. As the effects of demographics on the propensities of red light running in the two stages of crossing are expected to be the same, the parameters of demographics are constrained between the two stages. Formulation of the proposed random parameter logit regression model is given as follows.

Y_{it} = 1 denotes that pedestrian *i* violates the red light in stage *t*, and Y_{it} = 0 the otherwise. Suppose the probability of Y_{it} = 1 is *p*, then we have (Fricker and Zhang, 2019),

$$y_{it} \sim B\ inomial\ (p)$$

$$logit(p) = log(\frac{p}{1-p}) = \boldsymbol{X}_{it}\boldsymbol{\beta}' + \boldsymbol{Z}_i\boldsymbol{\alpha}' + \varepsilon_{it} \tag{5-1}$$

where $\boldsymbol{X_{it}}$ is the vector of unconstrained explanatory variables, $\boldsymbol{Z_i}$ is the vector of constrained explanatory variables, $\boldsymbol{\beta}$ is the vector of corresponding coefficients for unconstrained explanatory variables, $\boldsymbol{\alpha}$ is the vector of corresponding coefficients for constrained explanatory variables, and ε_{it} is the identically and independently distributed random error term respectively.

Equation (1) assumes that the effect of individual explanatory variable is fixed across observations. To account for the effect of unobserved heterogeneity, coefficients are assumed to be randomly distributed with the specification given as follows,

$$\beta_{it} = \beta_t{}^* + \varphi_{it}$$

$$\alpha_i = \alpha^* + \psi_i \tag{5-2}$$

where β_t^* and α^* denote the mean effects of the variables, and φ_{it} and ψ_i are normally distributed with the means of zero and variances of θ^2 and σ^2 respectively (Christoforou et al., 2010; Milton et al., 2008).

Then, the random parameter model is established based on the conditional probability specified as follows,

$$P(y_{it} = 1|x_{it}, \beta_{it}, z_i, \alpha_i) = F(\beta_{it}x_{it} + \alpha_i z_i) \tag{5-3}$$

Parameter estimation of the proposed random parameter logit regression model is carried out using the maximum likelihood approach using the mlogit package of *R* software (R Core Team, 2013) and NLOGIT (Version 5.0) software (Greene, 2012). If the standard error of a parameter is statistically significant at the 10% level, then the parameter will be specified as "random". The model is estimated using the simulated maximum likelihood with 200 Halton draws (Train, 2009). In addition, a stepwise iterative approach is applied to assess the random parameter (Islam and Jones, 2014; Zhai et al., 2019). The variables are tested one by one. The iterative process would continue until the improvement in overall model fit is incremental.

To assess the prediction performance of candidate models, the Akaike Information Criterion (AIC) is used. AIC takes into account both the model fit and model complexity. AIC is specified as follows,

$$AIC = -2\ln(L) + 2K \tag{5-4}$$

where L refers to the maximum likelihood function and K refers to the number of parameters respectively.

Table 5. 1 Summary of survey sites

Site location			Number of traffic lanes	Pedestrian signal phases	Pedestrian observed
1	Cheung Sha Wan Road/ Tonkin Street	Stage 1	3	104s 36s	621
		Stage 2	3	104s 36s	
2	Cheung Sha Wan Road/ Hing Wah Street	Stage 1	3	112s 57	718
		Stage 2	4	78s 91s	
3	Hung Hom South Road/ Po Loi street	Stage 1	2	67s 64s	583
		Stage 2	3	62s 40s 29s	
4	Gillies Ave South/ Baker Street	Stage 1	2	83s 47s	527
		Stage 2	3	77s 33s 20s	
5	Hung Hom South Road/ Tai Wan Road East	Stage 1	2	24s 122s	330
		Stage 2	2	20s 124s	
6	Hung Hom South Road/ Dyer Ave	Stage 1	2	105s 26s	553
		Stage 2	2	45s 62s 24s	

5.3 Data

In this study, effects of the factors including pedestrian demographics, behavioural characteristics, geometric design, signal time and traffic conditions on the propensity of red light running of pedestrians are investigated. For the pedestrian demographics, effects of gender and age (i.e., adolescent, younger adult and elderly) are considered. For the behavioural characteristics, social influences by the factors including the presence of a companion, number of other pedestrians waiting, and presence of a violator (non-compliance to red pedestrian signal) are considered. It is suspected that a pedestrian who is accompanied by a friend or family member may have a lower tendency to run the red light. Also, propensity of red light running may be lower when there are more pedestrians (especially none violates the red light) waiting.

For the signal time, factors considered are red time and maximum waiting time (time between the arrival of a pedestrian and the end of red). Maximum waiting time indicates the time that a violator would have to wait if he or she had complied with the pedestrian signal. It is suspected that the propensity of red light running may increase when the red time and maximum waiting time increase. To address the question of whether the situational features in the two stages (especially the green pedestrian phases are split) are interrelated, factors including signal of the second stage (Model 1) and waiting time before crossing the first stage (Model 2) are also considered. It is suspected that when the pedestrian signal of the second stage is green, the pedestrians may have a higher tendency to violate the red light and cross to the central island. On the other hand, when the waiting time before crossing to the island is long, pedestrians may become less patience in the subsequent stage. Also, pedestrians who comply to the red signal in the first stage tend to be obedient in the second stage, regardless of the waiting time.

Nevertheless, factors including traffic volume, percentage of heavy vehicle and number of traffic lanes are also considered. **Table 5.2** summarizes the characteristics of sample. For the non-compliance of the first stage, 2,747 pedestrians were surveyed (843 (30.4%) violated the red light). For the second stage, 2474 pedestrians were surveyed (423 (17.1%) violated the red light).

Table 5. 2 Descriptive statistics of the samples

Scope of work	Factor	Attribute	Stage 1				Stage 2			
			Count	Mean	%	Std. dev.	Count	Mean	%	Std. dev.
Outcome	Red light running violation	No	1931		69.6%		2051		82.9%	
		Yes	843		30.4%		423		17.1%	
Demographic	Gender	Male	1382		49.8%		1119		45.2%	
		Female	1392		50.2%		1355		54.8%	
	Age	Adolescent	626		22.6%		431		17.4%	
		Younger adult	1686		60.8%		1609		65.0%	
		Elderly	462		16.6%		434		17.6%	
Behavioural characteristics	With a companion	No	2291		82.6%		2004		81.0	
		Yes	483		17.4%		470		19.0%	
	Presence of a violator	No	1472		53.1%		1883		76.1%	
		Yes	1302		46.9%		591		23.9%	
	Number of pedestrians waiting	Min = 0 Max = 16		3.21		3.61		2.25		2.67
Geometric design	Number of traffic lanes	2	1603		57.8%		566		22.9%	
		3	1171		42.2%		1312		53.0%	
		4	N/A				596		24.1%	
Geographical location	Area	Site 1 and 2	1171		42.6%		1066		43.1%	
		Site 3, 4, 5 and 6	1630		57.4%		1408		56.9%	
Pedestrian signal time	Maximum waiting time (second)	Min = 0 Max = 130		49.24		30.26		16.92		19.25
	Red time (second)	Min = 24 Max = 132		94.39		20.26		55.14		24.63
	Pedestrian signal of	Green	2281		82.2%		N/A			

	the second stage	Red	493		17.8%					
	Waiting time before crossing the first stage (second)	Min = 0 Max = 121	N/A					28.22		32.67
Traffic condition	Traffic flow rate (vehicle/minute)	Min = 3.51 Max = 129.62		21.89		8.21		41.52		18.80
	% of heavy vehicle	Min = 0% Max = 100%		21.41		11.58		19.59		12.72

5.4 Results

In this study, random parameter logit regression models are developed to measure the association between possible factors and propensities of red light running of pedestrians in Stage 1 (Model 1) and Stage 2 (Model 2). Prior to the association measure, a multi-collinearity test is conducted to ensure that the independent variables included in the final model are not correlated. For instances, there is remarkable correlation between 'maximum waiting time' and 'cycle time', therefore, only the former is included in the final model. For all other independent variables, there is no correlation. Table 5.3 presents the parameter estimation results of the proposed random parameter logit regression models. To account for the possible confounding effects, some factors like male, elderly, number of lanes, red time and percentage of heavy vehicles are included in the model even they are not statistically significant (Elvik, 2002). Also, the interaction effects between personal characteristics (i.e., gender and age group) and situational features (i.e., presence of violator, with a companion, and signal time, etc.) are considered.

As shown in Table 5.3, for the pedestrian demographics, gender significantly affects the propensity of red light running at the 1% level. For instances, propensity of red light running of male pedestrians is higher (β = 0.872) than that of female. Also, age group is significantly associated with the propensity at the 1% level. For example, adolescents have a lower propensity (β = -0.302) to run the red light, compared with younger adults.

5.4.1 Model for pedestrian red light running in the first stage

In the first stage, for the behavioural characteristics, presence of a companion, presence of violator, and number of pedestrians waiting significantly affect the propensity of red light running, all at the 1% level. For instances, presence of a companion (β = -1.331) and increase in the number of pedestrians waiting (β = -0.108) are associated with the reduction in red light running violation propensity. However, presence of a violator is associated with the increase in red light running violation (β = 0.962). For the effect of geographical location, propensity of red light running at Site 3, 4, 5 and 6 is higher than that at Site 1 and 2 (β = 0.076).

For the signal time, maximum waiting time and pedestrian signal of the second stage significantly affect the propensity of red light running in the first stage, both at the 1% level. For instances, increase in maximum waiting time is associated with the increase in red light running propensity (β = 0.012). Also, if pedestrian signal of the second stage is green, propensity of red light running (Stage 1) increases (β = 0.579).

For the traffic condition, increases in the traffic volume (β = -0.271) and percentage of heavy vehicle (β = -0.016) are associated with the reduction in red light running propensity, both at the 1% level. For the geometric design, propensity of red light running of shorter crosswalk (i.e., when there are two traffic lanes) is significantly higher (β = 0.390), at the 1% level.

Table 5. 3 Estimation results of random parameter binary logit model

Scope of work	Factor		Stage 1 Coefficient	Stage 1 Standard error	Stage 1 Z-value	Stage 2 Coefficient	Stage 2 Standard error	Stage 2 Z-value
Constant			-1.453**	0.201	-3.31	-1.525**	0.322	-4.19
Demographics	Male		0.872**	0.078	10.28	0.872**	0.078	10.28
	Adolescent		-0.302**	0.102	-2.95	-0.302**	0.102	-2.95
	Elderly		Insignificant			Insignificant		
	Younger adult		Control			Control		
Behavioural characteristics	With a companion	Mean	-1.331**	0.171	-8.39	-1.020**	0.213	-4.71
		SD	1.515**	0.214	6.45	0.517*	0.231	2.08
	Presence of a violator		0.962**	0.094	10.15	1.380**	0.168	12.19
	Number of pedestrians waiting	Mean	-0.108**	0.017	-5.62	-0.150**	0.015	-2.67
		SD	N/A			0.168**	0.054	2.40
Number of traffic lanes	Two lanes		0.390**	0.148	3.30	Insignificant		
	Three lanes		Control			Control		
	Four lanes		N/A			-0.475*	0.201	-1.96
Geographical location	Area 1 (Site 1 and 2)		Control			Control		
	Area 2 (Site 3, 4, 5 and 6)		0.076**	0.031	2.41	1.231**	0.285	4.33
Pedestrian signal time	Maximum waiting time		0.012**	0.001	5.99	0.022**	0.003	6.70
	Red time		Insignificant			Insignificant		
	Pedestrian signal of the second stage is green	Mean	0.579**	0.124	3.84	N/A		
		SD	1.064**	0.358	7.18	N/A		
	Waiting time before crossing the first stage		N/A			-0.017**	0.003	-3.79
Traffic condition	Traffic flow rate		-0.271**	-0.082	-2.66	-0.294**	0.021	-6.70
	% of heavy vehicle		-0.016**	0.004	-4.89	Insignificant		

Interaction term	Presence of a violator x With a companion		-0.031^	0.015	-1.98	N/A		
	Male x Pedestrian signal of the second stage is green		0.714**	0.212	4.37			
	Adolescent x With a companion		0.601*	0.304	2.16			
	Presence of a violator x Maximum waiting time					0.681**	0.080	9.34
Goodness-of-fit	AIC		4312.3					
	Number of observations		5221					
	Unrestricted log likelihood		-1617.1					
	Restricted log likelihood		-1641.4					
	Chi-square statistics		48.6					

Notes:
*** statistically significant at the 1% level*
** statistically significant at the 5% level*
^ *marginally significant at the 10% level*

For the interactions between personal characteristics and situational features, ‘gender X pedestrian signal of the second stage’ (β = 0.714) and ‘adolescent X with a companion’ (β = 0.601) significantly affect the propensity of red light running at the 1% level and 5% level respectively. Also, ‘presence of a violator X with a companion’ (β = -0.031) marginally affect the propensity at the 10% level.

5.4.2 Model for pedestrian red light running in the second stage

In the second stage, as also shown in Table 3, for the behavioural characteristics, again, presence of a companion (β = -1.020) and increase in the number of pedestrians (β = -0.150) significantly reduce the propensity of red light running, both at the 1% level. In contrast, presence of a violator (β = 1.380) significantly increases the propensity at the 1% level. For the effect of geographical location, propensity of red light running at Site 3, 4, 5 and 6 is higher than that at Site 1 and 2 (β =1.231).

For the signal time, propensities of red light running of pedestrians are lower when the waiting time of the first stage increases (β=-0.017) at the 1% level. Also, increase in maximum waiting time (β = 0.022) is associated with the increase in red light running propensity at the 1% level of significance.

For the traffic condition, there is no significant association between percentage of heavy vehicle and propensity of red light running. However, increase in traffic volume (β = -0.294) is significantly associated with the reduction in red light running propensity at the 1% level. For the geometric design, propensity of red light running is lower when the crosswalk is long (i.e., four traffic lanes, β = -0.475) at the 5% level of significance.

Nevertheless, for the interactions between personal characteristics and situation features, ‘presence of a violator X maximum waiting time’ (β = 0.681) significantly increases the propensity of red light running at the 1% level.

5.5 Discussion

In this study, propensities of red light running of pedestrians in different stages of the two-stage crossing are investigated, with which the effects of pedestrian demographics, behavioural characteristics and social influences, geometric design, signal time, and traffic conditions are considered. In addition, possible interactions between personal characteristics and situational features are considered. Moreover, marginal effects of individual factors on the red light running propensities are estimated.

5.5.1 Interferences between crossing stages

5.7.1.1 Effect of pedestrian signal of the second stage on the red light running propensity in the first stage

As speculated, when the pedestrian signal of the second stage (i.e., crossing from the central island to the other side of the road) is green, propensity of red light running of pedestrians in the first stage (i.e., crossing to the central island) increases. As shown in Table 3 (Model 1), the parameter is normally distributed (with a standard deviation of 1.064), therefore, probability that a pedestrian would violate the red light in the first stage if the signal of the second stage is green is 70.4%. This could be attributed to the considerable ‘time saving’ anticipated for one to violate the red light and cross to the island (first stage), where the right of way of completing the crossing (second stage) is given. This echoes with the findings of previous studies that time saving is one of the major contributory factors that affect the crossing decision of pedestrians (Demiroz et al., 2015; Sinclair and Zuidgeest, 2016). In particular, there is no pedestrian signal countdown device in Hong Kong. Some pedestrians may consider that the time saving (for violating the red light and cross to the island, and complete the crossing immediately) are substantial. Such phenomenon is more profound when the pedestrian signal phases in different stages are split. For example, if one wait for the green pedestrian signal to cross to the island, the signal in the second stage would then turn ‘red’, hence, the total waiting time would increase remarkably. However, information on the acceptable waiting time is not available in current study. In the future study, it is worth exploring the trade-off between time saving and safety risk of pedestrians when making crossing decision in the perception survey. Therefore, it is possible to evaluate the effectiveness of possible countermeasures, i.e., modified signal time plan, pedestrian signal countdown device and pedestrian warning sign, in combating the red light running behaviours of pedestrians at the two-stage crossings.

5.7.2 Effect of waiting time in the first stage on the red light running propensity in the second stage

It is speculated that if the waiting time before crossing the first stage increases, propensity of red light running of pedestrians in the subsequent stage might increase (Hamed, 2001). However, as shown in Table 3 (Model 2), for the pedestrians who have longer waiting time in the first stage, propensities of red light running in the second stage are lower. It is speculated that the pedestrians who have waited for long (not violating the red light) tend to be more obedient. They are relatively less sensitive to the waiting time and anticipated time saving for non-compliance (Rosenbloom, 2009). Such phenomenon can be explained by the social control theory that peoples would limit the illegal acts because of internal morality and beliefs, and motivations are usually not considered (Hirschi and Stark, 1969). Also, it could be attributed to the safety orientation of road users (Lajunen et al., 1998). For example, the red light running rate in Stage 2 of pedestrians who do not need to wait in Stage 1 is 26.2%, that of pedestrians who have waited for less than 10 seconds is 22.5%, and the overall red light running rate is 17.1% (see Table 2) respectively. This is consistent to the finding of an empirical study at a multi-stage unsignalized crossing that there is positive correlation in the waiting time between different stages (Rosenbloom and Pereg, 2012). Nevertheless, it is worth investigating the effects of personal traits and risk perception on the propensity of red light running when comprehensive data is available in the attitudinal survey (Dai and Fishbach, 2013). Therefore, it is indicative to the development of effective road safety education and promotion strategies that can enhance the safety awareness and compliance of pedestrians. Also, the pedestrian signal time plan could be optimized, taking into account the acceptable waiting time of pedestrians.

5.5.2 Pedestrian demographics

Results indicate that propensities of red light running of male pedestrians are higher than that of female in both stages. This is consistent to the findings of previous studies (Guo et al., 2011; Rosenbloom, 2009; Xie et al.,2017). Indeed, fatal crash involvement rate of female pedestrians is also lower than that of male (Harre et al., 1996). As also shown in Table 3 (Model 1), there is significant interaction effect for ‘male X pedestrian signal of the second stage’. This suggests that male pedestrians tend to be more risk-taking and sensitive to the anticipated time saving for non-compliance. However, there is no significant difference in the red light running propensities in the second stage between male and female. Yet, it is worth exploring the gender effect on the safety attitude and hence the crossing behaviours using the perceptional survey in the future study (Ren et al., 2011).

For the effect of age, adolescent pedestrians have a lower tendency to run the red light in both stages, compared with younger adults. It could be because adolescents (especially for those who have attained higher education) tend to have stronger sense of conformity and law compliance (Lee and Tsang, 2004). However, there is significant interaction effect for ‘adolescent X with a companion’. This suggests that the sense of conformity of adolescents could be mediated by peer influence. For instances, presence of peer can impair the self-regulation and safety awareness, and the propensities of non-compliance increase (Barrett et al., 2006).

5.5.3 Social influences

Results indicate that the red light running propensities of pedestrians are lower when there is a companion. The parameters are normally distributed (with standard deviations of 1.51 in Stage 1 and 0.51 in Stage 2), therefore, probabilities of the pedestrians who have a companion would run the red light are 19.2% in the first stage and 2.4% in the second stage. In addition, propensities of red light running decrease when there are more pedestrians waiting. For instances, when the number of pedestrians waiting is increased by 1%, probabilities of red light running would reduce by 0.16% in the first stage and 0.17% in the second stage. This could be attributed to the influences of social norms

(Rosenbloom, 2009; Zhang et al., 2016; Russo et al., 2018). Moreover, when there is at least one other pedestrian violated the red light, propensities of red light running would increase. This suggests some peoples could have been motivated (to violate the traffic rules) after the first violator has appeared. However, this can be mediated by the presence of a companion (as shown in Table 3 (Model 1), there is significant interaction effect for 'presence of a violator X with a companion'). Above finding is indicative to the effective enforcement and penalty strategies that can improve the pedestrian safety. For instances, increases in the (manual or automated) enforcement and penalty levels can enhance the deterrent effects against red light running and other traffic violations (Chen et al., 2020).

5.5.4 Geometric design, signal time and traffic condition

For the effect of pedestrian signal time, propensities of red light running are positively associated with the maximum waiting time, in both the first and second stages. It can be because peoples are annoyed when they anticipate that the waiting times are long (Brosseau et al., 2013). When the maximum waiting time is increased by 1%, probabilities of red light running will be increased by 0.45% in the first stage and 0.32% in the second stage. Indeed, percentage of red light running in the first stage increases remarkably from 18.7% when the maximum waiting time is less than 20 seconds to 35.8% when the maximum waiting time is more than 40 seconds. Similar phenomenon can also be observed in the second stage. In addition, effect of maximum waiting time on the propensity of red light running in the second stage can be magnified by the presence of a violator. This is indicative to the planning of signal time phases and implementation of initiatives including pedestrian signal countdown (to green) devices that can mediate the influences of anticipated waiting time of pedestrians.

For the effect of traffic condition, when the traffic volume is increased by 1%, probabilities of red light running will be reduced by 0.48% in the first stage and 0.47% in the second stage respectively. In addition, propensities of red light running decrease when the percentage of heavy vehicles in the traffic increases. When the percentage of heavy vehicle is increased by 1%, propensities of red light running are reduced by 0.49% in Stage 1 and 0.44% in Stage 2 respectively. This could be attributed to the increase in the perceived risk when overall traffic flow and percentage of heavy vehicle increase (Koh et al., 2014; Wang et al., 2011; Koh and Wong, 2014). However, vehicular speed, which is closely related to the crash risk, is not measured in this study. In the future study, it is worth exploring the effects of pedestrian-vehicle interactions on the propensity of red light running of pedestrians, when comprehensive information on traffic characteristics (i.e., density, speed and flow) and vehicle trajectories are available.

For the effect of geometric design, increase in the number of traffic lanes (i.e., crosswalk length) is associated with the reductions in the propensities of red light running. For example, probability of red light running at the shorter crosswalk (i.e., crossing two traffic lanes) is 1.5 times higher than that of crossing three traffic lanes. Again, such finding is consistent to that of previous studies (Van Houten et al., 2007; de Lavalette et al., 2009; Diependaele, 2019).

5.6 Concluding remarks

Multi-stage pedestrian crossings, with split pedestrian signal phases, are commonly used at the urban signalized intersections that have high pedestrian and/or vehicular traffic flow. Studies have been focusing on the time delay, capacity and operation efficiency of multi-stage crossings. It is rare that the crossing behaviours of pedestrians at the multi-stage signalized crossings are attempted. Particularly, relationship between possible explanatory factors and propensities of red light running should be different in different stages when the pedestrian signal phases are split.

This study investigated the crossing behaviours of pedestrians at the two-stage signalized crossings based on the video observation surveys at six urban intersections in Hong Kong. Not only the influences of pedestrian demographics, behavioural characteristics, geometric design, pedestrian signal time and traffic condition, but also the interaction effects between personal characteristics and situational features on the propensities are considered.

Random parameter logit regression models are developed to model the relationship between possible explanatory factors and propensities of red light running in the first and second stages. There are remarkable interferences in the crossing behaviours between the two stages, with split pedestrian signal phases. Results indicate that propensity of red light running in the first stage is higher when the pedestrian signal of the second stage is green. In addition, for pedestrians who have a long waiting time before crossing the first stage, their propensities of red light running in the second stage are lower. In addition, social influences can affect the crossing behaviours. When there is a companion and there are more pedestrians waiting, propensities of red light running of pedestrians are lower. Moreover, effects of the social influences on red light running propensities can be mediated by pedestrian demographics and situational features. Above findings are indicative to effective enforcement, education and publicity strategies that can enhance the safety awareness and combat the red light running behaviours of problematic pedestrian groups. Also, the signal time plan can be optimized to reduce the pedestrian delay (waiting time). Nevertheless, it is worth exploring the effectiveness of advanced traffic control techniques (i.e., adaptive signal time plan in response to real-time pedestrian volume) that can enhance the operation efficiency and safety of signalized crossings.

Chapter 6 A two-stage safety evaluation model for the red light running behaviour of pedestrians using the game theory

6.1 Introduction

Pedestrian safety has been of major concern in road safety research since pedestrians are more vulnerable to fatality and severe injury in road crashes (World Health Organisation, 2018). Red light running violation of pedestrians is one of the key contributory factors to pedestrian-vehicle crashes (Wang et al., 2020). It 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 behaviour (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 be indicative to the implementation of remedial measures including geometric design, automated enforcement system, and signal time plan that can mitigate the safety risk attributed to the red light running behaviour of pedestrians.

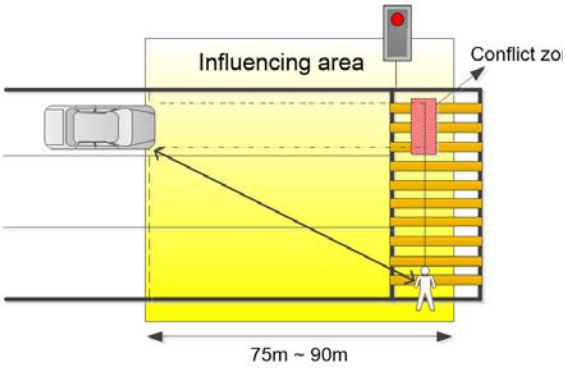
In this study, a two-stage framework is proposed to predict the real-time safety risk attributed to the red light running behaviour of pedestrians, with which the effects of pedestrian characteristics, traffic conditions, vehicle dynamics, and pedestrian-vehicle interactions are considered. In the first 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 organised as follows. Section 6.2 describes the data collection and analysis methods. Section 6.3 presents the modelling results of yield behaviours of pedestrian and driver, and associated conflict risk. Section 6.4 discusses the implications of the results. Section 6.5 provides the concluding remarks and future research directions.

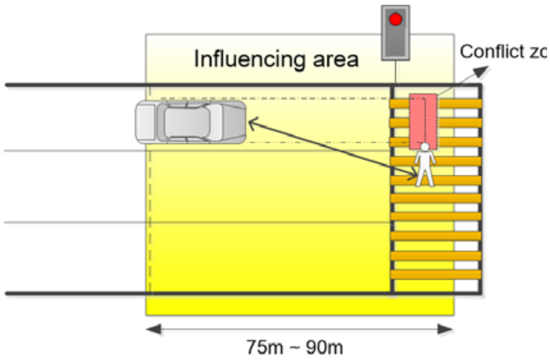
6.2 Method

6.2.1 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 6.1** depicts the “influencing area” and “conflict area” 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 6. 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 area, 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:

$$EU_{cross} = p_{yield} \times a\boldsymbol{U} + \boldsymbol{c}_1 \quad (6\text{-}1)$$

$$EU_{not\ cross} = b\boldsymbol{V} \quad (6\text{-}2)$$

Drivers' utilities:

[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.

$$EU_{yield} = d\boldsymbol{M} \tag{6-3}$$

$$EU_{not\ yield} = (1 - p_{cross}) \times e\boldsymbol{W} + \boldsymbol{c}_2 \tag{6-4}$$

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 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.

Table 6. 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 inter-related. 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:

$$p_{yield} = \frac{exp[EU_{yield}(1 - p_{cross})]}{exp[EU_{yield}(1 - p_{cross})] + exp[EU_{notyield}]} \tag{6-5}$$

Choice probability of pedestrian:

$$p_{cross} = \frac{exp[EU_{cross}(p_{yield})]}{exp[EU_{cross}(p_{yield})] + exp[EU_{notcross}]} \tag{6-6}$$

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 $p_{cross} = \boldsymbol{H}\left(p_{yield}\right)$, 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:

$$\Delta EU_{cross} = (EU_{cross} - EU_{notcross}) \tag{6-7}$$

Driver:

$$\Delta EU_{yield} = (EU_{yield} - EU_{notyield}) \tag{6-8}$$

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

Pedestrian:

$$LL_{pedestrian}(a: S, V)$$

$$= \sum_i \{ ln[\varphi(\Delta EU_{cross})] \times I\{y_i = 1\} + ln[1 - \varphi(\Delta EU_{cross})] \times I\{y_i = 0\}\} \tag{6-9}$$

Driver:

$$LL_{driver}(b: S, W)$$

$$= \sum_j \{ ln[\varphi(\Delta EU_{yield})] \times I\{y_j = 1\} + ln[1 - \varphi(\Delta EU_{yield})] \times I\{y_j = 0\}\} \tag{6-10}$$

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),

$$LL = LL_{pedestrian}(a: S, V) + LL_{driver}(b: S, W) \tag{6-11}$$

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, 2021b). For instance, the logit QRE usually converges within 200 iterations.

6.2.2 Modelling 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,

$$p_{conflict} = p_{cross} \times (1 - p_{yield}) \tag{6-12}$$

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,

$$PET = \Delta TTA = |TTA_{veh} - TTA_{ped}| = |\frac{d_{veh}}{v_{veh}} - \frac{d_{ped}}{v_{ped}}| \tag{6-13}$$

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

$$p'_{conflict} = kp_{conflict} = kp_{cross} \times \left(1 - p_{yield}\right) \tag{6-14}$$

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 6.2**, 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.

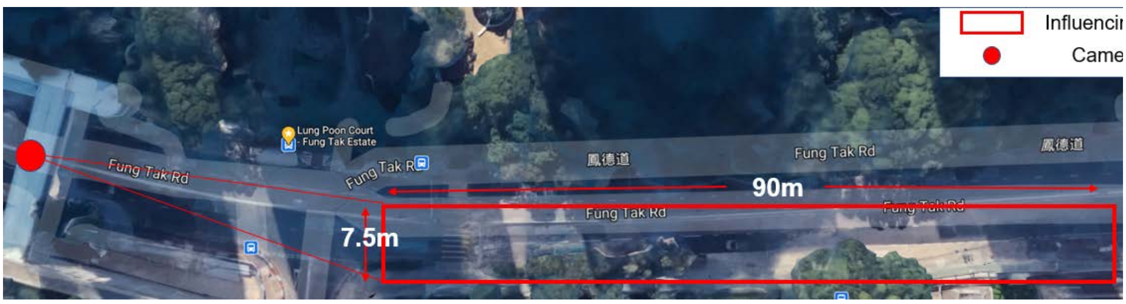
Table 6. 2. Risk of pedestrian-vehicle conflicts

Risk level	Description
0 (Negligible)	PET > 6 seconds
1 (Minor)	2.5 seconds ≤ PET ≤ 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.

6.3 Data

The video observation surveys were conducted at four signalized crosswalks in Hong Kong during the period from January 2021 to March 2021. **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 6. 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 and age of pedestrian are recorded manually. **Table 3** summarizes the variables considered in this study.

Figure 6. 3 Trajectory tracking of pedestrian and vehicle

Table 6. 3. Variables considered in this study

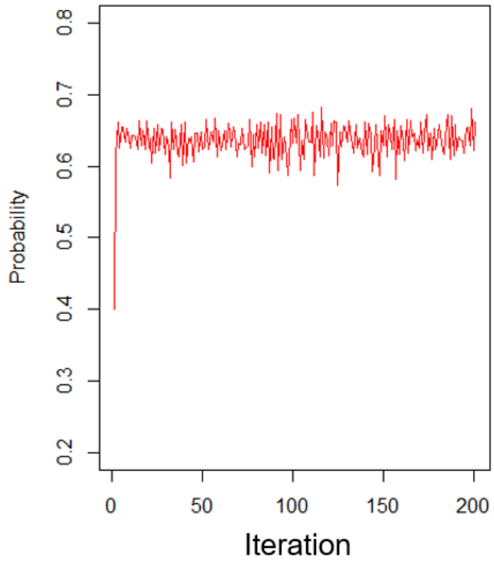
Variable	**Description**	**Type**	**Range**	**Count/ Mean**	**Percentage/ Standard Deviation**
Choice decision					
Pedestrian's decision	Crossing behaviour of pedestrian	Indicator	Cross: 1; Otherwise: 0	328	46.9%
Driver's decision	Yield behaviour of driver	Indicator	Yield: 1; Otherwise: 0	412	59.0%
Pedestrian					
Pedestrian gender	Gender of pedestrian	Indicator	Male: 1; Female: 0	363	52.0%
Pedestrian age	Age of pedestrian	Indicator	Elderly: 1; Otherwise: 0	160	22.9%
Pedestrian distance	Distance of pedestrian from the conflict area	Continuous	0 – 11.0 (meter)	4.76	3.12
Walking speed	Walking speed of pedestrian	Continuous	0 – 2.3 (meter/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	349	50%
Driver					
Vehicle distance	Distance of approaching vehicle from the conflict area	Continuous	0 – 85 (meter)	59.42	17.84
Vehicle speed	Speed of approaching vehicle	Continuous	0 – 18.1 (meter/second)	11.23	3.87

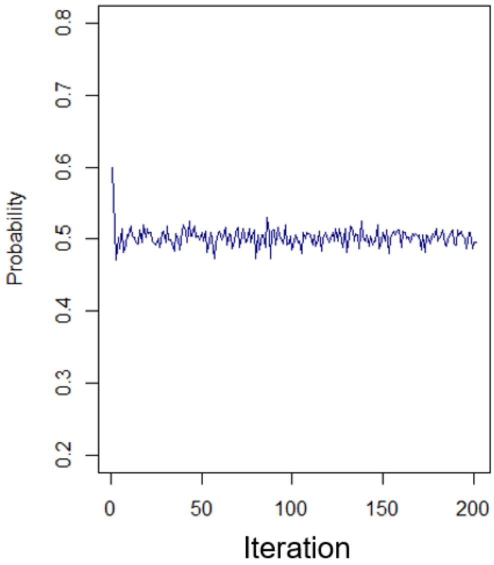
6.4 Results

6.4.1 Interactions between vehicle and pedestrian

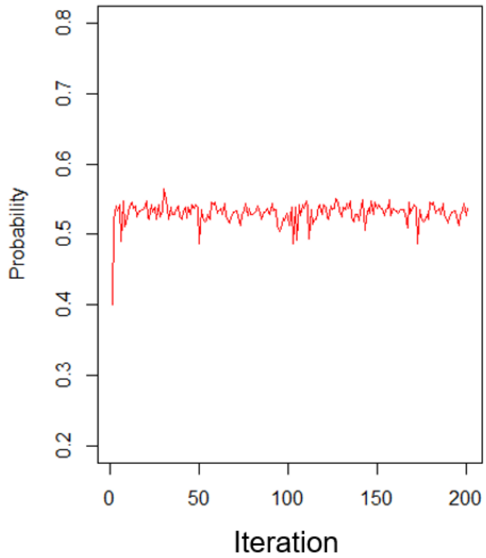
In the logit QRE for pedestrian-driver interaction, initial values of p_{cross} and p_{yield} are set as 0.6 and 0.6, and the step size of iteration is 0.001, respectively. **Figure 6.4** illustrates the trace plots of p_{cross} and p_{yield} with 200 iterations. The solution is converged within 200 iterations for both interactions. As shown in **Figure 6.4**, p_{cross} = 0.37 and p_{yield} = 0.50 for the first interaction, and p_{cross} = 0.47 and p_{yield} = 0.50 for the second interaction, respectively.



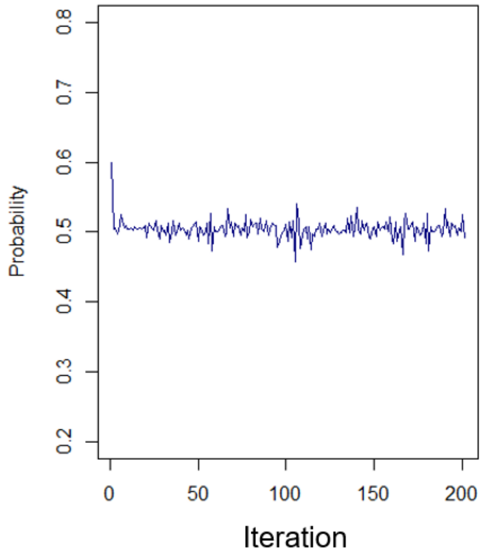
(a) First interaction – pedestrian (not cross)



(b) First interaction – driver (yield)



(c) Second interaction – pedestrian (not cross)



(d) Second interaction – driver (yield)

Figure 6. 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 6.4**. For instance, empirical distribution of parameters using bootstrap simulation can be given (Train, 2009). As shown in **Table 6.4**, pedestrian gender, waiting time and walking speed, and vehicle speed significantly affect the decision of pedestrian, all at the 5% level. For instance, male pedestrian (Coefficient = 0.50 for the first interaction; coefficient = 1.09 for the second interaction) has a higher utility to cross. Additionally, walking speed (1.32; 0.52) is positively associated with the pedestrian's utility to cross. However, vehicle speed (-0.02; -0.03) and pedestrian's waiting time (-0.04; -0.08) are negatively associated with the pedestrian's utility to cross.

As also shown in **Table 6.4**, vehicle type, distance and speed, and pedestrian age significantly affect the decision of driver, all at the 5% level. For instance, vehicle speed (0.08; 0.06), walking speed (0.02; 0.03), and presence of older pedestrian (0.04 for the first interaction) 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 (-0.25; -0.71) than that of other vehicle type. **Figure 6.5** 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 (10.4 ± 6.0%) is lower than that of the second interaction (11.4 ± 6.4%).

Table 6. 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	-0.65*	-2.71	-1.61**	-3.66
Male pedestrian	0.50**	3.31	1.09**	3.12
Walking speed	1.32**	3.83	0.52**	3.67
Vehicle speed	-0.02**	-7.33	-0.03**	-3.75
Waiting time	-0.04**	-3.89	-0.08**	-7.18
Expected utility of driver to yield				
Constant	-1.56**	-4.70	-1.89**	-5.46
Vehicle distance	-0.02**	-4.25	-0.03**	-3.57
Vehicle speed	0.08**	12.83	0.06**	4.75
Older pedestrian	0.04**	3.01	IS	
Heavy vehicle	-0.25**	-4.08	-0.71**	-2.73
Walking speed	0.02**	3.33	0.03**	2.81

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

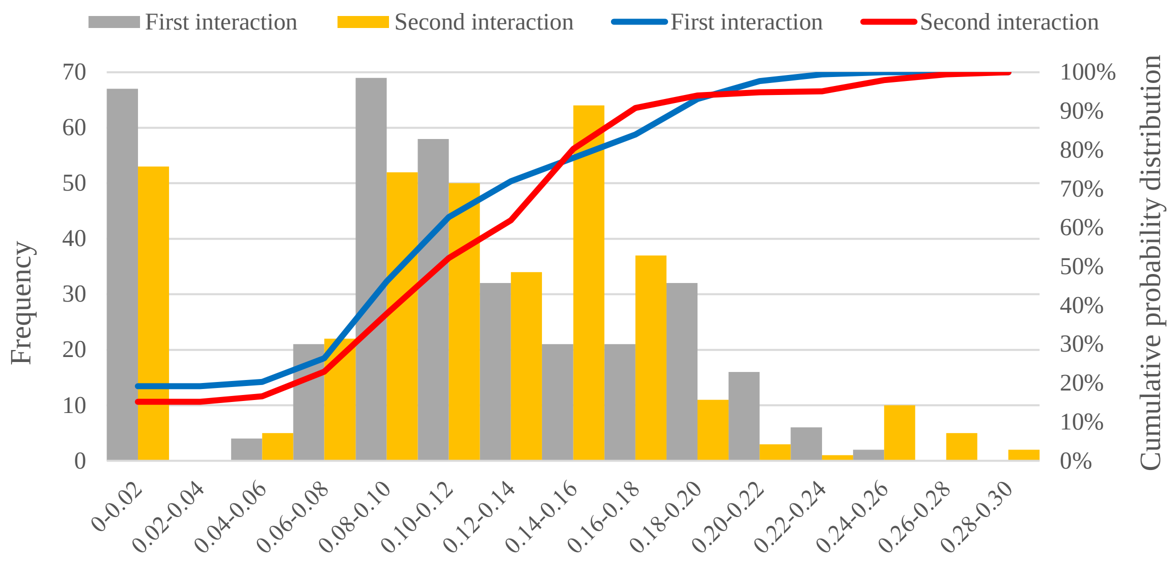


Figure 6. 5 Distribution of the probabilities of potential conflicts

6.4.2 Pedestrian-vehicle conflict risk

Table 6.5 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 6.5**, pedestrian gender, age, walking speed and 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 = 0.29 for the first interaction; coefficient = 0.26 for the second interaction) for more severe pedestrian-vehicle conflicts is higher. Additionally, vehicle speed (0.38; 0.25) is positively associated with the likelihood of more severe pedestrian-vehicle conflicts. However, likelihood of older pedestrian (-1.64; -1.81) to for more severe pedestrian-vehicle conflicts is lower. Furthermore, walking speed (-0.64; -0.36), anticipation of pedestrian to cross (-1.51 for the second interaction), waiting time (-0.12; -0.36), vehicle distance (-0.96; -1.03), anticipation of driver to yield (-2.31 for the second interaction) are negatively associated with the likelihood of more severe pedestrian-vehicle conflicts. Nevertheless, likelihood of heavy vehicle (-0.44 for the second interaction) for more severe pedestrian-vehicle conflicts is lower.

Table 6. 5. Results of parameter estimation of bivariate ordered Probit model

Factor	First interaction		Second interaction	
	Coefficient	**(*t*-statistic)**	**Coefficient**	**(*t*-statistic)**
Constant	0.231*	(2.01)	IS	
Male pedestrian	0.287*	(2.24)	0.255*	(2.51)
Older pedestrian	-1.643*	(-2.35)	-1.807*	(-2.14)
Walking speed	-0.641*	(-2.50)	-0.357*	(-2.21)
Anticipation of pedestrian to cross	IS		-1.512*	(1.99)
Waiting time	-0.123**	(6.75)	-0.357*	(2.12)
Vehicle distance	-0.957**	(-8.31)	-1.030**	(-7.25)
Vehicle speed	0.381**	(4.62)	0.247**	(4.15)
Anticipation of driver to yield	IS		-2.312**	(3.21)
Heavy vehicle	IS		-0.437*	(1.98)
Threshold parameter	2.17**	(15.12)	2.42**	(6.24)
Correlation parameter	0.234**			
Restricted loglikelihood	-698.65			
Unrestricted loglikelihood	-325.40			
McFadden Pseudo R^2	0.43			
AIC	624.9			

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

6.5 Discussion

6.5.1 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). Additionally, presence of an older pedestrian who violates the red light would increase the utility of driver to yield. It could be because of the driver's anticipation that more severe injury would be incurred when an older person is hit in the collision. Hence, the driver would be more cautious when an older pedestrian is found violating the red light (Asher et al., 2012).

On the other hand, walking speed and 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. Therefore, he or she must yield to avoid the crash. However, 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).

6.5.2 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; Zhang and Fricker, 2021a; b). Results of this study indicate that gender, age 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. However, contrary to conventional wisdom, likelihood of more severe conflict of older pedestrian is lower than the counterpart (Asher et al., 2012). This may be because drivers tend to be more cautious when they see an older pedestrian walking on the road. This is particularly true in Hong Kong since drivers may anticipate that older pedestrians have a higher tendency to run the red light (Zhu et al., 2021a).

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, 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). 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 area 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).

6.6 Concluding remarks

This chapter presents the evaluation on the safety consequence of red light running behaviours of pedestrians using a two-stage modelling framework. In the first stage, interactions between driver and pedestrian at the crosswalk are modeled as a simultaneous two-player game using the quantal response equilibrium (QRE), with which errors in the anticipations of pedestrian and driver are considered. Then, the expected utilities of driver (to yield) and pedestrian (to cross) in the interactions at two moments are estimated. In the second stage, association between the risk of pedestrian-vehicle conflicts and relevant explanatory factors is modeled, based on post-encroachment time (PET), using a bivariate ordered Probit regression model.

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, older 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 and older 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 measures, i.e., local area traffic management, speed limit, and targeted enforcement, that could deter against the red light running behaviours of pedestrians. Therefore, overall pedestrian safety at the signalized crosswalk could be enhanced.

Chapter 7 Conclusions and recommendations

7.1 General conclusions

In this study, attempts have been made to assess the red light running behaviour and safety of pedestrians in Hong Kong.

Chapter 2 reviews the literature on red light running behaviour and safety of pedestrian from several aspects. First, factors affecting the propensity of pedestrian red light running behaviour as well as the studies on multi-stage crossings are summarized. Second, the methods of data collection are presented. Then, modelling issues for pedestrian red light running behaviour are illustrated. Lastly, Studies on safety evaluation of pedestrians at the intersection level are reviewed. Finally, several research gaps are identified.

In Chapter 3, a questionnaire survey is utilized to investigate the effects of perceived risk, anticipated waiting time, weather condition, presence of violators, and other personal characteristics on the red light running behaviours of pedestrians. Then, a regret-based multinomial logit model is adopted to analyse the choices between (i) comply with pedestrian signal, (ii) not comply but wait for a suitable gap, and (iii) not comply and cross immediately of pedestrians. Contribution of this study is twofold: First, effects of the trade-off between safety and time, as well as the situational features and personality traits, on the propensities of red light running violation of pedestrians are gauged using a stated preference method. Second, effects of unobserved heterogeneity and correlation between the choices in different scenarios of the same individual are considered using a panel mixed approach. Results indicate that propensities of red light running violation of pedestrians are positively associated with anticipated waiting time, but negatively associated with perceived relative risk. The safety versus time trade-off of individual can be gauged using the regret-based model. For instance, compliance of pedestrian signal is more sensitive to the change in waiting time than that in safety risk. In addition, situational features including weather condition, presence and type of violator, and presence of warning sign all affect the propensities of red light running violation of pedestrians. Peoples have a higher tendency to run the red light when they see another violator, especially when the violator is an adolescent. Furthermore, males and peoples who are 18 to 24 years old and risk-taking have a higher tendency to run the red light. Such findings should enhance the understanding on the relationship between personal characteristics, choice decision, and red light running behaviours of pedestrians. They are indicative to remedial traffic control measures (i.e., variable message sign and flashing warning sign), enforcement strategies, and targeted road safety education against the red light running behaviour of vulnerable pedestrian groups.

In Chapter 4, we examined both the personal (gender, age, pedestrian behaviour) and environmental (signal time and traffic condition) factors affecting the individual decision of red light running violation using the video observation survey at the hot spots of pedestrian crashes. Also, effects of the presence and behaviour of other pedestrians in the same cycle on the propensity are considered. Moreover, interaction effects by personal and environmental factors on the propensity are considered. For the personal factors, it is known that female pedestrians generally have lower propensity of red light running, compared with males. This study reveals that presence of a violator and traffic volume can moderate the association between gender and propensity of red light running. For example, propensity of red light running of female pedestrians increases when other pedestrians violate the red light. Also, propensity of red light running of female pedestrians reduce when the traffic volume is high. On the other hand, previous studies suggested older pedestrians were risk-averse and had lower likelihood to violate the red light. However, this study reveals that older pedestrians have a higher likelihood to violate the red light. It could be because of the low educational attainment of older peoples in Hong Kong. Moreover, it is interesting to find that propensity of red light running of older pedestrians would reduce when there is a companion. For the environmental features, previous studies indicate that when there is a pedestrian signal countdown device, ‘time to green’ is positively associated with the propensity of red light running. This study reveals that similar phenomenon can occur even when the pedestrian signal countdown device is absent in Hong Kong. More importantly, social norms, as reflected by the presence and behaviour of other pedestrians, has a favorable effect on the propensity. Moreover, pedestrians who have a companion can be even more motivated (by the traffic violation of other pedestrians), compared with the pedestrians who are alone. Such finding is indicative to the effective enforcement and educational strategies that could enhance the safety awareness of targeted pedestrian group and deter against the red light running violation of pedestrians. Moreover, it is worth exploring the effectiveness of advanced traffic control techniques, i.e., variable pedestrian signal time that is responsive to pedestrian volume and pedestrian signal countdown device, in combating the red light running violation of pedestrians. In the extended research, effects of social norms, safety perception and anticipated traffic condition on the propensity of red light running violation can be gauged using an attitudinal model. Therefore, understanding on the pedestrian crossing behaviour, and the interventions by the personal and environmental factors can be enhanced.

Next, Chapter 5 presents the study that investigated the crossing behaviours of pedestrians at the two-stage signalized crossings based on the video observation surveys at six urban intersections in Hong Kong. Not only the influences of pedestrian demographics, behavioural characteristics, geometric design, pedestrian signal time and traffic condition, but also the interaction effects between personal characteristics and situational features on the propensities are considered. Random parameter logit regression models are developed to model the relationship between possible explanatory factors and propensities of red light running in the first and second stages. There are remarkable interferences in the crossing behaviours between the two stages, with split pedestrian signal phases. Results indicate that propensity of red light running in the first stage is higher when the pedestrian signal of the second stage is green. In addition, for pedestrians who have a long waiting time before crossing the first stage, their propensities of red light running in the second stage are lower. In addition, social influences can affect the crossing behaviours. When there is a companion and there are more pedestrians waiting, propensities of red light running of pedestrians are lower. Moreover, effects of the social influences on red light running propensities can be mediated by pedestrian demographics and situational features. Above findings are indicative to effective enforcement, education and publicity strategies that can enhance the safety awareness and combat the red light running behaviours of problematic pedestrian groups. Also, the signal time plan can be optimized to reduce the pedestrian delay (waiting time). Nevertheless, it is worth exploring the effectiveness of advanced traffic control techniques (i.e., adaptive signal time plan in response to real-time pedestrian volume) that can enhance the operation efficiency and safety of signalized crossings.

Finally, in Chapter 6, we aim to evaluate the safety consequence of red light running behaviours of pedestrians using a two-stage modelling framework. In the first stage, interactions between driver and pedestrian at the crosswalk are modeled as a simultaneous two-player game using the quantal response equilibrium (QRE), with which errors in the anticipations of pedestrian and driver are considered. Then, the expected utilities of driver (to yield) and pedestrian (to cross) in the interactions at two moments are estimated. In the second stage, association between the risk of pedestrian-vehicle conflicts and relevant explanatory factors is modeled, based on post-encroachment time (PET), using a bivariate ordered Probit regression model. 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, older 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 and older 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 measures, i.e., local area traffic management, speed limit, and targeted enforcement, that could deter against the red light running behaviours of pedestrians. Therefore, overall pedestrian safety at the signalized crosswalk could be enhanced.

7.2 Main findings and contributions

The main findings are concluded below.

1) Trade-off between safety and time in the red light running behaviour among different groups

A random regret minimization approach is applied to reflect the trade-offs variance under different situational features. The results show that compliance of pedestrian signal is more sensitive to the change in waiting time than that in safety risk. In addition, situational features including weather condition, presence and type of violator, and presence of warning sign all affect the propensities of red light running violation of pedestrians. Peoples have a higher tendency to run the red light when they see another violator, especially when the violator is an adolescent. Furthermore, males and peoples who are 18 to 24 years old and risk-taking have a higher tendency to run the red light. In general, risk-return rate ranges from 0.5 to 1.5 (% per second). In other word, pedestrians are willing to accept 15 to 44% increase in safety risk for the saving of 30 seconds.

2) Roles of personal and environmental factors as well as the interaction effects

Contribution of this study is of two-fold. Firstly, both the individual-level (personal demographics and behaviour) and cycle-level (traffic condition and signal time) factors are included in the analysis of individual decision of red light running violation. Secondly, influence of social norms (presence of a companion, number of pedestrians around and violation of other pedestrians) on the individual decision is examined. Results indicate that pedestrian gender, age, number of lanes, presence of a companion, number of pedestrians around, presence of other violators in the same cycle, time to green, red time, traffic volume, and percentage of heavy vehicles all affect the propensity of red light running violation of pedestrians. Also, there are significant interaction effects by pedestrian's gender and age, presence of other violators, with a companion, and traffic volume on the propensity.

3) Crossing behaviour and safety of pedestrian at two-stage crossings with split pedestrian signal phases

There are remarkable interferences in the crossing behaviours between the two stages, with split pedestrian signal phases. Results indicate that propensity of red light running in the first stage is higher when the pedestrian signal of the second stage is green. In addition, for pedestrians who have a long waiting time before crossing the first stage, their propensities of red light running in the second stage are lower. In addition, social influences can affect the crossing behaviours. When there is a companion and there are more pedestrians waiting, propensities of red light running of pedestrians are lower.

Moreover, effects of the social influences on red light running propensities can be mediated by pedestrian demographics and situational features.

4) Safety evaluation model of pedestrian red light running behaviour

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, older 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 and older 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.

Based on the results from the proposed research questions, this thesis is able to make contributions to vulnerable road user (i.e. pedestrians) management and educational strategies, effective penalties and enforcement strategies against red light violations of pedestrian, as well as safety countermeasures. We provide some potential implications derived from the above findings. For examples, (i) in the context of vulnerable road user (i.e., pedestrian) management and educational strategies in an aging society like Hong Kong, higher propensity of red light running violation of older pedestrian is an alarming issue. Same as other modern societies, Hong Kong is facing the problem of ageing population. Proportion of population older than 65 years is expected to increase from 16% in 2016 to over 25% in 2035. Elderly populations are concentrated in the early developed urban areas, which have frequent pedestrian activities and conflicts between pedestrian and vehicular traffic. More importantly, over 30% of pedestrian casualties are elderly (1,064 in year 2017) in Hong Kong (Transport Department, 2018). Therefore, it is important to develop effective enforcement, educational and publicity initiatives that can improve the safety awareness and combat the red light running violation behaviour of older pedestrians. For instance, regular popularization and guidance of traffic rules knowledge for the elderly (i.e., publicity activities in elderly homes) is highly recommended. (ii) For the effectiveness of penalties, the presence of the first violator could have an adverse impact on the red light propensity of other pedestrians, increases in the certainty (i.e. enforcement level) and severity (i.e. penalty level) of penalties may be of essence to deter against the red light running violation of pedestrians. (iii) Despite that warning signs are installed at the hot spots of pedestrian crashes (i.e., more than five pedestrian injuries per year) in Hong Kong, variable message sign and real-time traffic-actuated signal that may improve the safety awareness of pedestrians are recommended. (iv) For effects of social influence and behaviour of other pedestrians, we found that peoples tend to follow the behaviour of a person who shares the same characteristics, which indicates that targeted enforcement measures against red light running violation of pedestrians should be imposed at the strategic locations, e.g., schools and elderly homes, where peoples who share the same characteristics may gather.

7.3 Limitations

Despite the contributions to the literature described in the above paragraphs, this research should be interpreted in the context of the limitations. Firstly, with respect to the stated preference survey, the study is limited to a few alternative-specific variables (i.e., anticipated waiting time and perceived relative risk) only in the SP design. It is anticipated that traffic conditions in terms of traffic volume, vehicle composition, and vehicular speed can also affect the propensities of red light running violation of pedestrians. Hence, it is worth exploring the pedestrians' behaviours in response to the road environments and real-time traffic conditions when more comprehensive behavioural data are obtained using the methods including virtual reality (VR) experiment in the future study. Furthermore, to improve the model performance, a latent model with one RRM and RUM in each segment can be incorporated into a hybrid model structure in the future study.

Secondly, for the two observation studies, effect of vehicular speed on the red light running behaviour of pedestrians is not assessed. Also, some environmental factors like weather and lighting condition were not considered. Second, effects of vehicular speed and drivers' yielding behaviour on the red light running behaviour of pedestrians were not assessed.

There were limitations for the safety evaluation model as well. 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.

7.4 Recommendations for future research

Section 7.1 and 7.2 has outlined the contributions of this thesis regarding the red light running behaviour and safety of pedestrians. Yet, the current work can be further extended in the future. The recommendations for future research in four aspects are listed.

7.4.1 Crossing behaviour and safety of pedestrian using Virtual Reality technology

Further studies could explore the pedestrian gap acceptance or red light running behaviour by using more advanced method, i.e., Virtual Reality experiment. Deb et al. (2018) investigated pedestrian preferences for external features on a fully autonomous vehicle in VR. Their results showed a significant change in pedestrian crossing due to the external displays. The advantage of VR experiment is that not only the realistic behaviour could be potentially revealed, but also the underlying preference could be analysed by showing different designed scenarios. It is anticipated that more insightful findings could be presented by conducting the experiments.

7.4.2 Real-time safety evaluation and prediction of pedestrian safety at signalized crossings

As we discussed in chapter 6, it is rare that safety consequence of pedestrian risky behaviour is attempted. We made some attempts on this issue by proposing a two-stage safety evaluation model. However, it is possible and indeed important to make effort on real-time safety evaluation and prediction for pedestrians at the individual level or intersection level in the future. With the rapid development of advanced technology and Big Data related resources, real-time safety evaluation and prediction systems could be possibly realized by incorporating real-time monitoring, real-time computer vision technology, advanced deep learning methods (i.e., model-free imitation learning) and real-time risk analysis outcomes.

7.4.3 Modelling the relationships between red light running behaviour, pedestrian-vehicle conflicts and pedestrian-vehicle crashes

In future studies, it will be worthwhile to explore the complex (direct or indirect influence) relationships between risky behaviour, pedestrian-vehicle conflict and crashes. Advanced technology should be developed to address several issues: First, to investigate collisions that involve pedestrian violations and thus to identify the factors that impact their occurrence and understand the relationship between the violation behaviour and the severity of such collisions. Second, the relationship between the serious conflicts and crashes that both involve pedestrian violations should be revealed by using both trajectory data and historical data. Finally, the complex relationships between the behaviour, conflicts and crashes could be potentially drawn.

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Appendix

Variable	Choice alternative		
	Comply with pedestrian signal	**Not comply but wait for a suitable gap**	**Not comply and cross immediately**
Waiting time	30 second	20 second	0 second
Perceived relative risk	0 %	30%	60%
Weather condition	Raining condition		
Presence and type of violator	An elderly pedestrian is violating the red signal		
Presence of warning sign	No		

Given the scenario (e.g., raining, an elderly pedestrian is violating the red signal, and no warning sign), and waiting time and perceived relative risk for each choice alternative shown above. Which alternative would you choose? (Select one only)

□Comply with pedestrian signal
□Not comply but wait for a suitable gap
□Not comply and cross immediately

Figure A1. Illustration of a stated preference scenario in the questionnaire

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