Highlights

(1) We examine the safety effects of law enforcement cameras at non-signalized crosswalks.

(2) Both Unmanned Aerial Vehicle (UAV) and roadside video are used for data collection.

(3) Law enforcement cameras can increase the conflict severity and yielding probability.

(4) Supplementary measures should be taken to improve the performance of cameras.

Safety effects of law enforcement cameras at non-signalized crosswalks: a case study in China

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Abstract

Pedestrians are vulnerable when crossing the street, especially at non-signalized crosswalks. In China, in spite of the priority that laws entitle the pedestrians, the yielding rates at non-signalized crosswalks are relatively low. In light of this situation, law enforcement cameras have been used to increase the percentage of drivers yielding to pedestrians. This study investigated the effectiveness of law enforcement cameras on drivers yielding behavior and vehicle-pedestrian conflicts at non-signalized crosswalks. Using Unmanned Aerial Vehicle (UAV) and roadside video recording, information including pedestrian characteristics, vehicular characteristics and environmental factors are collected. The conflict indicators used include Post-Encroachment Time (PET), Time to Collision (TTC), and Deceleration to Safety Time (DST). In this study, a conflict classification framework based on PET, TTC and DST using Support Vector Machine algorithm was employed. An ordered logit regression model was used to identify the factors contributing to the conflicts. Then, binary logit regression models were constructed to analyze the effects of law enforcement cameras on drivers yielding behavior. Conflict study revealed that the implementation of law enforcement cameras and the front vehicle non-yielding behavior would increase the conflict severity, while the presence of the elderly, number of lanes between pedestrian and vehicle and yielding behavior of side vehicles are found to decrease conflict severity. Yielding behavior analysis showed that the illegitimate yielding behavior percentages are over 10%, indicating the necessity of improving the awareness of yielding rules. The implementation of law enforcement cameras and the presence of the elderly would increase the yielding and legitimate yielding probability, while the presence of children, front vehicle non-yielding behavior and high upstream vehicle speed would decrease the yielding and legitimate yielding probability. We recommend that supplementary facilities and measures should be used to improve the safety performance of law enforcement cameras.

Keywords: law enforcement camera; pedestrian safety; non-signalized crosswalk; pedestrian-vehicle conflict; driver yielding behavior

1 Introduction

Despite the recognized benefits of walking as a sustainable transport mode, pedestrians are considered as vulnerable users on the road (Chao et al., 2017; Zhuang and Wu, 2011). As reported in 2016, around 22.55% of road crashes and 26.50% of road fatalities were pedestrians in china (Traffic Management Bureau of the Ministry of Public Security, 2017). The same problem also occurred in other developing countries due to the high population density and traffic volume (Zhang C et al., 2019; Chao et al., 2017). Moreover, pedestrians are found vulnerable at the crosswalks, particularly at non-signalized ones (Chao et al., 2017; Zhuang and Wu, 2011; Malenje et al., 2019; Raghavendra Ravishankar and Nair, 2018). So, it is of high importance to regulate the travel behavior of motor vehicles at non-signalized crosswalks, and therefore increase the percentage of drivers yielding to pedestrians. For instance, the priority law for pedestrians has been implemented in China, with various policies to enhance the probability of yielding at these sites. However, the percentage of drivers yielding to pedestrians is still relatively low due to the lack of monitoring. Law enforcement cameras have been used to monitor and penalize violations at non-signalized crosswalks in Nanjing, China since 2017 (Nanjing Municipal Public Security Bureau, 2017). This policy requires drivers to yield to pedestrians at non-signalized crosswalks, and the violation would lead to 50-Chinese-Yuan fine and three-point deduction in the driver license (12 points in total).

A series of measures have been applied to improve the pedestrian safety at non-signalized crosswalks, including crosswalks design (Iasmin et al., 2016), overhead flashing devices, side mounted signs (Lacoste et al., 2014; Houten et al., 2018; Fu et al., 2018), pedestrian crosswalk warning system, law enforcement program (Høye and Laureshyn, 2019; Sandt et al., 2016) and speed control measures (Chao et al., 2017; Gitelman et al., 2016). Moreover, to evaluate the safety effects of these measures, conflict analysis and yielding behaviors analysis were widely conducted (Iasmin et al., 2016; LaCoste et al., 2014; Bennett et al., 2014; Høye and Laureshyn, 2019; Sandt et al., 2016). However, the safety effects of law enforcement cameras measures for capturing and penalizing non-yielding behavior at non-signalized crosswalks are rarely examined in previous studies. This study analyzed the safety effects of law enforcement cameras at non-signalized crosswalks using the roadside and UAV video data in Nanjing. Two estimation models: (1) ordered logit model for the conflict analysis; and

(2) binary logit model for the yielding behavior analysis, in this study are employed. The results can help with the pedestrian infrastructures design, and traffic management at non-signalized crosswalks. Also, it is informative to the implementation of law enforcement cameras for other cities.

This paper is organized as follows. A review of literature on pedestrian safety analysis is presented in the next section. The method and data used for analysis are described in Sections 3. The results and discussions are presented in Section 4. Conclusions are given in the final section.

2 Literature review

2.1 Safety effects of measures on pedestrians

A number of studies have been conducted to examine the effects of various measures on pedestrian safety. For instance, previous studies concluded that speed humps are effective in reducing vehicle speeds and improving pedestrian safety (Chao et al., 2017; Gitelman et al., 2016). Also, it is indicated that brick design on crosswalks could increase the alertness of left-turning vehicles, thus increase the pedestrian safety (Iasmin et al., 2016). Furthermore, rectangular rapid flashing beacon (Moshahedi et al., 2018), crosswalk marking (Fu et al., 2018; Gitelman et al., 2017), pedestrian crosswalk warning system (Høye and Laureshyn, 2019), law enforcement program (Sandt et al., 2016), overhead flashing devices and side mounted signs (Lacoste et al., 2014; Houten et al., 2018; Fu et al., 2018) were found to have positive influence on the protection of pedestrians.

However, in terms of law enforcement cameras, most of the early studies focused on speed enforcement cameras and red-light-running enforcement cameras at intersections (Martínez-Ruíz et al., 2019; Retting et al., 1999; Savolainen et al., 2016), while the effects of law enforcement cameras for capturing non-yielding behavior at non-signalized crosswalks are rarely examined. Additionally, most of the above-mentioned studies were conducted based on the roadside mounted camera data, of which the perspective needs to be calibrated using coordinate transformation and projection methods. So, errors would be caused in the trajectory data extraction, such as inconsistences in the coordinate. Some previous studies have used Unmanned Aerial Vehicle (UAV) video data to investigate pedestrian-vehicle conflicts, which can provide an overlook view of the study area and ensure the accuracy of trajectory data (Chen et al., 2019; Zhu et al., 2019). This study used both UAV and roadside mounted camera video to collect the trajectory data and the detailed information of pedestrians on the road.

2.2 Factors affecting pedestrian safety

Factors affecting pedestrian safety can be classified into three categories: pedestrian characteristics, vehicular characteristics and environmental factors at crosswalks (Liu and Tung, 2014; Yagil., 2000; Zhuang and Wu, 2011; Salamati et al., 2013; Olszewski et al., 2016; Lacoste et al., 2014).

Regarding pedestrian characteristics, previous study indicated that elderly would face a higher road-crossing risk than the youth, which can be attributed to the degradation of cognitive performance and mobility (Liu and Tung, 2014; Raghavendra Ravishankar and Nair, 2018). A study by Zhang C et al (2019) found that the presence of female has positive influence on reducing the conflicts between motor vehicles and pedestrians, which is consistent with other studies (Raghavendra Ravishankar and Nair, 2018; Kumar et al., 2019). Also, the group size of pedestrians is positively correlated to pedestrian safety at crosswalks (Zhuang and Wu, 2011; Malenje et al., 2019; Raghavendra et al., 2018; Kadali and Vedagiri, 2016). Additionally, Almodfer et al (2016) and Kumar et al (2019) found that high pedestrian waiting time may cause more conflicts. Also, previous studies indicated that pedestrians who took evasive actions, such as looking or gesturing at vehicles, have lower probability of being involved in conflicts (Zhuang and Wu, 2014; Zhuang and Wu, 2011). In contrast, pedestrians using mobile phone while crossing the street would face higher risk (Zhou et al., 2019; Zhang H, 2019).

In terms of vehicular characteristics, an increase in driving speed was found correlated to the increase in pedestrian-vehicle conflicts (Salamati et al., 2013; Liu and Tung, 2014; Zhang C et al., 2019; Olszewski et al., 2016; Kadali and Vedagiri, 2016; Moshahedi et al., 2018). Abrupt breaking or passing in front or behind a pedestrian at high speed could also increase the pedestrian risk (Olszewski et al., 2016; Houten et al., 2018). Moreover, previous studies revealed that larger vehicle (e.g. bus and truck) is safer for pedestrians, because pedestrians would wait for adequate gap to cross (Kadali and Vedagiri, 2016).

A series of studies recommended to install pedestrian-related infrastructures at crosswalks, such as speed-control measures, pedestrian refuge and median barrier, to improve pedestrian safety (Chao et al., 2017; Zhang C et al., 2019; Kadali and Vedagiri., 2016; Moshahedi et al., 2018). It is indicated that pedestrian-vehicle conflicts would increase with the number of vehicle lanes (Zhang C et al., 2019; Malenje et al., 2019; Sandt et al., 2016). Furthermore, weather conditions and temporal variation may also affect pedestrian safety. For instance, rainy and snowy weather would make it hard for drivers to react timely at the occurrence of pedestrians (Lacoste et al., 2014; Moshahedi et al., 2018). Probability of dangerous conflicts are significant higher during night and afternoon (Fu et al., 2016; Sandt et al., 2016).

2.3 Conflict severity classification

Surrogate safety measures have been widely used in many conflict analysis studies, and indicators including Post-Encroachment Time (PET), Time-to-Collision (TTC), Time-to-Accident (TA), Lane-based Post-Encroachment Time (LPET) and Deceleration to Safety Time (DST) have been used to identify pedestrian-vehicle conflicts (Fu et al., 2016; Kathuria and Vedagirib, 2020; Iasmin et al., 2016; Hupfer, 1997). In some previous studies, conflicts are classified based on predetermined threshold values of these indicators (Zangenehpour et al., 2016; Caliendo and Guida, 2012; Chen et al., 2019; Sayed et al., 2013; Zhang C et al., 2017). For instance, in a study by Fu et al (2016), pedestrian-vehicle interactions with PET less than 5s were considered as conflicts, while those with PET less than 1.5s were considered as serious conflicts. However, predetermined threshold could be inappropriate if traffic condition heterogeneity existed. Instead, clustering and classification method (e.g. support vector machine, import vector machine and k-means clustering) with integration of various indicators are used for conflicts classification in a few studies, in which the heterogeneity of traffic conditions is considered (Kathuria and Vedagiri, 2020; Ren et al., 2012; Ni et al., 2016). In this study, support vector machine (SVM) classification algorism based on indicators of Post-Encroachment Time (PET), Deceleration to Safety Time (DST) and Time-to-Collision (TTC) is adopted for conflict classification.

3 Method

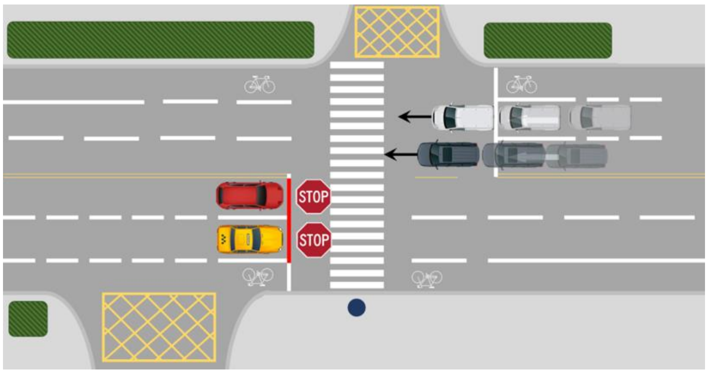
3.1 Yielding rules in Nanjing

To increase drivers' yielding rate and improve pedestrian safety at non-signalized crosswalks, the law enforcement camera was first introduced in Nanjing in 2017. By August 2020, more than 100 law enforcement cameras are in operation, and the average daily non-yielding violation rate has decreased around 60% (Xinhua net, 2019). As reported by Traffic Administration Bureau of the Ministry of Public Security of Nanjing, the yielding rules at non-signalized crosswalks can be categorized into 3 scenarios:

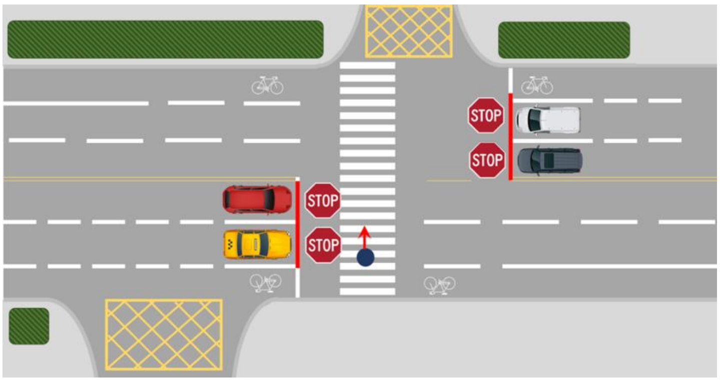
Scenario 1: When the pedestrian is waiting at the roadside, vehicles in the same direction should stop before the stop line, while the opposite direction could keep proceeding, see Fig.1 (a);

Scenario 2: When the pedestrian is on the crosswalk, vehicles in both directions should stop before the stop line, see Fig.1 (b);

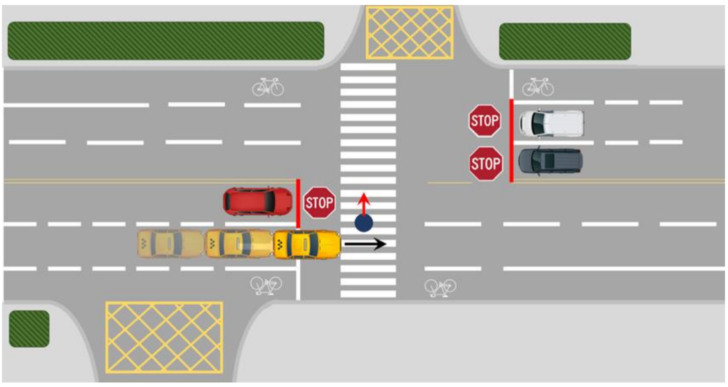
Scenario 3: When the pedestrian has left the lane, vehicle on the corresponding lane could proceed, see Fig.1 (c).



(a) The illustration of scenarios 1



(b) The illustration of scenarios 2



(c) The illustration of scenarios 3

Fig.1. Illustration of the yielding rules in Nanjing in different scenarios.

3.2 Study area

Four non-signalized crosswalks (site 1, 2, 3, 4) in Nanjing were selected to evaluate the safety effects of law enforcement camera. Site 1 and site 3 are treatment sites, where the law enforcement cameras are implemented. To control for the effects of traffic characteristics on pedestrian safety, site 2 and site 4, without law enforcement cameras, are respectively selected from the same road segment which corresponds to the treatment sites, as shown in Fig. 2 (a) and (b). The information of these four sites is shown in the Table 1.

(a) Treatment site 1 and control site 2. (b) Treatment site 3 and control site 4.

Fig. 2. Location of treatment and control sites.

Table 1 details of the selected sites

Groups	Sites	Location	Lanes per direction	Speed limits(km/h)	Median barrier	Curb parking
Group 1	Treatment Site 1	Bauhinia Road	2	50	No	Yes
	Comparison Site 2	Bauhinia Road	2	50	No	Yes
Group 2	Treatment Site 3	QinHuai Road	3	50	Yes	No
	Comparison Site 4	ShangYuan Avenue	3	50	Yes	No

3.3 Data collection

To reduce the bias of roadside mounted camera data (Chao et al., 2017; Fu et al., 2018; Houten et al., 2018), the UAV and roadside camera videos were both applied in this study. The trajectories of pedestrians and vehicles could be observed from the UAV view, and the roadside mounted camera data provides the information on the characteristics of pedestrians and vehicles. Take site 1 as an example, Fig. 3 shows the views and locations of UAV and roadside camera. A total of 680 minutes video data was obtained on study period. Table 2 presents the detailed information of data collection.

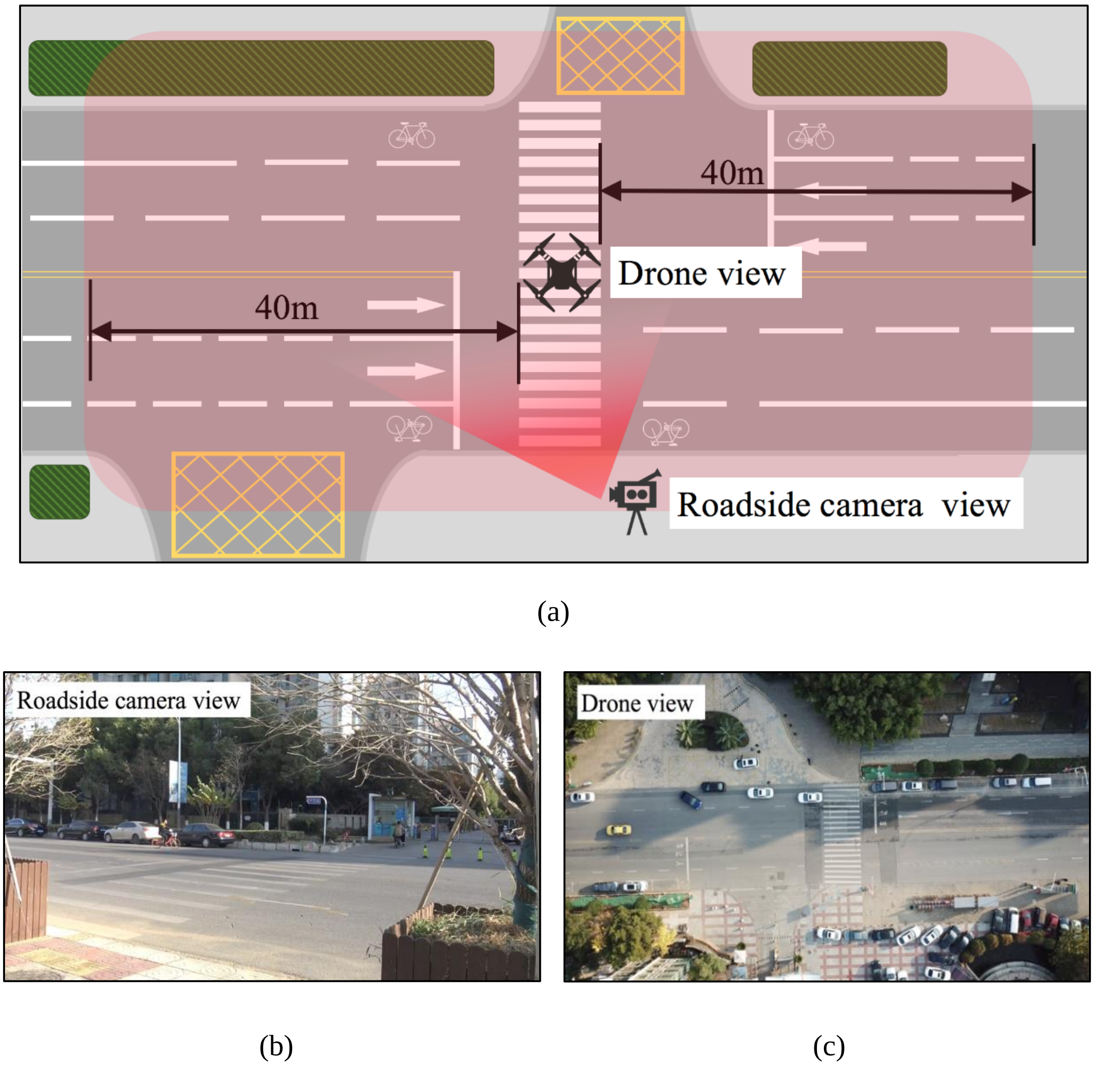


Fig. 3. Camera locations (a) and views (b, c) at site 1.

Table 2 description of video data recording

Groups	Sites	Date	Time	Duration(mins)
Group 1	Treatment Site 1	2019.11.14	9:00 am-10:30 am	90
		2019.11.15	9:00 am-11:20 am	140
	Control Site 2	2019.12.3	15:00 pm-16:30 pm	90
		2019.12.4	9:00 am-10:30 am	90
		2019.12.6	15:00 pm-16:30 pm	90
Group 2	Treatment Site 3	2019.12.16	15:30pm-17:00pm	90
	Control Site 4	2019.12.23	14:30 pm-16:00 pm	90

Furthermore, Tracker was applied to extract the information of motor vehicles and pedestrians from UAV video data (1080p, 25fps), including the coordinate and speed and acceleration data. To smooth the road users' path, the video was played at a time interval of 0.20s. A total of 343 vehicle-pedestrian interaction trajectory data were collected. The extraction procedure is shown in Fig. 4.

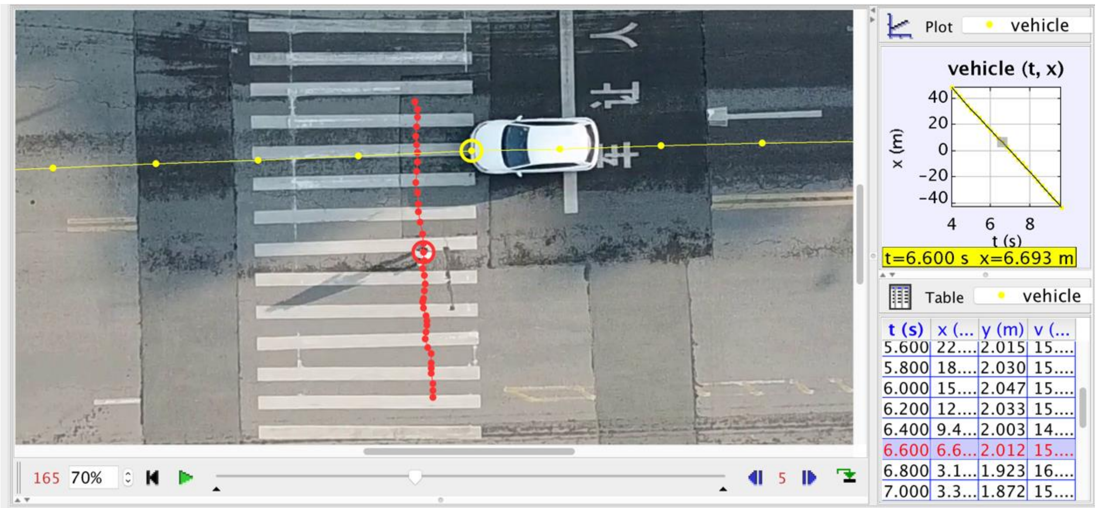


Fig.4. path trajectory of a pedestrian-vehicle interaction at site 1

Other potential influencing factors affecting pedestrian-vehicle interactions are also considered in this study. Pedestrians of different age, physically disabled or carrying luggage could have different walking speed, and thus affecting pedestrian-vehicle interactions (Forde and Daniel, 2020). Additionally, pedestrians waiting at the curb or median can also affect drivers' detection of waiting pedestrian (Zhao et al., 2020). In addition, vehicle type and upstream average speed are also associated with pedestrian-vehicle interactions (Salamati et al., 2013; Kadali and Vedagiri, 2016). Furthermore, the behavior of the front and side vehicles was also included in our model, which is rarely considered in the previous studies (Salamati et al., 2013; Liu and Tung, 2014; Olszewski et al., 2016; Houten et al., 2018). The conflicting vehicle behavior could be influenced by the adjacent vehicles. Finally, environmental factors including "number of lanes between pedestrian and vehicle" and "number of lanes of the crosswalk" (Zhang C et al., 2019; Sandt et al., 2016) are related to the distance between pedestrian and approaching vehicle, thus affect pedestrian-vehicle interactions. All the factors considered in this study are extracted from the roadside and UAV video data using Adobe Premiere Pro 2020 (Adobe, 2020). The description of these factors is summarized in Table 3.

Table 3 variables considered in the model

Factors	Description
Treatment	Whether the crosswalk was implemented with camera. (yes (1)/no (0))
Disability	Whether the pedestrian has any physical disabilities. (yes (1)/no (0))
Luggage	Whether the pedestrian carries any luggage or not (yes (1)/no (0))
Pednumber	Number of pedestrians crossing together (0:one, 1:two, 2:more than three)
Old	Whether the pedestrian(group) is(contains) elderly (yes (1)/no (0))
Child	Whether the pedestrian(group) is(contains) child (yes (1)/no (0))
Pedposition	Position of pedestrian (curb (0)/median (1))
Nextcveh	Whether the vehicle next to the conflicting vehicle yield (yes (1)/no (0))
Frontveh	Whether the vehicle in front of the conflicting vehicle not yield (yes (1)/no (0))
Vehicle type	Conflicting vehicle type (car (0)/bus, trucks (1))
Upspeed	The upstream average speed of the conflicting vehicle
P-Vlanes	The numbers of lanes between the pedestrian and conflicting vehicle (1~4)
Lanes	The numbers of lanes of the crosswalk

3.4 Conflict analysis

3.4.1 Surrogate safety indicators

Surrogate safety indicators like TTC and PET have been widely used to analyze traffic conflicts (Zangenehpour et al., 2016; Kathuria and Vedagirib, 2020). TTC describes the time that remains until a collision between two road users would have occurred if the collision course and speed difference are maintained (Hayward, 1971). PET is defined as the time from the end of encroachment to the time that the through road user actually arrives at the potential point of collision (Allen et al., 1977). However, a study by Hupfer et al (1997) pointed that PET and TTC only indicate the distance of a collision occurs without considering the evasive action of road users. Later, the indicator DST was applied to describe the necessary deceleration to reach the last PET. Thus, PET, TTC and DST are combined to evaluate the pedestrian safety in this study. The calculation of these indicators is shown below.

(1) Post-Encroachment Time (PET)

$$PET = T_2 - T_1$$

Where, T_1 referred to the time when the first road user left the conflict zone, and T_2 referred to the time when the second road user entered the conflict zone.

(2) Time-to-Collision (TTC)

$$TTC(i)_1 = max(\frac{d_p(i) + w(j)}{v_p(i)}, \frac{d_v(i)}{v_v(i)})$$

$$TTC(i)_2 = max(\frac{d_p(i)}{v_p(i)}, \frac{d_v(i)}{v_v(i)})$$

$$TTC_{min} = min(TTC(i))$$

$TTC(i)_1$ indicates that pedestrian passes first, and $TTC(i)_2$ means that vehicle passes first; $d_v(i)$ is the distance from the front of the vehicle to the conflicting zone; $d_p(i)$ is the distance from the front of the pedestrian to the conflicting zone; $w(j)$ is the width of the vehicle, and $v_v(i)$ and $v_p(i)$ is the Speed of vehicle and pedestrian at time "*i*" respectively.

(3) Deceleration to Safety Time (DST)

When pedestrian passes first:

$$t_{DST_x}(i) = \frac{d_p(i)+w(j)}{v_p(i)} + x$$

$$DST_x(i) = \frac{2(v_v(i) * t_{DST_x}(i) - d_v(i))}{t_{DST_x}(i)^2}$$

When vehicle passes first:

$$t_{DST_x}(i) = \frac{d_v(i)+l(j)}{v_v(i)} + x$$

$$DST_x(i) = \frac{2(v_p(i) * t_{DST_x}(i) - d_p(i))}{t_{DST_x}(i)^2}$$

Then,

$$DST_{max} = max(DST_x(i))$$

Where $l(j)$ refers to the length of the conflicting vehicle, and x is the required safety time, x=5s, which is consistent with other studies (Fu et al., 2016; Zangenehpour et al., 2016).

3.4.2 The classification of potential conflicts and severity

Similar with previous studies (Kathuria and Vedagiri, 2020; Iasmin et al., 2016), five types of interactions are considered in this study, of which the video clips would be selected: (1) Pedestrian slows down or stops to let the vehicle passes first; (2) Vehicle passes firstly and pedestrian swerves behind the car to cross the road; (3) Vehicle speed up at the occurrence of pedestrian to passes first; (4) Vehicle slows down or stop to let the pedestrian passes first; and (5) Pedestrian speed up at the occurrence of vehicle to passes first. Trained observers reviewed the video clips and estimated the conflict severity for each interaction based on the description in Table 4, which is consistent with early studies (Kathuria and Vedagiri, 2020; Ni et al., 2016; Van der Horst et al., 2014). As shown in Table 4, the conflicts severity are classified into three categories: (1) safe passage; (2) slight conflict; (3) serious conflict, which were coded as 0, 1 and 2 respectively. Observers would score each interaction, and the average scores are rounded to the integers between 0 and 2, which are the final results of conflict severity estimation. Table 4 presents the estimation results for four sites.

Table 4 conflicts description and severity estimation results at four sites

Conflicts severity	Description	Site 1	Site 2	Site 3	Site 4
safe passage	The pedestrian and the vehicle pass the conflict zone comfortably without any evasive action.	18	37	51	27
slight conflict	The pedestrian or the vehicle or both accelerates or decelerates or swerve to avoid a collision.	67	18	16	16
serious conflict	The pedestrian or the vehicle or both must decelerate and stop to avoid the collision.	16	29	13	35

3.4.3 Estimation of the effects of law enforcement cameras on conflict severity

In this study, an ordered logit model is employed to examine the safety effects of law enforcement cameras (Zangenehpour et al., 2016; Stipancic et al., 2016; Pai and Saleh, 2008). The probability of outcome *i* (potential conflicts) is calculated by:

$$Pr(outcome_j = i) = Pr(k_{i-1} < \beta x_{kj} + \varepsilon_{ij} \leq k_i)$$

Where x_{kj} is the vector of law enforcement cameras and other potential influencing factors, and k_{i-1} is the cut-off points, k is the number of possible outcomes; β is the vector of parameters; ε_{ij} is the error term which is assumed to be logistically distributed in ordered logit.

3.5 Yielding behavior analysis

3.5.1 Yielding behavior classification

In most previous studies, vehicle yielding behaviors are only classified into two categories, yielding and non-yielding (Moshahedi et al., 2018; Lacoste et al., 2014; Malenje et al., 2019; Fu et al., 2018). However, according to the rules, some behaviors would be also treated as illegitimate even if yielding to the pedestrian, such as slowly approaching the crosswalk or stopping after the stop line. Thus, the drivers yielding behavior were classified into three categories in this study: (i) legally yielding, only when vehicles stop before the stop line (see Fig. 5 (a)); (ii) illegally yielding, including stopping after the stop line and slowly approaching the crosswalk while yielding (see Fig. 5 (b), (c)); (iii) not yielding, when vehicle passes directly without yielding (see Fig. 5 (d)).

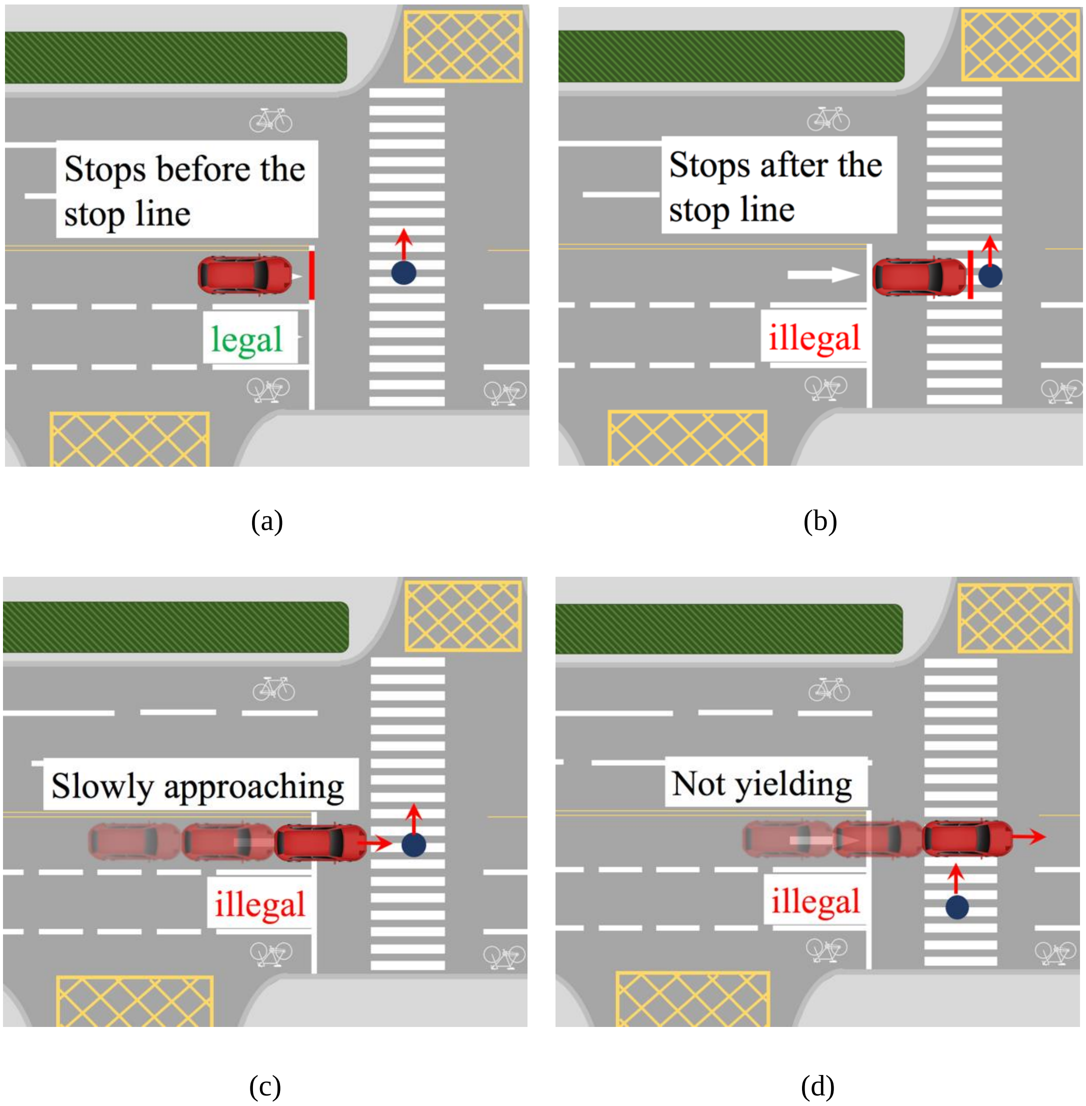


Fig. 5. The classification of drivers' yielding behavior

3.5.2 Estimation of the effects of law enforcement cameras on yielding behaviors

Binary logit models are applied to examine the effect of law enforcement cameras on drivers yielding behavior, in which the dependent variable is 'yielding or not' (0/1) and 'legitimate yielding or not' (0/1). The model formulation is:

$$Pr(y_j \neq 0|x_j) = \frac{exp(x_j\beta)}{1 + exp(x_j\beta)}$$

Where y_j is the choice of vehicle j; x_j is the vector of law enforcement cameras and other potential influencing factors, and β is the vector of parameters.

4 Results and discussion

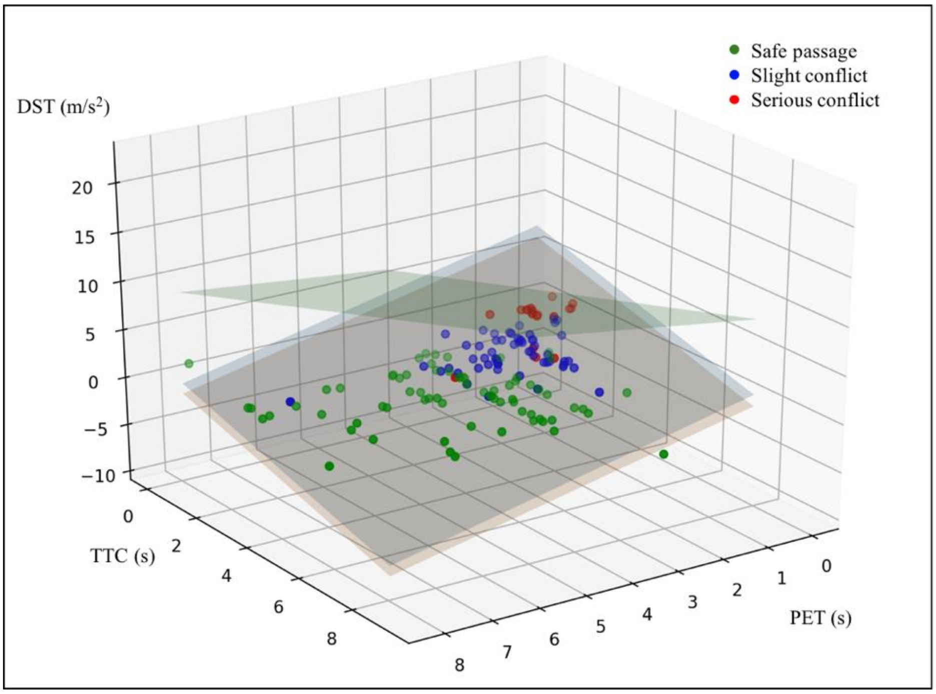
4.1 Conflict severity analysis

Table 5 descriptive statistics of PET, TTC and DST

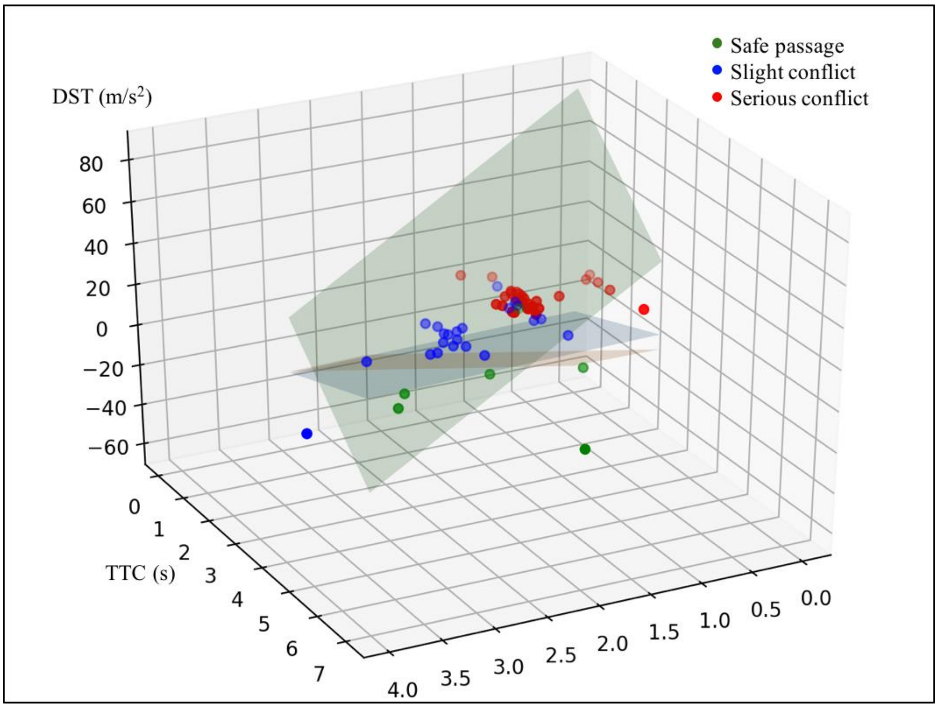
Indicators	Type	Site 1	Site 2	Site 3	Site 4
PET(s)	Max	8.200	6.910	8.130	8.040
	Min	0.100	0.040	0.080	0.080
	Mean	3.380	2.338	3.105	2.226
TTC(s)	Max	9.370	7.775	7.193	7.017
	Min	0.014	0.712	0.035	0.085
	Mean	3.892	3.165	3.359	2.332
DST(m/s2)	Max	2.589	2.469	2.474	2.278
	Min	-0.162	0.188	0.085	0.084
	Mean	0.831	0.792	0.917	0.842

Table 5 shows the estimation results of surrogate safety indicators PET, TTC and DST， which are used for SVM classification. Two scenarios were investigated considering different deceleration rate between pedestrian and vehicle: (i) pedestrian passes first; and (ii) vehicle passes first. Moreover, around 80% trajectory data was applied for the training data, and other 20% were used for test data. Fig. 6 shows the classification results of SVM classification. Take "pedestrian passes first" scenario for an example, dots representing the severe conflicts are located in the TTC range between 0 to 2.00s, PET range between 0 to 1.00s and DST over 1.00m/s^2, while dots representing slight conflicts and safe passage are widely scattered in the outer area. The computed accuracy results of training and test data were presented in Fig. 7. The results show that all accuracy values are above 75%, which satisfies the accuracy requirement for classification.

Based on the scatter plot of indicators and conflicts classification results, threshold values for each conflict severity were proposed and presented in Table 6. It is worth noting that, for “vehicle passes first” scenario, deceleration rates for pedestrians were all relatively low and widely spread, while TTC and PET took dominant roles in determining the severity. Thus, only TTC and PET were adopted as indicators for “vehicle passes first” scenario. Furthermore, the proposed indicators threshold values were validated using 20% of datasets in each scenario. Fig. 8 and Fig. 9 presents the severity prediction accuracy of the proposed thresholds. The overall prediction accuracy for “pedestrian passes first” and “vehicle passes first” are 70% and 65% respectively, indicating that thresholds for “pedestrian passes first” scenario are more accurate. However, the thresholds for slight conflicts were more likely to underestimate conflict severity in both scenarios.



(a) Pedestrian passes first



(b) Vehicle passes first

Fig.6. Classification of conflicts for both interaction categories

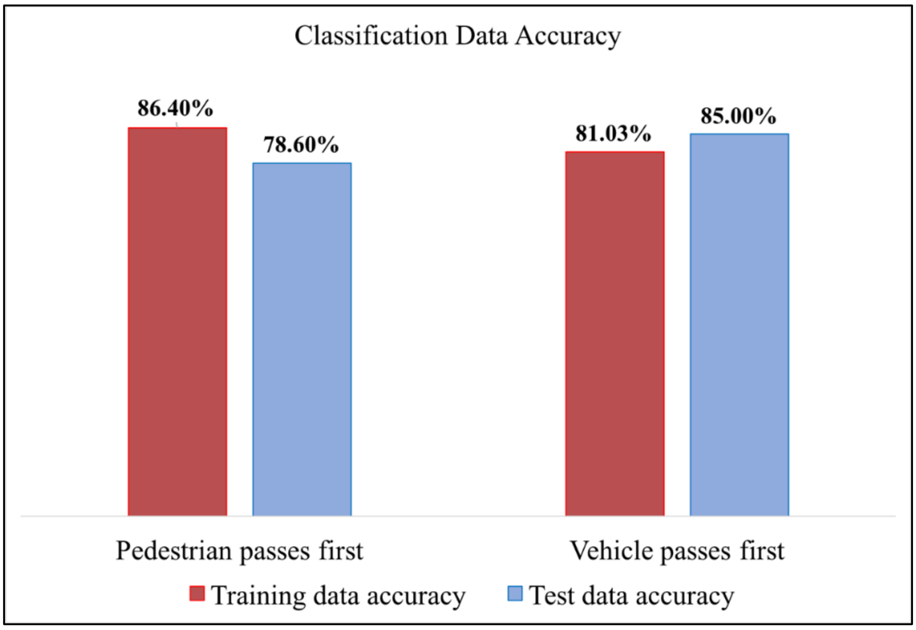


Fig. 7. The computed accuracy for training data and test data in both scenarios

Table 6 proposed indicators threshold values in two scenarios

Scenarios	Indicators	Severity level		
		Safe passage	Slight conflicts	Serious conflicts
Pedestrian passes first	PET (s)	>3.30	1.00-3.30	0.00-1.00
	TTC (s)	>4.00	2.00-4.00	0.00-2.00
	DST (m/s^2)	<1.50	<1.50	>1.00
Vehicle passes first	PET (s)	>2.00	1.00-2.50	0.00-1.00
	TTC (s)	>3.00	1.00-3.00	0.00-2.00
	DST (m/s^2)	/	/	/

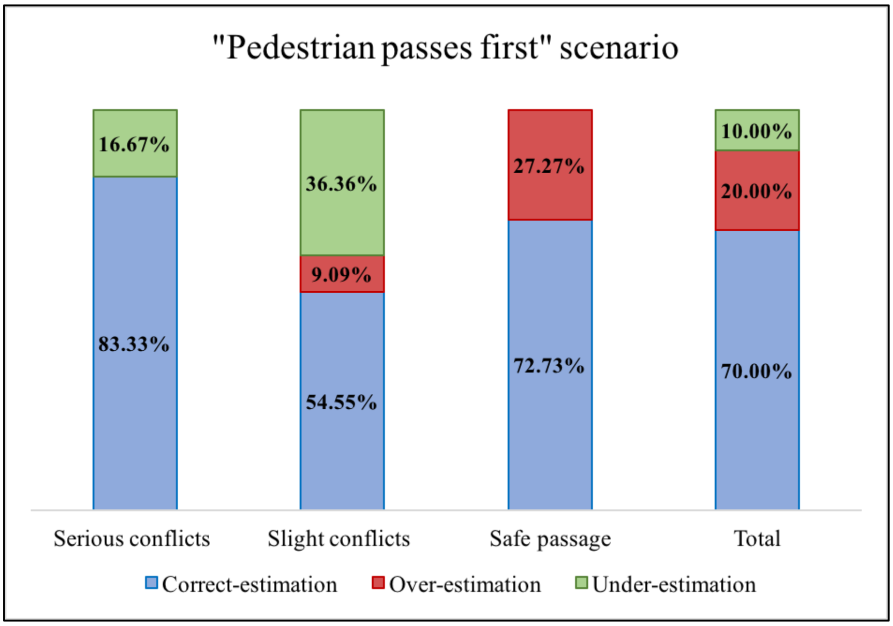


Fig. 8. Estimation accuracy for "Pedestrian passes first" scenario

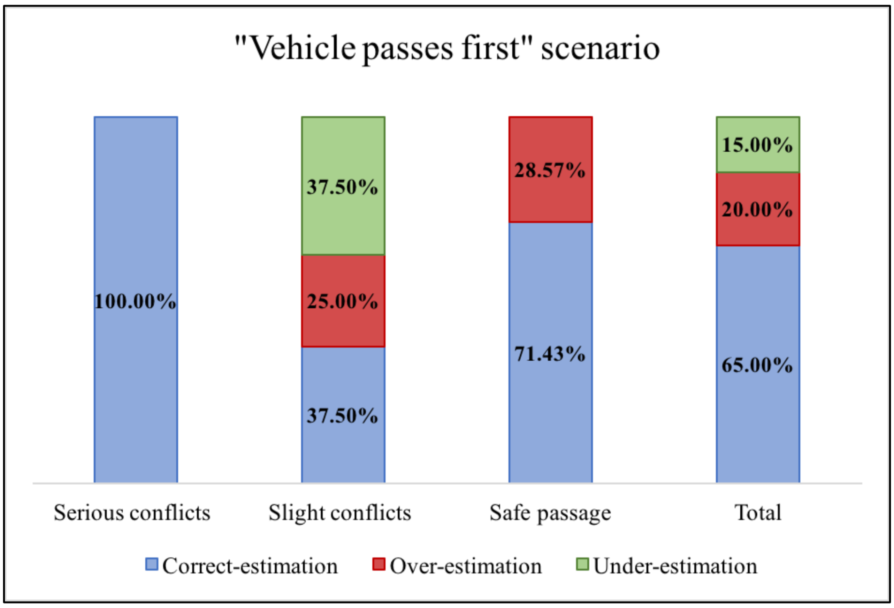
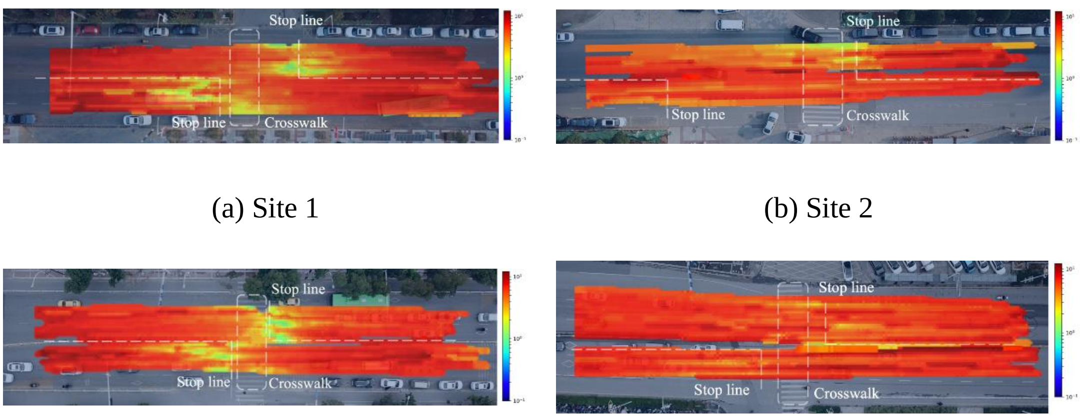


Fig. 9. Estimation accuracy for "Vehicle passes first" scenario

Based on the conflict classification results, an ordered logit model was developed to estimate the effects of law enforcement cameras on conflict severity. As shown in Table 8, installing law enforcement cameras at non-signalized crosswalks would increase the conflict severity between pedestrians and vehicles. It may be attributed to the heterogeneity of pedestrians' perception of safety in different traffic conditions. For example, a study by Pawar and Patil (2016) found that the probability of pedestrians accepting a gap decreases with the increase in the approaching vehicle speed. In this study, as shown in Table 7 and Fig. 10, the vehicle average speed at upstream, crosswalk and downstream areas of control sites (site 2 and site 4) were greatly higher than that of the treatment sites (site 1 and site 3). Consequently, pedestrians at the crosswalk without law enforcement cameras would be more cautious and wait for an adequate gap to cross, while pedestrians at the crosswalk with law enforcement cameras tend to accept smaller gaps, which would increase the conflict severity.

Table 7 descriptive statistics for vehicle speed (m/s) observations.

Sites	Obs.	Upstream speed		Crosswalk speed		Downstream speed	
		Mean	Std.err.	Mean	Std.err.	Mean	Std.err.
Site 1	82	8.657	2.464	6.689	2.844	9.112	1.990
Site 2	80	9.427	2.776	8.321	3.364	9.663	2.733
Site 3	73	7.866	1.959	5.436	2.846	8.083	1.621
Site 4	77	9.105	2.458	8.030	3.011	9.957	1.985



(a) Site 1

(b) Site 2

(c) Site 3

(d) Site 4

Fig. 10. Heat-maps of vehicle speed distribution of the observations

As for the effects of pedestrian characteristics, the presence of the disabled and pedestrian carrying luggage show no significant effects on conflict severity. This may be due to the limited observations of these pedestrians (2.3% and 10% respectively). Inversely, the presence of the elderly is significantly associated with lower conflict severity, since drivers are more likely to yield to the elderly considering their mobility degradation, and thus reduce conflict risks. However, no association can be established between the presence of child and conflict severity. A possible reason is that all the children observations were accompanied by adults in this study, thus children would behave more safely and cross the street along with the adults. Additionally, pedestrian waiting position also has no effect on the vehicle-pedestrian conflicts. It can be interpreted that at crosswalks without curb parking, drivers could have a clear sight of the roadside waiting pedestrians, however, at crosswalks with curb parking, blocked sights may lead to more cautious behavior from both pedestrians and the drivers (Cloutier et al., 2017).

Regarding the effects of vehicular characteristics, adjacent vehicle behavior, such as the front vehicle non-yielding behavior and side vehicle yielding behavior are significantly associated with conflict propensity. The results imply that the front vehicle non-yielding behavior could increase the conflict severity, while the side vehicle yielding behavior could reduce the risk. The results indicate that drivers may follow the front vehicle subconsciously and therefore ignore the presence of pedestrian. Conversely, the yielding behavior of the side car could regard as a reminder of the presence of pedestrian. The results show that the vehicle upstream average speed has no effect on conflict severity.

In terms of the effects of environmental factors, results indicated the “number of lanes *(4)* between pedestrian and vehicle” is significant associated with the conflict severity. A possible reason is that more lanes between pedestrian and vehicle leads to more react time and stopping distance for drivers, thus conflicts could be avoided. However, number of lanes of the crosswalk has no effect on conflict severity.

Table 8 model results for conflict severity and influencing factors

Conflict severity analysis	Coef.	Std.err.	P-value
Treatment	-0.431	0.215	0.045
Disability	/	/	/
Luggage	/	/	/
Vehicle type	/	/	/
Old	-0.572	0.303	0.059
Child	/	/	/
Position of pedestrian	/	/	/
Num. of Lanes between ped. and veh. (1) (ref.)			
Num. of Lanes between ped. and veh. (4)	-1.092	0.587	0.063
Num. of Lanes between ped. and veh. (2, 3)	/	/	/
Number of lanes of the crosswalk	/	/	/
Number of pedestrian (1) (ref.)			
Number of pedestrian (2, ≥3)	/	/	/
Upstream speed	/	/	/
Front vehicle non-yielding behavior	0.947	0.284	0.001
Side vehicle yielding behavior	-0.908	0.286	0.001
Cut-off 1	-1.021	0.259	0.000
Cut-off 2	0.574	0.255	0.000
Num. of obs.	343		
Log likelihood	-349.321		

Notes: / denotes insignificant.

4.2 Yielding behavior analysis

Based on the yielding rules in Nanjing, Table 9 shows the distribution of drivers yielding behaviors at each site. It is found that around 80% of drivers choose to yield to pedestrian at treatment sites, which is higher than that at control sites. Additionally, the percentage of non-yielding and illegitimate yielding behaviors at control sits are slightly higher during analysis periods. Furthermore, the percentage of illegitimate yielding behaviors at treatment sites (site 1, site 3) are both more than 10% (15.84% and 10.00% respectively). Therefore, it is necessary to implement effective education measures to improve the awareness of yielding rules and increase drivers legitimate yielding rates.

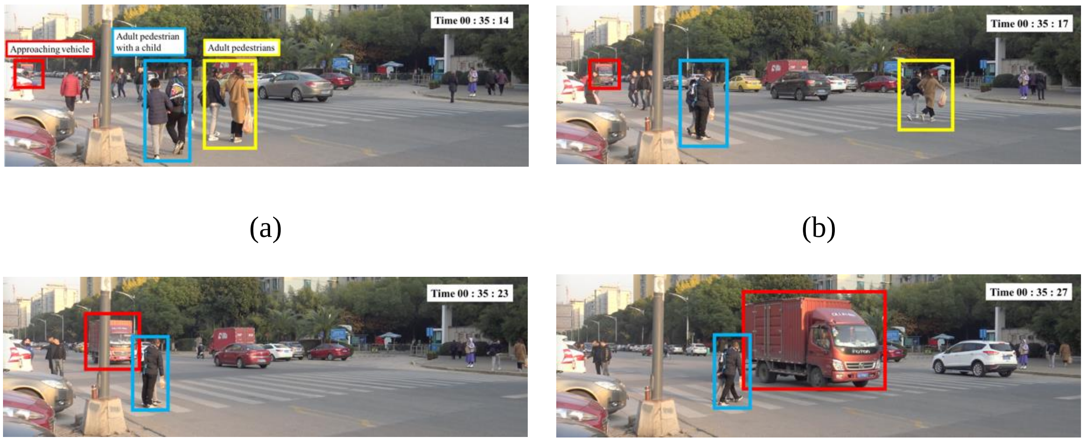
Table 9 drivers yielding behavior classification at four sites

Yielding behavior		Site 1	Site 2	Site 3	Site 4
No yielding		18(17.82%)	30(35.71%)	17(21.25%)	33(42.30%)
Yielding	Legitimate	67(66.33%)	34(40.47%)	55(68.75%)	28(35.89%)
	Illegitimate	16(15.84%)	20(23.81%)	8(10.00%)	17(21.79%)

To evaluate the effects of law enforcement cameras on driver yielding behaviors, binary logit models were employed. Table 10 shows that the implementation of law enforcement cameras is positively associated with yielding and legitimate yielding behavior, which is consistent with our expectation.

Regarding pedestrian characteristics, no evidence is found to support the association between the presence of the disabled and pedestrian carrying luggage and drivers yielding behavior. However, the presence of the elderly and child are both significantly associated with drivers yielding behavior. The results indicate that the presence of the elderly has positive effect on drivers yielding and legitimate yielding behavior, which can be interpreted that drivers tend to yield to the elderly concerning their degradation of mobility (Zhao et al., 2020).

Additionally, the presence of child is negatively associated with drivers yielding and legitimate yielding behavior. It is observed that most of the adults with children would wait at the roadside even if the approaching vehicle has decelerated. Considering the low walking speed of children, adults tend to wait for a safer gap to cross. However, this behavior would mislead the drivers about pedestrians' crossing intention, thus leads to non-yielding behavior and illegitimate yielding behavior. For example, as shown in Fig. 11(a) and Fig. 11(b), an adult with a child and two adult pedestrians arrived at the crosswalk almost simultaneously, with a red truck approaching the crosswalk. However, two adult pedestrians decided to run over the crosswalk, while the pedestrian with a child stood still at the roadside. In Fig. 11(c) and Fig. 11(d), the truck has decelerated and showed intention to yield, but the pedestrian with a child still choose to wait until the truck has passed.



(a) (b)

(c) (d)

Fig. 11. Example of the crossing behavior of an adult pedestrian with a child

In terms of the effects of vehicular characteristics, the results suggest that front vehicle non-yielding behavior is negatively associated with the following drivers yielding and legitimate yielding behavior. A possible reason is that drivers may follow the front vehicle subconsciously and passes directly without yielding. However, the yielding behavior of the side vehicle is not significantly associated with drivers yielding behavior. Additionally, an increase in upstream average speed is associated with the decrease in drivers yielding and legitimate yielding probability, which is consistent with previous studies (Sandt et al., 2016; Moshahedi et al., 2018; Bertulis et al., 2014). This can be attributed to the insufficient reaction and braking time caused by high speed. As shown in Table 7, the vehicle average speed at upstream and crosswalk areas of control sites (site 1, site 3) were significantly higher than that of the treatment sites (site 2, site 4), indicating that the drivers tend to pass the site without law enforcement camera at high speed, which may result in non-yielding or illegitimate yielding behavior.

The factor "number of lanes between pedestrian and vehicle" is not significantly associated with drivers yielding behavior. It is possible that the experiment sites are all minor roads and relatively narrow, on which drivers could detect pedestrians and make yielding decisions timely. Yet, it is worth exploring the effect of relative position of pedestrian and vehicle on conflicts and yielding behavior, if sites with more lanes are available in the dataset. Additionally, factor “number of lanes of the crosswalk” has no significant effect on drivers yielding behavior.

Table 10 model results for drivers' yielding behavior and influencing factors

Yielding behavior analysis	Legitimate yielding or not			Yielding or not		
	Coef.	Std.err.	P-value	Coef.	Std.err.	P-value
Treatment	1.075	3.650	0.000	0.892	0.362	0.014
Disability	/	/	/	/	/	/
Luggage	/	/	/	/	/	/
Vehicle type	/	/	/	/	/	/
Old	0.715	1.800	0.073	1.165	0.562	0.038
Child	-0.873	-1.870	0.061	-1.119	0.565	0.048
Position of pedestrian	/	/	/	/	/	/
Front vehicle non-yielding behavior	-1.863	-4.210	0.000	-2.750	0.478	0.000
Num. of lanes between ped. and veh. (1)(ref.)						
Num. of lanes between ped. and veh. (2,3,4)	/	/	/	/	/	/
Number of lanes of the crosswalk	/	/	/	/	/	/
Number of pedestrian (1) (ref.)						
Number of pedestrian (2, ≥3)	/	/	/	/	/	/
Upstream speed	-0.643	-7.420	0.000	-0.655	0.089	0.000
Side vehicle yielding behavior	/	/	/	/	/	/
Cons.	4.289	5.800	0.000	6.045	0.871	0.000
Num. of obs.		343			343	
Log likelihood		-153.726			-118.689	

Notes: / denotes insignificant.

5 Conclusion

This paper investigated the safety effects of law enforcement cameras at non-signalized crosswalks in Nanjing. The pedestrian-vehicle interactions data were extracted from UAV and side-mounted camera video. Based on these observations, conflict and yielding behavior analysis were conducted to evaluate the safety effects of law enforcement camera on pedestrians. Other influencing factors are also investigated, including pedestrian characteristics, vehicular characteristic and environmental factors.

In conflict analysis, an ordered logit model was developed to estimate the effects of law enforcement cameras on conflict severity. Results indicate that the implementation of camera would increase the conflict severity, which could be due to the heterogeneity of pedestrians' perception of safety in different traffic conditions. Moreover, the presence of the elderly, more lanes between pedestrian and vehicle and the yielding behavior of side vehicle would decrease conflict severity, while the non-yielding behavior of front vehicle could increase conflict severity.

In yielding behavior analysis, it is found that over 10% drivers disobey the rules when yielding to pedestrians. Furthermore, the model results reveal that the implementation of enforcement cameras would increase the yielding and legitimate yielding probability. The presence of the elderly is also associated with more yielding and legitimate yielding behavior, while the presence of children, front vehicle non-yielding behavior and high upstream vehicle speed would decrease the yielding and legitimate yielding probability.

Based on the results, this study also has several recommendations for improving pedestrian safety at non-signalized crosswalks:

(1) A problem observed in our study is that some drivers may not have sufficient time to yield to pedestrians due to high speed. One possible reason is that the drivers did

not notice the crosswalk ahead. Thus, traffic calming measures (e.g. speed humps), as well as warning facilities (e.g. side-mounted flashing warning signs and in-car warning system) (Calvi et al., 2020), can be used as supplementary measures to improve the performance of law enforcement cameras.

(2) Although most drivers show courtesy to pedestrians at non-signalized crosswalks, a certain percentage of yielding behavior is illegal. Education is necessary to improve drivers' awareness of yielding rules and increase drivers legitimate yielding rates.

(3) As discussed earlier, there might be misunderstanding between the drivers and pedestrians, which leads to illegal yielding or unsafe crossing. The communication between pedestrians and drivers is important for conveying intention message. Proper gestures (e.g. L-bent-level gesture) could be popularized among pedestrians and drivers to increase the perception of safety (Zhuang and Wu, 2014; Zandi et al., 2020).

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