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# The estimation of vehicle speed and stopping distance by pedestrians crossing streets in a naturalistic traffic environment

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## ABSTRACT

The ability to estimate vehicle speed and stopping distance accurately is important for pedestrians to make safe road crossing decisions. In this study, a field experiment in a naturalistic traffic environment was conducted to measure pedestrians' estimation of vehicle speed and stopping distance when they are crossing streets. Forty-four participants (18–45 years old) reported their estimation on 1043 vehicles, and the corresponding actual vehicle speed and stopping distance were recorded. In the speed estimation task, pedestrians' performances change in different actual speed levels and different weather conditions. In sunny conditions, pedestrians tended to underestimate actual vehicle speeds that were higher than 40 km/h but were able to accurately estimate speeds that were lower than 40 km/h. In rainy conditions, pedestrians tended to underestimate actual vehicle speeds that were higher than 45 km/h but were able to accurately estimate speeds ranging from 35 km/h to 45 km/h. In stopping distance estimation task, the accurate estimation interval ranged from 60 km/h to 65 km/h, and pedestrians generally underestimated the stopping distance when vehicles were travelling over 65 km/h. The results show that pedestrians have accurate estimation intervals that vary by weather conditions. When the speed of the oncoming vehicle exceeded the upper bound of the accurate interval, pedestrians were more likely to underestimate the vehicle speed, increasing their risk of incorrectly deciding to cross when it is not safe to do so.

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## 1. Introduction

### 1.1. Background

With the increasing use of automobiles worldwide, pedestrian safety is quite a problem to be solved. According to a report issued by WHO ([World Health Organization, 2013](http://www.who.int)), approximately 270,000 pedestrians worldwide were killed in 2010, accounting for 22% of the total fatalities caused by traffic accidents. During the year of 2010 in Germany, nearly 500 pedestrians were killed, accounting for 13% of the road traffic fatalities; France has similar pedestrian fatality rates to Germany. The African region has the highest road traffic fatality rate, and 38% of these fatalities are pedestrians ([World Health Organization, 2013](http://www.who.int)). In the United States, 4280 pedestrians were killed and nearly 70,000 were wounded in traffic

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accidents in 2010 (National Highway Traffic Safety Administration, 2012). In China (Traffic Administration Bureau, 2010), the total fatalities caused by road traffic accidents have decreased slowly during the past ten years. However, the number of pedestrians killed in traffic accidents remains huge. In 2010, 16,281 pedestrians were killed in automobile accidents, accounting for 24.96% of the total traffic accident fatalities, while 44,629 pedestrians were injured, accounting for 17.57% of the total traffic accidents injuries. It requires great efforts to improve pedestrian safety and decrease the pedestrian fatalities. To some extents, knowing more about the crossing behaviors of the pedestrians may be helpful to figure out the causes of the accidents and improve pedestrian safety.

Although accidents may result from unsafe behaviors of the vehicle drivers, unsafe behaviors of the pedestrians due to poor judgments of the distance away and/or speed of approaching vehicles (Hunt, Harper, & Lie, 2011) has also been shown to play a role. Street-crossing is a continuous interaction between pedestrians and oncoming vehicles (Svensson & Hyden, 2006). A pedestrian makes a crossing decision based on the judgment of whether a gap in the traffic is large enough to pass safely. Gap judgment is a complex task that involves accurate perception and integration of distance and speed information (Oxley, Ihsen, Fildes, Charlton, & Day, 2005). By means of either simulated experiments (Oxley et al., 2005; Simpson, Johnston, & Richardson, 2003) or field surveys (Yannis, Papadimitriou, & Theofilatos, 2013), previous research has showed that pedestrians' gap selections were primarily based on vehicle distance and less so on the corresponding time gap.

In general situations, as a simulated study showed (Oxley et al., 2005), pedestrians tend to make more positive crossing decisions (press the "YES" key representing they would cross the street) when the distance gap is large, ignoring the increased vehicle speed. It seems that pedestrians sometimes do not take vehicle speeds into account when making crossing decisions. Hence pedestrians will probably choose insufficient time gaps, which are inversely proportional to the vehicle speeds especially when vehicles travel at high speed. Another explanation may be that although pedestrians do consider the vehicle speed, the speed they considered was not judged accurately due to insufficient estimation ability. In this case, inaccurate estimation of vehicle speed may lead to more dangerous street-crossing decisions, thus it is important to explore the ability of pedestrians to accurately estimate vehicle speed while crossing streets.

Pedestrian judgments of vehicle gaps are usually conservative in most occasions: First, pedestrians have already left a buffer in their critical gaps, as evidenced by the safety margin in Zhuang and Wu (2012). That is, vehicles usually arrived after pedestrians had passed for some time  $t$ . In the most extreme case,  $t$  equals zero, which means that pedestrians have made a highly risky decision that will put them in a near miss. Second, to ensure safety, pedestrians usually assume that drivers do not change speed after seeing them. If the driver yields, the available gap becomes larger. The two conservative estimations, acting as buffer mechanisms, ensure that pedestrians can cross safely in most cases, even when they unintentionally misjudged the gap. In emergent situations, pedestrians who are urgent to cross the street could use up this buffer zone to cross with the minimum gap: the gap allows them to pass with a safety margin of zero ( $t = 0$ ) if the vehicle brakes for them. Obviously, this gap presented in distance is the vehicle's stopping distance. Therefore, the ability to make safe estimations (accurate or overestimations) of vehicle stopping distances is also important. As no studies were available on this topic, it is included in the study to explore the relationship of pedestrian-estimated and actual stopping distance.

## 1.2. Speed estimation

Pedestrian speed estimation is under explored in literature; The only study we found was Troscianko's work (Troscianko, Wright, & Wright, 1999). In that study, ten participants were asked to estimate the vehicle in real traffic from an interior site that generally eliminated nonvisual cues. The results showed that participants significantly underestimated vehicle speed (Troscianko et al., 1999). Although the experimental control is rigorous, the observation site is not the natural site where most pedestrians estimate vehicle speed, and the sample size is not big enough, which decreased its external validity. Therefore, this study will conduct a field study to investigate the speed estimation of pedestrians. Besides the natural context of study, this work also explored how different environmental factors related with speed estimation.

Since previous work on pedestrian speed estimation is rare, related studies were reviewed here to find possible factors that might affect pedestrians' speed estimation. An analysis of speeding records conducted by Cherry and Andrade (2001) indicates that brightly colored vehicles regularly receive tickets for comparatively lower speeds, meaning that bright color may lead to overestimations of speed. Horswill and Plooy (2008) investigated the effect of reducing image contrast on speed estimation in a simulated experiment and found vehicle speeds were perceived to be slower in reduced contrast condition. A common weather condition that may reduce the contrast is a rainy condition, as the heavy sky is gloomy and the raindrops block the line of sight. Therefore, rainy conditions, as compared with sunny ones, may have a different effect on how pedestrians estimate speed. Besides the two factors borrowed from driver studies, a factor peculiar to pedestrian is that they need to estimate speed at different positions. As shown by Zhuang and Wu (2011), pedestrians crossing a wide road usually cross it in halves separately. It was also found that pedestrian crossing the second stage is more risky in making decisions than when they are at the roadside (Li & Fernie, 2010). It may be possible that their estimations of vehicle speed are not the same at the two positions. Therefore, the experiment included view position as one possible factor and set two levels for it: at the roadside, and on the traffic island (the middle of the road).

Consequently, we have three factors (weather, vehicle color, view position) that should be incorporated into the current work when addressing pedestrians' speed estimation of the approaching vehicle.

Basic psychological studies on visual perception of velocity can provide the current work with some ideas about other factors that may affect the estimation. Brown (1931) carried out a series of experiments to investigate the phenomenal speed

of objects and figured out some key results helpful to the current work. The phenomenal speed tends to vary inversely with the distance between a moving object and the participant. This effect is also true for field brightness. Field brightness is the intensity of the illumination of the movement field. In the vehicle speed estimation context, it varies with different weather conditions. Another factor is the moving directions of the objects relative to observers. [Brown \(1931\)](#) found that the estimated speed of vertical movement was higher than that of horizontal movement. In this study, the moving direction of the object varies with different view lanes (near side and far side). Therefore, two additional factors borrowed from basic psychological studies are the view distance of pedestrians and the view lane. To sum up, although important, pedestrian speed estimation is under investigated in previous research. The pedestrian speed estimation study carried out by [Troscianko \(1999\)](#) has limited external validity due to its unnatural settings. Moreover, according to previous work on drivers' speed estimation and basic psychological study on visual perception, situational factors such as vehicle color, contrast, brightness, and view distance may affect the final estimation. Therefore, this study aims to investigate pedestrians' estimations of vehicle speed in natural settings, considering vehicle color, view distance, view lane, weather condition and view position.

### 1.3. Stopping distance estimation

The ability to accurately estimate a vehicle's stopping distance is important for making safe street-crossing decisions especially in emergent situations. Previous work on this topic is rare. Since pedestrians who underestimate the vehicle stopping distance especially in emergent situations may encounter more danger while crossing streets, this study tries to find out during which condition pedestrians would underestimate the stopping distance. Similar to the speed estimation survey, the following factors would be incorporated into current work to investigate their effects on stopping distance estimation: vehicle color, view lane, weather condition and view position.

In this study, a field survey using a simulated street-crossing process was carried out to investigate the estimation of vehicle speed and stopping distance by pedestrians. On the basis of previous work and perception theory, some factors, including weather, view distance and vehicle color, were taken into account to explore their effects on estimation bias.

## 2. Method

### 2.1. Participants

There were forty-four participants with an equal number of men and women, ranging from age 18 to 45 years old (Sample Mean = 24.36 years.). The age group of 18 to 45 years old was chosen for two reasons. For one thing, this (18, 45) age group covered the age range of main road users (see [Zhuang and Wu \(2011\)](#)'s observation/survey of pedestrian age) and accounted for almost 60% of global road traffic deaths ([World Health Organization, 2013](#)). For another thing, to get well validated data in the real setting, the current study conducted the outdoor experiment. As a result, it was hard to recruit children and old pedestrians to take part in our field study for various reasons (e.g. worry about safety).

Twelve participants had driver licenses, while others were regular road users without a driver's license. All participants were in good health and had normal sight.

### 2.2. Experiment location

Two sites with steady oncoming traffic and clear visibility for participants were selected in Beijing to collect data. The first site is near a university, with a crossroad nearly 500 m upstream from the study location. The second site faces an office building with a crossroad nearly 250 m downstream from the study location. Both of the two roads are in midblock and have a speed limit of 70 km/h. The width of each vehicle lane is 3.5 m. The pedestrian flow is busy particularly at noon and 5 o'clock in the afternoon. [Fig. 1](#) shows the sketch of the site to measure the estimation of the vehicle speed and stopping distance. Both sites are two-way roads with two lanes on each side and have crosswalks without traffic lights. Pedestrians individually have to judge whether the gap is safe between oncoming vehicles while crossing the street. Pedestrian crossing was observed at the starting point of the crosswalk.

### 2.3. Apparatus and materials

A Bushnell 10–1921 radar gun, with an accuracy of  $\pm 1.6$  km/h, was used to measure actual vehicle speed. The radar gun was in disguise so that it would not be discovered directly by the drivers. Two synchronized cameras were used in this experiment. One camera was set up near the pedestrian to record pedestrians' performance and target vehicles' information. The other camera was set up behind the speed gun to collect speed data (see [Fig. 1](#)).

Two estimation points were chosen according to prior experiments to investigate the effects of the view distance on the speed estimation. The far point was defined as being 90 m away from the observation site and the near point defined as 50 m away from the observation site. In terms of emergent condition security, the distance of 90 m is far enough and safe enough, so it was not necessary or particularly useful to estimate the stopping distance for this far point. Hence the stopping distance estimation was only conducted at the near point.

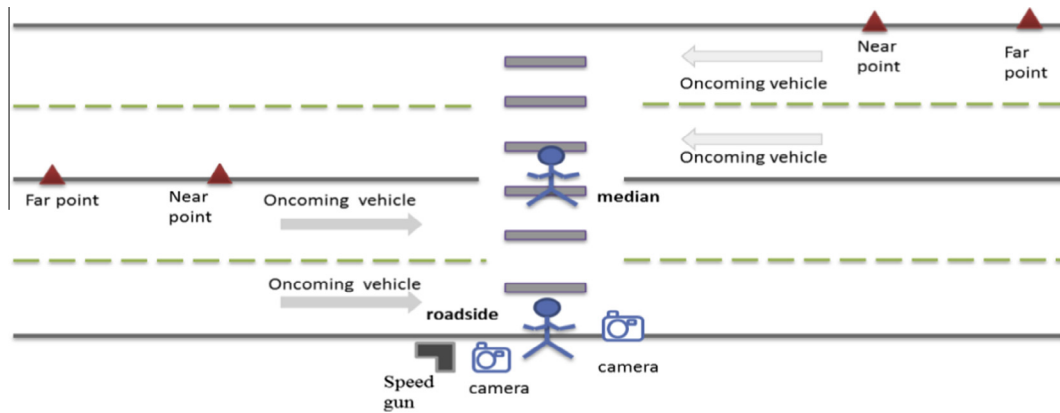


Fig. 1. The sketch of the site to measure the estimation of the vehicle speed and stopping distance in a naturalistic traffic environment.

Foam boards printed with different numbers were used to mark the estimation points and measure pedestrian's estimation of stopping distance. Fig. 2 gives an overall view of the distribution of foam boards. The board with a "0" printed on it represented the 90 m estimating point while the board with a "1" represented the 50 m estimating point. The remaining boards were divided equally in 5 m steps for 50 m.

Five factors were included to investigate their effects on speed estimation and stopping distance estimation. With the exception of the view distance (50 m and 90 m), lane and view position were manipulated with two levels of lane (near side and far side) and two levels of view position (roadside and median). The weather (sunny or rainy) and vehicle color were recorded as control variables, too. In accordance with previous research, the vehicle colors were divided into two levels: the bright color included white, silver, red and yellow, and the dark color including blue, green, brown, gray, purple and black (Cherry & Andrade, 2001).

#### 2.4. Procedure

There were many uncertainties and constraints in this field survey, thus it was difficult to carry out the experiment with strict control. However, we tried to control as many variables as possible on the basis of natural observation. To simulate the street-crossing process, each participant needed to complete equal estimating task at two different positions. The first view position is on the roadside and the second view position is in the middle of the road (the traffic island). Considering experiment safety, the participants do not need really cross the street before or after the estimation task. Only after participants completed their estimation tasks at the road side, can they begin the estimation on the traffic island. Each view position contained three tasks: speed estimation at 90 m, speed estimation at 50 m and stopping distance estimation at 50 m. The three parts in one position were carried out in a random order between participants. The number of vehicles being estimated between different levels of each variable was controlled to be equal to the greatest extent.

Two well-trained experimenters were recruited to conduct the experiment. Before the formal test, the experimenters received 3-day systematic training in this study: First, they were trained to use the radar gun, including how to hold it, which buttons to press, and how to read its readings. Second, after learning the usage of the speed gun, the experimenters kept practicing together until they could collect the vehicle speed quickly and accurately. In the formal test, when the target vehicle was approaching, the main experimenter would provide the participant with detailed messages regarding the vehicle, including variables to be estimated (vehicle speed or stopping distance), estimation point, lane, vehicle type and color. Participants would continue watching the target vehicle and then verbally report (Scialfa, Guzy, Leibowitz, Garvey, & Tyrrell, 1991) its speed or stopping distance as quickly as possible the moment the vehicle travelled through the estimation point.<sup>1</sup> For reporting estimating value of stopping distance, participants were instead asked to visualize where the vehicle would stop if the driver suddenly pressed down hard on the brakes at the estimation point and use the number printed on the boards to mark the stopping point. The data reported by participants and detailed messages of the target vehicle would be recorded in a table immediately by the main experimenter. The assistant experimenter recorded the target vehicle's actual speed measured by the radar gun. Participants could not see the actual speed so that the feedback of estimating accuracy could be prevented.

The actual stopping distance was calculated by the following equation (Wu, 2010):

$$S = \frac{k(v^2 - 0.5\phi g t/k)^2}{\phi g} \quad (1)$$

<sup>1</sup> This method is adapted from another study in driving behavior research field (Scialfa et al., 1991). In the study, drivers were asked to verbally estimate speed of vehicles that are running on an automotive test track.

where  $S$  is the actual stopping distance,  $k$  is the braking torque/braking force function coefficient,  $v$  is the actual vehicle speed,  $\varphi$  is the tire/road interface coefficient of adhesion, and  $g$  is the gravitational acceleration (Eskandarian & Delaigue, 2004; Wu, 2010).

### 3. Results

This section included two parts: speed estimation results and stopping distance estimation results. For each part, a descriptive analysis of the observation was conducted, followed by analysis of the contributing factors on estimation bias. More specifically, important factors derived from a stepwise regression were analyzed in detail on how the factors and their interactions influenced estimation bias.

#### 3.1. Speed estimation

##### 3.1.1. Descriptive analysis

The observation covered 1043 vehicles in total, and remained 1032 cases after removing cases with extreme estimations bias (outside three standard deviations). The following Table 1 shows the characteristics of the sample. In Table 1, all speed related variables have the unit “kilometer per hour”, and view distance has the unit “meter”. Most observations (83.2%) were conducted on sunny days due to the natural climate in Beijing. The data were balanced in terms of vehicle lane, view position, and view distance. However, 7.1% of the observations missed the vehicle color due to high demands on the recorder. The average actual speed was 47 km/h, discretized into nine levels that would be used for later analysis. Estimated speed was generally lower (42 km/h), resulting in an average underestimation of 5.4 km/h.

##### 3.1.2. Stepwise regression of speed perception bias and its predictors

The underestimation of vehicle speed may lead to risky and dangerous decisions in crossing the street. This section aims to find factors related to pedestrian judgment and finally identify factors contributing to the misjudgment. To this end, a correlation was conducted after transforming the categorical variables into dummy variables. The results can be seen in Table 2.

In Table 2, speed estimation bias is positively correlated with actual speed ( $r = .359, p < .001$ ) but has a negative correlation with median position ( $r = -.066, p < .05$ ). This means that participants estimated speed more accurately when they stood at the median but less accurately when the vehicle speed was higher. Since the other factors also have significant correlation (e.g. vehicle color and actual speed), stepwise regression was conducted to identify the important predictors of speed estimation bias (see Table 3). The analyses result show that the linear relationship between dependent variable and independent variables is significant ( $F = 77.460, p < 0.001$ ), representing that it is proper to build the linear model. In

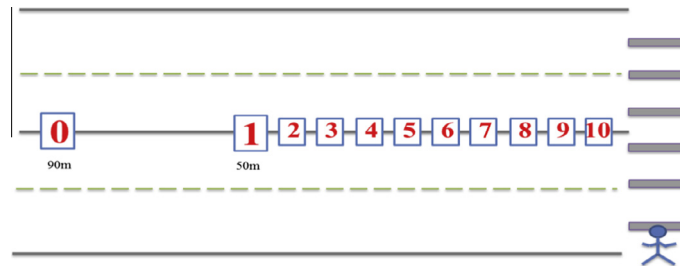


Fig. 2. The distribution of the foam boards while conducting stopping distance estimation experiment in a naturalistic traffic environment.

Table 1

Descriptive statistics for speed estimation observations.

Variable	Level	N	Variable	Level	N	Variable	Mean	Std. Dev
Weather	Rainy	173	Actual speed level (km/h)	$\leq 30$	38	Actual speed	46.99	8.95
	Sunny	859		(30, 35]	71	Estimated speed	41.59	11.59
Vehicle color	Bright	428	(35, 40]	134	Speed estimation bias <sup>a</sup>	5.40	11.24	
	Dark	531	(40, 45]	196				
Vehicle lane	Far	513	(45, 50]	243				
	Near	519	(50, 55]	177				
View position	Roadside	506	(55, 60]	107				
	Median	526	(60, 65]	43				
View distance	50	528	>65	23				
	90	504						

<sup>a</sup> Speed estimation bias = actual speed – estimated speed. It represents the accuracy of the speed estimation made by pedestrians.

addition, the value of tolerance is close to 1 and the VIF is very small (Tolerance = 0.99, VIF = 1.001), representing no collinearity between the independent variables. Hence, the current data satisfy the criteria needed for using stepwise regression.

In Table 3, only the actual speed and weather entered the final regression function. These two factors had a significant linear relationship with speed estimation bias,  $F(2, 956) = 77.5$ ,  $p < .001$ , accounting for 13.8% of the total variation. Since the constant is significantly lower than zero, it can be deduced that both accurate and inaccurate estimations existed in the speed judgment process. The speed-estimation equation provided by the stepwise regression was used to derive the accurate estimation speed. On sunny days, participants accurately estimated vehicle speed around 34 km/h, while on rainy days the estimated speed increased to 39 km/h.

In order to get the speed range of accurate and inaccurate estimations, actual speed was divided into 9 groups with an increment of 5 km/h. On rainy days, the sample sizes for some groups were small (<10), so they were merged into nearby groups iteratively. As shown in Fig. 3, on sunny days, people accurately estimated vehicle speed when speeds were not faster than 40 km/h with  $t_s < 1.78$ ,  $p_s > .08$ . When actual speed was larger than 40 km/h, pedestrians greatly underestimated speed  $t_s > 3.31$ ,  $p_s < .01$ . On rainy days, the trend was different. When vehicle speed was lower than 35 km/h, it was estimated to be

**Table 2**  
Correlation among speed estimation bias and other variables.

Variables	Speed estimation bias	Actual speed	View distance	Far_lane	Median	Rainy
Actual speed	.359**					
View distance	-.015	.045				
Far_lane <sup>a</sup>	.025	-.032	.010			
Median	-.066*	-.007	.003	.002		
Rainy	-.036	.029	-.013	<.0001	-.004	
Dark	.052	.104**	-.024	-.040	-.037	.030

\*  $p < .05$ .

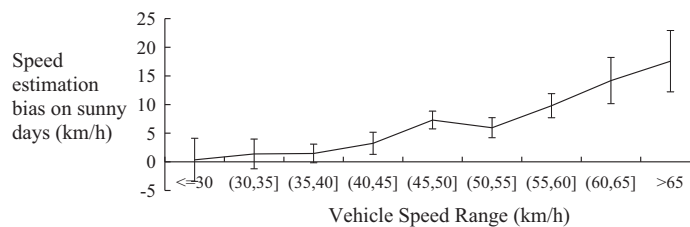
\*\*  $p < .01$  level.

<sup>a</sup> The categorical variables were recoded into dummy variables. For instance, vehicle lane was coded into 1 if in the far lane, and 0 if in the near lane. Therefore, the table only presents "Far\_lane" relative to "Near\_lane". Other variables were processed similarly.

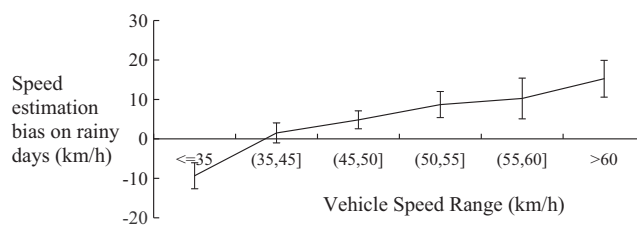
**Table 3**  
Stepwise regression of speed estimation bias and contextual predictors.

Variables	Coefficients	Std. coefficients	<i>t</i>	<i>p</i>	$\Delta R^2$
(Constant)	-16.10		-8.89	<.0001	
Actual speed	.47	.37	12.29	<.0001	.134
Rainy	-2.17	-.07	-2.39	.017	.005

Adjusted  $R^2 = .138$ .



(a) Speed estimation bias on sunny days



(b) Speed estimation bias on rainy days

**Fig. 3.** Relationship of speed estimation bias and actual speed. Error bars represent a 95% confidence interval of estimation bias.

higher,  $t_{16} = -6.02$ ,  $p < .001$ . On the contrary, people underestimated vehicle speed when it was larger than 45 km/h,  $t_s > 4.28$ ,  $p_s < .001$ . The range of accurate estimation was smaller on rainy days than that of sunny days: people had accurate estimations in the range (35, 45],  $t_{49} = 1.19$ ,  $p = .24$ . Considering the speed distribution of the observed vehicles, on sunny days, people accurately estimated 25.5% of the vehicles, while they underestimated 74.5% of them. On rainy days, the speed of 28.9% of the vehicles was estimated accurately while 61.3% were underestimated. The unique phenomenon on rainy days was that people overestimated 9.8% of the speeds of the vehicles.

### 3.2. Stopping distance estimation

#### 3.2.1. Descriptive analysis

The stopping distance estimation covered 872 vehicles, most observed on sunny days (85.0%), as were the speed estimation observations. In Table 4, the stopping distance estimation bias (in short, stop distance estimation bias) is the result of the actual stopping distance minus the perceived stopping distance. Table 4 shows that stopping distance estimation bias had a negative value (−5.16 m), indicating that people generally overestimated vehicles stopping distances.

#### 3.2.2. Stepwise regression of stopping distance estimation bias and its predictors

In emergent situations, underestimation of stopping distance is dangerous to pedestrians trying to cross before drivers. Therefore, this section aims to figure out the factors that lead to underestimation. Similar to the analysis of speed estimation bias, a correlation was first conducted. The result is shown in the following Table 5.

Table 5 shows a positive correlation with vehicle speed and stop distance estimation bias ( $r = .283$ ,  $p < .01$ ), meaning that people were more likely to underestimate stopping distance when the vehicle speed was higher. The predictors also had significant correlations within themselves, like vehicle color and vehicle lane. Therefore, stepwise regression was adopted to figure out the most important predictors. The analyses result show that the linear relationship between dependent variable and independent variables is significant ( $F = 66.39$ ,  $p < 0.001$ ), representing that it is proper to build the linear model. In

**Table 4**  
Descriptive statistics of stopping distance related variables.

Variable	Level	N	Variable	Level	N	Variable	Mean	Std. Dev
Weather	Rainy	131	Actual speed level	≤30	39	Actual speed	45.95	9.45
	Sunny	741		(30,35]	67	Estimated stop distance	22.05	8.76
Vehicle color	Bright	375		(35,40]	101	Actual stop distance	16.89	6.55
	Dark	451		(40,45]	203	Stop distance estimation bias <sup>a</sup>	−5.16	9.02
Vehicle lane	Far	429		(45,50]	195			
	Near	443		(50,55]	133			
View position	Roadside	418		(55,60]	85			
	Median	454		(60,65]	29			
				>65	20			

<sup>a</sup> Stop distance estimation bias is calculated by actual stopping distance minus estimated stopping distance, representing the accuracy of the stopping distance estimation made by pedestrians.

**Table 5**  
Correlation among stopping distance estimation bias and other variables.

Variable	Stop distance estimation bias	Actual speed	Far_lane	Median	Rainy
Actual speed	.283**				
Far_lane <sup>a</sup>	.036	−.039			
Median	.032	−.111**	−.008		
Rainy	.019	.008	−.016	−.024	
Dark	.063	.080*	−.101**	.019	.037

\*  $p < .05$ .

\*\*  $p < .01$  level.

<sup>a</sup> The categorical variables were recoded into dummy variables. For instance, vehicle lane was coded into 1 if in the far lane, and 0 if in the near lane. Therefore, the table only presents “Far\_lane” relative to “Near\_lane”. Other variables were processed similarly.

**Table 6**  
Stepwise regression of stopping stop distance estimation bias and contextual variables.

Variables entered	Coefficients	Std. coefficients	t	Sig.	$\Delta R^2$
(Constant)	−20.591		−11.642	0	
Actual speed	0.305	0.273	8.148	0	0.075

Adjusted  $R^2 = .073$ .

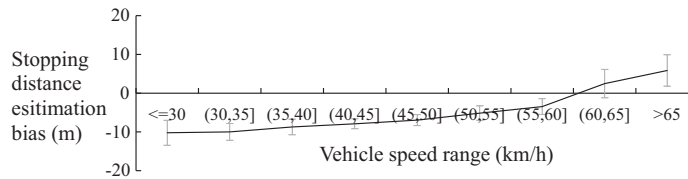


Fig. 4. Stopping distance estimation bias in different vehicle speed ranges.

addition, the value of tolerance is 1 and the VIF is very small (Tolerance = 1, VIF = 1), representing no collinearity between the independent variables. Hence, the current data satisfy the criteria needed for using stepwise regression.

Table 6 shows the regression results. Only one variable was a significant predictor of stopping distance estimation bias: actual speed. It had a significant linear relationship with the stopping distance estimation bias,  $F(1, 824) = 66.39$ ,  $p < .001$  and accounts for 7.3% of the total variation (adjusted  $R^2 = .073$ ).

Similar to the previous analysis of accurate and inaccurate speed estimation ranges, vehicle speed was split into groups with a speed increment of 5 km/h. The following Fig. 4 shows the relationship of stopping distance estimation bias and the final speed groups. *T*-test shows that only in the group (60, 65] km/h, people had relatively accurate estimations, where  $t_{28} = 1.37$ , and  $p = .18$ . When vehicle speeds were lower than this range, participants were likely to overestimate the stopping distance, where  $ts < -3.4$ , and  $ps < .01$ . On the contrary, people underestimated stopping distances when vehicles had speeds higher than 65 km/h,  $t_{19} = 3.05$ ,  $p < .01$ . Considering that the observed vehicles whose speeds fell within the range (60, 65] km/h and over 65 km/h only constituted 3.3% and 2.3% (respectively) of the entire sample, which were small percentages, people generally overestimated the vehicle stopping distances.

#### 4. Discussion

This study aimed to first investigate a pedestrian's ability to estimate vehicle speed and stopping distance while crossing the street, and then figure out what factors relate to that ability to estimate. From this study, we found that actual vehicle speed significantly related with both the speed and stopping distance estimations. In addition, the weather conditions entered the final speed estimation regression equation probably show a significant linear relationship with speed estimation bias. This section first discussed the indication of these findings, followed by their applications. Limitations due to field setting were also discussed.

Speed underestimation, which may lead to dangerous street-crossing decision-making, is prevalent in high end of the speed range. The speed estimation bias generally increases with the higher vehicle speed. More specifically, in sunny conditions, pedestrians underestimated vehicle speed when actual speed was in (40, 45] km/h group and the underestimation is more severe in groups with higher speed. In rainy conditions, however, people only begin to underestimate speed until it rises to (45, 50] km/h group, higher than that of the sunny days. Their accurately estimated speed range also shared the similar pattern: the speed range for rainy days was higher than that of the sunny days. At the lower range where the speed is less than 35 km/h, they even overestimated vehicle speed. Pedestrians' increased caution in rainy days may account for these results. It is more dangerous to cross road in rainy days. Pedestrians may become more conservative about available crossing chances, thus their criteria for estimating speed may decreased, resulting in an offset to higher estimation in rainy days. In fact, in the regression function, the coefficient of "rainy" is  $-2.17$ , indicating the existence of the offset as compared with sunny days.

In stopping distance estimation analyses, similar to the speed estimation, there is an accurate estimation interval range from 60 to 65 km/h. When vehicles travel over 65 km/h, pedestrians generally underestimate stopping distances, leading to more dangerous crossing decisions especially in emergent situations. Nonetheless, not so many vehicles travel at a speed greater than 65 km/h on urban roads, and pedestrians who are urgent to cross the road will walk fast, which to some extent increases the safety margin. Hence the probability of being hit by a car in an emergent condition is not high. Besides the vehicle speed and weather condition, there are no other considered factors, including vehicle color, vehicle lane, view position, that seem to significantly affect the speed estimation. In regards to the stopping distance, only vehicle speed appears to have a significant effect on its estimation. These findings have practical applications in guiding road design and implications for further research aimed at improving pedestrian security. In streets with high pedestrian volume, the speed limit on roads should be within the range of pedestrians' accurate estimations or overestimations. Regardless of the weather, this should be less than 45 km/h. The current work offers some ideas for developing an apparatus for a pedestrian assistant system aimed at helping pedestrians making safe crossing decisions by detecting the speed of oncoming vehicles, and giving a warning if the vehicle speeds exceed the safety threshold. The safety threshold we assumed was integrated by a pedestrian's walking speed, personal estimating ability, the distance between the pedestrian and an oncoming vehicle, and other related factors. It is also helpful for developing further training programs aimed at improving pedestrian's street-crossing security. The ability to estimate and integrate speed and distance information of the oncoming vehicles is one of the key components of safe street-crossing (Oxley et al., 2005). By doing estimating training exercises, people may perform better at speed estimation and stopping distance estimation.



The findings also have theoretical implications for future work. In previous studies on pedestrian decision making (e.g. gap acceptance (Yannis et al., 2013), a pedestrian behavior model (Zhuang & Wu, 2013)) used vehicle speed as pedestrians' perceived speed, which is inaccurate according to our findings.

Although this study was conducted on urban streets with crosswalks, the results may be available in the study of the unmarked road crossing behavior too. At unmarked roadways, people tend to cross the street positively and tentatively, instead of waiting for certain safe gaps on the roadside (Zhuang & Wu, 2011). In some conditions, yielding vehicles may cause more danger when pedestrians cross unmarked roads (Zhuang & Wu, 2012). To ensure road-crossing security, unmarked roadway crossing behaviors require more interactions with approaching vehicles. Therefore, it is more important for people to estimate the vehicle speed and stopping distance accurately.

In vehicle speed estimation analyses, the present study not only confirms part of the findings of the indoor experiment (Troscianko et al., 1999) but also goes further to show a significant underestimation of speed when a vehicle travels beyond the speed threshold. In sunny conditions, the speed interval of underestimating is higher than 40 km/h. In rainy conditions, the interval is higher than 45 km/h. Different from results of the observation study completed by Cherry and Andrade (2001), but similar to the experiment conducted by Troscianko et al. (1999), no significant effect of color was found in the current work.

Oxley et al. (2005) found that people choose gaps to cross mainly based on the vehicle distance rather than the vehicle arrival time (in other words, the vehicle speed). According to the results in this study, the cause of selecting gaps mainly based on distance may be not only the easier processing of the distance information, but also the growing underestimating bias with the increase in vehicle speed. The higher the vehicle speed is, the bigger the underestimation bias will be. In other words, the difference between two vehicle speeds perceived by the pedestrian is not noticeable.

There are several limitations in this work that need further investigation. First of all, due to the natural climate of Beijing (lack of rain), it is difficult to collect equal data on rainy days compared with sunny days. Thus the weather effects on speed and stopping distance estimation may not get full expression. This may partly be the reason why weather condition did not have a significant effect on stopping distance estimation. Second, this study was only conducted during the daytime, leaving dark estimation not considered. Compared with the daytime estimation, the dark estimation ability of pedestrians is more important and useful as the poor light at night may cause more traffic accidents. Thirdly, all of the participants were adults aging 18–45 years old, excluding children and the elderly from our sample. Since the ability of estimating vehicle speed changes during one's life span, age needs to be taken into consideration as one of the variables to get a comprehensive understanding and more generalizable findings on the issue. Finally, the regression results of the speed estimation and the stopping distance estimation analyses had a small explanation ratio to the total variation. It may be attributed to the peculiarity of this study. This study is not lab-based study. In order to collect data in real scene, we had almost no control on the experiment except manipulating the view distance and the way to report the estimating value. Therefore, we are not able to measure those factors that cannot be seen directly in this study, such as participants' personality, risk perception, visual acuity. These potential factors may have effects on pedestrians' speed estimation and stopping distance estimation. Hence, to further explore the speed and stopping distance estimation, more factors should be considered in future studies. As the results in this study show, vehicle speeds estimated by pedestrians are different from actual vehicle speeds, but their relationships remain unknown. In future studies, the question about what the relation between the estimated speed and actual speed is can be further studied.

In conclusion, pedestrians have accurate estimation intervals in different weather conditions. When the speed of the oncoming vehicle exceeds the upper bound of the accurate interval, pedestrians are more likely to underestimate the vehicle speed, increasing their risk of incorrectly deciding to cross when it is not safe to do so.

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