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Investigating Contributing Factors of Hard-Braking Events on Urban Road Network

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Abstract. Hard-braking constitutes a critical surrogate measure of traffic safety on urban road networks. Efforts aiming to unveil the effects of contributing factors on the occurrence of hard-braking are inadequate. This study extracted the hard-braking event (HBE) and ordinary-braking event (OBE) by GPS trajectories from float cars. The effect of several factors on HBE was examined, including the factors of time, pre-braking behaviors, and road characteristics. The possibility of HBE was compared with that of OBE through binary logistic models (BLM). To further disclose the influence of factors, we considered the interaction between variables (BLM-VI) in modeling. The analysis results indicate that the BLM-VI is superior to the classical BLM in goodness-of-fit and factor interpretation. For the factors, peak hours on weekdays and daytime on weekends are positively linked to HBE, while driving at night is not. HBEs can be triggered by pre-braking behaviors such as speeding and approaching an intersection, but it is not likely to occur after changing lanes. Roads with work zones or intensive accesses can decrease the possibility of HBE. The factors of on-road parking, median divider, and one-way control have mixed effects on HBE when they interact with the factor of speed limits.

Keywords: Hard-braking event · Contributing factors · Urban road networks · Binary logistic model · Variable interaction

1 Introduction

Brake is a common reaction for drivers to obey the traffic controls or avoid incidents on-road. Among the braking behaviors, those whose decelerative velocity is extremely large are called hard-braking/harsh-braking. Hard-braking can indicate drivers strive to dodge a critical event involved or minimize its damage if it is inevitable [1]. As such, hard-braking typically serves as a kinematic indicator or surrogate measure of incidents in the urban area, such as conflict, crash, etc. [2, 3], and is widely used by the insurance industry [4].

Hard-braking tends to be triggered by both subjective and objective reasons. In some cases, hard-braking can be related to the lack of alert. For instance, past studies

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revealed that hard-braking is associated with distracted driving [5], driving at high speed [1], and miscalculating the speed of the following vehicle [6]. For other cases, hard-braking is likely to be found in scenarios with safety risks that are inclined to be ignored. These scenarios contain driving on downhill roads, approaching an intersection, and dazzling due to sunlight in the daytime [7–9]. Due to these reasons, drivers usually have difficulties slowing down in advance of critical events because the response time-to-brake is increased [10].

Recent studies highlighted the effects of road characteristics on hard-braking. They suggested hard-braking is likely to be found on longer roads, secondary roads, and roundabouts with wide entries [2, 9]. However, their conclusions are limited in two aspects. First, nearly all of them focus on hard-braking frequency, while they failed to use an exposure (such as traffic flow) or adopt a categorical response to evaluate the actual hard-braking risk across scenarios. Second, considering the complexity of road networks, there are still factors of many kinds that need to be examined. Fortunately, naturalistic driving data have been used to extract braking behaviors [1, 7, 8], which would be inspired to fill the gaps above.

According to the review, we found several knowledge gaps among the analyses of hard-braking. Hereby, this study is conducted to explore the effect of factors including time, vehicle maneuvers prior to the brake (pre-braking behaviors), and road characteristics on hard-braking in urban road networks. The current study justifies the validity of using a large amount of float car data to extract braking events. Moreover, this study finds several pre-braking behaviors and road characteristics that are significantly associated with hard-braking.

2 Materials and Methods

2.1 Process of Raw Data

In the current study, floating car data (FCD) were used. The FCD were recorded through the vehicular GPS devices installed in taxis [11]. These data include the GPS trajectories of 5,755 taxis with a frequency of 0.1 Hz, which were generated in November 2016 in Chengdu. We restricted the study area to a rectangular zone because the road and environmental characteristics had been previously collected (Fig. 1). Each GPS point was matched to its nearest road by a map-matching algorithm. The specific steps of the algorithm are listed as follows [12, 13].

1) Prepare the digital Geo-map within the study area, the map layers consist of boundary, road geometry, facilities, etc.;
2) Manually measure the coordinate of the centerline and the center point for each road and intersection, respectively;
3) Choose a floating car and extract its trajectories from the first GPS point recorded through the timestamp, then load these GPS points to the Geo-map;
4) Match the GPS points to their nearest road centerlines with an improved Euclidean distance;
5) Check the trend of driving angle of the adjacent GPS points to filter U-turn and wrong-way driving behaviors, then remove these GPS points.
6) Redo step 1) to step 6) with another floating car.

Fig. 1. Study area

2.2 Identification of Hard Braking Event

The braking events and hard-braking events are extracted from the FCD in the first two weeks of November (14 days). In order to minimize the possible error of identification, we deleted the FCD on curve segments. The identification steps of a braking event and hard braking event are given by:

1) First, select a pairwise point of adjacent GPS points generated by one vehicle. Note that the time interval of each pairwise of points is 10 s, which is determined by the frequency of the GPS device.
2) Record the instant speed of the start-point and the end-point of this pairwise point, respectively.
3) We assume that the vehicle movement between the two points is approximately close to uniformly accelerated motion so the accelerated velocity can therefore be calculated as

$$a_{m,m+1} = \frac{v_{m+1} - v_m}{t_{m,m+1}} \tag{1}$$

where $a_{m,m+1}$ is the accelerated velocity of the pairwise points $(m,\ m+1)$, v_{m+1} and v_m are the speed on point m (start-point) and point $m+1$ (end-point), respectively, $t_{m,m+1}$ is the difference of time between the two points.

4) The pairwise points whose accelerated velocity is <-0.2 g (g means the gravitational acceleration, i.e., $9.8\,\mathrm{m}/\mathrm{s}^2$) are defined as a hard braking event (HBE), while pairwise points whose accelerated velocity is $[-0.1$ g, -0.2 g$]$ are treated as an ordinary-braking event (OBE). Both HBE and OBE are sorted as braking events. Pairwise points whose accelerated velocity is $(-0.1$ g, 0 g$)$ are classified as slight slowdown rather than braking events.

The definition of HBE is achieved through the threshold of the accelerated velocity. However, such a threshold varies among the existing studies. Most studies defined the HBE with the threshold of [−0.75 g, −0.2 g], with the minimum acceptance of −0.2 g [14–16]. Botzer et al. [17] suggest a varying threshold of [−0.6 g, −0.2 g] due to the uncertainty of driving conditions. Here, we adopted a tolerable threshold of −0.2 g suggested by Olson et al. [16]. This is because the severe HBEs are quite rare in the current study area where is not associated with obvious changes in gradient.

Additionally, while the assumption of treating vehicle movement as uniformly accelerated motion may be problematic in reflecting the real-time path, it does not hamper the effectiveness of capturing HBE. Figure 2 presents the speed changes either set by our assumption or reflected by the actual movement. We provide several speed changes reflected by the possible actual paths (dash lines) for the study vehicle during the interval of the GPS record (10 s). For the threshold of −0.2 g that equals to the slope of the bold red line (assumption), no matter what the actual movement of the vehicle is, there will be at least one interval of the actual paths that has an accelerated velocity <−0.2 g (between the start-point and the end-point). In a sense, the assumption of uniformly accelerated motion can effectively capture the HBE during the interval of pairwise points, although not all the HBEs of a vehicle are fully recorded.

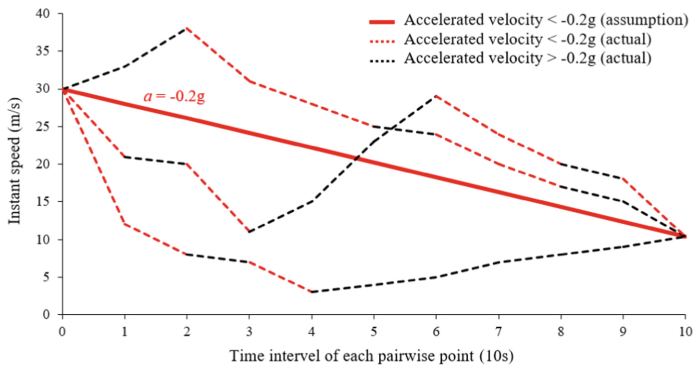

Fig. 2. The changes on vehicle speeds during the interval of the GPS record

The process of identification above is conducted to each float car through the plate number. Finally, the study recorded 12,424 HBEs and 344,823 OBEs extracted from the float cars during the study period.

2.3 The Measure of Potential Factors

Factors of time, driving behavior, traffic conditions, and road characteristics are associated with risky events such as crashes, speeding, conflicts, etc. [18–20], thus are considered in this study. All factors are processed to be categorical variables. Table 1 lists the description of these key factors.

2.4 Statistical Methods

This study aims to examine the effect of factors on triggering HBEs compared with OBE. To this end, we used a binary logistic model (BLM) to measure the effect of factors on HBE risk. In the binary logistic model, whether a braking event is HBE was selected as dependent variables. Besides, we also examined the interaction between categorical independent variables through a binary logit model with variable interaction (BLM-VI) to prevent any biased estimation. Note that the BLM and BLM-VI only include the variables with variance inflation factor (VIF) <5.

Table 1. Description and explanation of key factors

Type	Factor	Explanation
Time	Time of day	Whether the HBE.OBE occurs on daytime (=0), peak hours (=1), or at night (=2)
	Weekend	Whether the HBE/OBE occurs on weekend (=0 if no and = 1 if yes)
Pre-braking behavior	Speeding	Speeding before an HBE/OBE (=0 if no and = 1 if yes)
	Lane-changing	Chang lanes or steer before an HBE/OBE (=0 if no and = 1 if yes)
	Approaching an intersection	The distance between an HBE/OBE and an intersection is less than 30 m (=0 if no and = 1 if yes)
Road characteristics	Speed limit	The posted speed limit of the road where an HBE/OBE occurs (=0 if ≥ 60 km/h, = 1 if 30–60 km/h, = 2 if ≤ 30 km/h)
	Work zone	HBE/OBE is located nearby a work zone (=0 if no and = 1 if yes)
	One-way control	HBE/OBE occurs on a road with one-way control (=0 if no and = 1 if yes)
	On-road parking	HBE/OBE occurs on a road where on-road parking is observed (=0 if no and = 1 if yes)
	Median divider	HBE/OBE occurs on a road with median divider (=0 if no and = 1 if yes)
	Accesses per km	The number of accesses per each kilometer on the road where an HBE/OBE occurs (=0 if ≤ 10, = 1 if 10–13.5, = 2 if ≥ 17)

3 Results and Discussions

3.1 Estimates of Contributing Factors of HBE

Table 2 lists the estimates and goodness-of-fit of BLM and BLM-VI. The factor of speeding is eliminated from BLM since it is severely multicollinear with the factor of speed limits. The results show that driving at night ($\beta = -0.643$), implementing lane-changing maneuver ($\beta = -0.716$), roads with 10–13.5 accesses per km ($\beta = -0.111$) and $\geq$17 accesses per km ($\beta = -0.215$), and work zone ($\beta = -0.141$) significantly decrease the possibility of HBE. Conversely, approaching an intersection ($\beta = 0.292$), speed limits of 30–60 km/h ($\beta = 0.406$) and $\leq$30 km/h ($\beta = 1.231$), on-road parking ($\beta = 0.137$), and median divider ($\beta = 0.238$) significantly increase the possibility of HBE. It is also noticed that driving on-peak hours, roads with 13.5–17 accesses per km, and weekends are not significantly related to the occurrence of HBE.

It is noted that four factors that do not interact with others in both models show a similar trend in affecting HBEs. However, the remaining factors in BLM-VI are interactive and show discrepant signs and significance as compared with those in BLM. More specifically, estimates of BLM-VI indicate that peak hours on weekdays ($\beta = 0.091$) are positively associated with HBEs, while the effect of peak hours in BLM is insignificant overall. Speeding is removed in BLM due to multicollinearity. Conversely, it could be a good indicator in BLM-VI if this behavior occurs on roads with a speed limit of $\leq$30 km/h ($\beta = 1.039$) or $\geq$60 km/h ($\beta = 1.069$). On-road parking and median divider are positively associated with HBEs in BLM. However, on-road parking is only positively linked to HBEs on roads whose speed limit is <30 km/h ($\beta = 0.367$) or 30–60 km/h ($\beta = 0.179$), while median divider merely increases HBE risk on $\geq$60 km/h roads ($\beta = 0.337$). We also notice that one-way control, which is insignificant in BLM, has varied effects across the speed limits as estimated by BLM-VI ($\beta = -1.046$ for speed limits of <60 km/h, $\beta = -0.395$ for speed limits of 30–60 km/h and $\beta = 0.418$ otherwise). In addition to the difference of estimates, it shows that BLM-VI is superior to BLM in goodness-of-fit (7918 vs. 10,431 for AIC; −3,933 vs. −5,203 for log-likelihood). This justifies the necessity and benefit of accounting for variable interaction. As a result, we adopt the estimates of BLM-VI to interpret the contribution of factors.

Table 2. Estimation results of BLM and BLM-VI.

BLM			BLM-VI		
Variable	Mean (β)	S.D.	Variable	Mean (β)	S.D.
Intercept	−3.091*	0.025	Intercept	−3.176*	0.027
Time of day			Time of day × Weekend		
[peak hours]	0.037	0.025	[night] × [yes]	−0.573*	0.036
[night]	−0.643*	0.023	[peak hours] × [yes]	−0.017	0.044
[daytime]	0[a]	–	[daytime] × [yes]	0.065*	0.026

(*continued*)

Table 2. (*continued*)

BLM			BLM-VI		
Variable	Mean (β)	S.D.	Variable	Mean (β)	S.D.
–	–	–	[night] × [no]	−0.638*	0.028
–	–	–	[peak hours] × [no]	0.091*	0.03
–	–	–	[daytime] × [no]	0^a	–
Lane-changing			Lane-changing		
[yes]	−0.716*	0.02	[yes]	−0.677*	0.02
[no]	0^a	–	[no]	0^a	–
Speed limit			Speeding × Speed limit		
[30–60 km/h]	0.406*	0.029	[yes] × [≤30 km/h]	1.039*	0.048
[≤ 30 km/h]	1.231*	0.304	[yes] × [30–60 km/h]	−0.075	0.049
[≥ 60 km/h]	0^a	–	[yes] × [≥60 km/h]	1.069*	0.038
–	–	–	[no] × [≤30 km/h]	2.691*	0.066
–	–	–	[no] × [30–60 km/h]	1.516*	0.045
–	–	–	[no] × [≥60 km/h]	0^a	–
Approaching an intersection			Approaching an intersection		
[yes]	0.292*	0.024	[yes]	0.295*	0.024
[no]	0^a	–	[no]	0^a	–
On-road parking			On-road parking × Speed limit		
[yes]	0.137*	0.03	[yes] × [≤30 km/h]	0.367*	0.055
[no]	0^a	–	[yes] × [30–60 km/h]	0.179*	0.065
–	–	–	[yes] × [≥60 km/h]	−0.375*	0.055
–	–	–	[no] × [≤30 km/h]	0^a	–
–	–	–	[no] × [30–60 km/h]	0^a	–
–	–	–	[no] × [≥60 km/h]	0^a	–
Median divider			Median divider × Speed limit		
[yes]	0.238*	0.02	[yes] × [≤30 km/h]	−0.297*	0.089
[no]	0^a	–	[yes] × [30–60 km/h]	−0.205*	0.078
–	–	–	[yes] × [≥60 km/h]	0.337*	0.022
–	–	–	[no] × [≤30 km/h]	0^a	–
–	–	–	[no] × [30–60 km/h]	0^a	–
–	–	–	[no] × [≥60 km/h]	0^a	–
NA			One-way control × Speed limit		
–	–	–	[yes] × [≤30 km/h]	−1.046*	0.187
–	–	–	[yes] × [30–60 km/h]	−0.395*	0.106

(*continued*)

Table 2. (*continued*)

BLM			BLM-VI		
Variable	Mean (β)	S.D.	Variable	Mean (β)	S.D.
–	–	–	[yes] × [≥60 km/h]	0.418*	0.069
–	–	–	[no] × [≤30 km/h]	0[a]	–
–	–	–	[no] × [30–60 km/h]	0[a]	–
–	–	–	[no] × [≥60 km/h]	0[a]	–
Accesses per km			Accesses per km		
[10–13.5]	−0.111*	0.026	[10–13.5]	−0.261*	0.028
[13.5–17]	0.029	0.027	[13.5–17]	−0.04	0.028
[≥17]	−0.215*	0.027	[≥17]	−0.167*	0.026
[≤10]	0[a]	–	[≤10]	0[a]	–
Work zone			Work zone		
[yes]	−0.141*	0.04	[yes]	−0.082*	0.039
[no]	0[a]	–	[no]	0[a]	–
Log-likelihood	−5,203		−3,933		
AIC	10,431		7,918		

Note: * indicates the variable is significant at 95% confidence interval; [a] means the factor is set as reference so its coefficient equals to 0; NA means the variable is not available.

3.2 Explanation of Contributing Factors

For the effect of time-related factors, we found that peak hours on weekdays and daytime on weekends are associated with HBEs. The two periods usually have more traffic activities and larger traffic volumes, which could cause a higher risk of traffic incidents [21]. Conversely, driving at night tends to encounter fewer incidents and experience better traffic conditions, consequently reducing the HBE risk.

With respect to the pre-braking behaviors, lane-changing maneuver requires the vehicle to move slower and carefully steer to the target lane, which is not likely to encounter a sudden brake. Speeding, as expected, can trigger HBEs. This is attributed to the drivers could have difficulties responding fast while speeding and need to implement emergency brakes if an unexpected incident occurs [22]. Note that speeding on roads with a 30–60 km/h speed limit is not linked to HBEs, which may be that fewer incidents are found on these roads. Drivers who approach an intersection are more likely to encounter HBEs, possibly owing to the situation that drivers are unaware of the forthcoming change on the signal phase when they are about the get across the intersection [23].

Interestingly, speed limits interact with several road characteristics and yield mixed effects on HBEs. A reasonable explanation is that these characteristics have varied functions across the road class. Therefore, for the factor of on-road parking, moving vehicles are more easily affected by vehicles entering/leaving a parking space set on secondary or branch roads that have fewer available lanes, increasing HBE risk on roads with lower speed limits as well. Median divider and one-way control could raise the travel speed so they may be more likely to cause HBEs on arterial roads where rear-end conflicts are common [24]. The findings also show that access density and work zone are associated with lower HBE risk, which implies that the factors can decrease the vehicle speed and eventually hamper the occurrence of HBE.

4 Conclusion

Hard-braking events are usually related to safety incidents thus serve as surrogate measures. Our study investigated the effect of factors including time, road design, and pre-braking behavior on HBEs in urban areas. The effect of contributing factors is explored by binary logistic models with variable interaction.

Results demonstrate that HBEs tend to occur at the daytime on weekends and peak hours on weekdays, while is less likely found at night. Speeding on roads with a speed limit of ≤30 km/h or ≥60 km/h and approaching an intersection can trigger HBEs, yet changing lanes prior to the brake does not lead to an HBE. On-road parking tend to cause HBEs on roads with lower speed limits (<60 km/h); Median divider and one-way control are associated with the occurrence of HBE if the corresponding roads have a speed limit of ≥60 km/h. Also, HBE risk reduces as the roads are observed with intensive accesses or work zone. We also highlight the consideration of variable interaction in modeling harsh driving behaviors to obtain a robust estimation.

There are two limitations that need to be further revised. First, the modeling approach can be extended with random effects/parameters approaches which are able to capture unobserved heterogeneity [25–27]. Second, the driver's socio-demographic information, enforcement, and underlying spatial-temporal effects can be combined to extend the modeling approach [28–30]. Also, we recommended that countermeasures such as warning system can be used to restrict harsh driving behaviors [31].

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