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Analysis of cut-in behavior based on naturalistic driving data

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ABSTRACT

Cut-in maneuvers, when vehicles change lane and move closely in front of a vehicle in the adjacent lane, are very common but adversely affect roadway capacity and traffic safety. Yet little research has comprehensively explored cut-in behavior, particularly in China, which has a challenging driving environment and is often used for connected and autonomous vehicle testing. This study developed an extraction algorithm to retrieve 5608 cut-in events from the Shanghai Naturalistic Driving Study. The data were used to identify cut-in characteristics, including motivation, turn signal usage, duration, urgency, and impact. Results showed that almost half of drivers did not use a turn signal when cutting in, and that cut-ins had a shorter time to collision (TTC) than other lane changing. A lognormal distribution was found to produce the best fit for cut-in duration, which varied from 0.7 s to 12.4 s. As characteristics were found to vary by roadway type and motivation, multilevel mixed-effects linear models were developed to examine the influencing factors of cut-in gap acceptance. Acceptance of lead and lag gaps was significantly affected by environmental variables, vehicle type, and kinematic parameters, which has important implications for microsimulation, as does the large variance in duration that makes specifying duration essential when setting scenarios. Improvement in safety education is warranted by the high degrees of risk and aggression shown by TTC and turn signal usage; but the ability of drivers, who needed to yield to the cut-in, to predict danger and adopt safe, suitable, and timely strategies suggests that advanced driver assistance systems and connected and autonomous vehicles can learn similar responses.

1. Introduction

Lane change maneuvers are common on the road, but studies have shown that lane changing tends to cause negative shockwaves (i.e., one car brakes so others must subsequently brake) (Cassidy and Bertini, 1999). Cut-ins, in which lane-changing vehicles move into the space ahead of a relatively closely following vehicle in the adjacent lane, are potentially dangerous and may lead to traffic collisions. Improper lane changes, including overtaking and unsafe cut-ins, account for 4.9% of all 2015 crashes in China (Traffic Management Bureau of the Public Security Ministry, 2016); and in the U.S., unsafe lane changes and merge maneuvers account for approximately 5% of all crashes and 7% of all crash fatalities (Hou et al., 2015). Analyzing cut-in behavior is therefore important for safety studies, but is also valuable for other applications such as roadway capacity modeling (Zhou and Peng, 2015).

Cut-ins are dangerous because they unpredictably change the safety gap between vehicles. This effect on the safety gap additionally causes interference to advanced driver assistance systems (ADAS) and connected and autonomous vehicles (CAVs) (Dou et al., 2016; Casner et al., 2016). A following vehicle equipped with ADAS, or with partially automated driving (SAE's Level 2), must adjust its following gap in response to the cut-in, resulting in unnecessary and often emergency acceleration and braking that contribute not only to wasted fuel and emissions, but also to traffic waves which worsen the situation further (Sultan et al., 2002). Cut-in behavior is one reason why advanced technologies such as ADAS need to be tested in various complicated situations before going into mass production (Bazilinskyy et al., 2015).

Since the first lane change model was proposed by Gipps (1986), researchers in developed countries have devoted substantial effort to investigating and modeling lane change characteristics. Several comprehensive examinations of lane changing have been conducted in the U.S. since the 1990s (Olsen et al., 2002; Lee et al., 2004; Chen et al., 2015), and their insight into the behaviors and parameters associated with lane changes (Olsen et al., 2002) have been applied to driving simulation systems, which have since been commonly used for the further study of lane change and other driving behaviors. However, while it is well known that China's traffic systems have developed

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rapidly during recent years, few studies of driving behavior have analyzed lane change maneuvers in China due to limited data collection methods. As a result, most simulation models are based on western research, where the cultural environment, including driving style, vehicle type, and traffic regulations, may differ from that of developing countries (Lindgren et al., 2008). Chinese drivers face, for example, a challenging driving environment of omnipresent pedestrians, electric bikes, bicycles, aggressive drivers, and, indeed, frequent lane changes, which are performed nearly three times more often than in the U.S. (Wang and Li, 2016). In addition to the possible unsuitability of simulation models, some ADAS and CAV functions may also not be suitable in China, as their algorithms and strategies are calibrated and tested using data from other nations; consequently, their functions may be inefficient or unreliable when the vehicle faces an abrupt cut-in from an adjacent lane. The increased popularity of CAV testing in China increases the requirement for more effective and robust advanced traffic technologies appropriate to China.

To better address this need, real-world driving data were collected through the Shanghai Naturalistic Driving Study (SH-NDS). NDS has been shown to offer a new and complementary approach to existing methods for understanding driving behavior in normal, impaired, and safety-critical situations (Regan et al., 2012). The SH-NDS data collection started in December 2012 and ended in December 2015, during which 60 licensed drivers travelled a total of approximately 161,055 km (Zhu et al., 2017). Using the SH-NDS's significant quantity of Chinese driving data, this study comprehensively explores cut-in behavior, including comparing Chinese and U.S. cut-in behavior, for the purpose of contributing to the international development of lane change theory and its various applications, including traffic simulation, ADAS, and CAV.

2. Literature review

Few studies have focused on cut-in characteristics specifically, and those have addressed a limited number of characteristics, mostly for practical application. To explore the following distances at which cut-in events occur, for example, Nodine et al. (2016) analyzed distance and headway; and Kim et al. (2017) studied decision-making when drivers encountered cut-in vehicles on highways. Most of the literature addressed in this section therefore pertains to lane changing in general.

2.1. Lane change characteristics analyses

Characteristics analyses are typically conducted using microscopic traffic simulation software such as CORSIM (FHWA, 1998), MITSIM (Yang and Koutsopoulos, 1996) and SITRAS (Hidas and Behbahanizadeh, 1999). For example, when drivers decide to change lanes, they must consider the possibility, necessity, and desirability of the maneuver (Gipps, 1986). Using MITSIM, Yang and Koutsopoulos (1996) proposed classifying lane changes as either mandatory or discretionary, a classification that has since become prevalent in lane change research. Mandatory lane changes are executed when the driver must leave the current lane, e.g., to use an off-ramp to exit a freeway or to avoid a work zone. Discretionary lane changes are executed when a lane change is not required, but the driver perceives that driving conditions in the target lane are better, e.g., for maintaining a desired speed (Toledo et al., 2003).

Next Generation Simulation (NGSIM) data are also frequently used to explore lane change behavior; e.g., Thiemann et al. (2008) calculated lane change duration, time gaps, and time to collision (TTC), and Toledo and Zohar (2007) investigated duration. Other studies use naturalistic driving study (NDS) data. Olsen et al. (2002) used NDS to conduct a comprehensive examination of lane changes in the U.S., including frequency, duration, urgency, and severity of lane changes in relation to maneuver type, direction, and other classification variables. In China, lane change frequency, turn signal usage, and rear mirror usage were explored by Dang et al. (2014) and Wang and Li (2016), using real vehicle experimental data and naturalistic driving data, respectively.

Turn signal usage is an important characteristic of lane changes. Using a turn signal when changing lanes is a statutory law in many countries, as a safer environment is created when the intention of the lane changer is more clearly delivered to surrounding vehicles (Dang et al., 2014). A turn signal, when used properly, enhances the flow of traffic and prevents near-crash situations (Ponziani, 2012). Lee et al. (2004) and Ponziani (2012) found that neglected turn signal use when changing lanes caused more crashes than distracted driving.

Duration, another crucial characteristic, starts with the lane changing vehicle initiating movement in its original lane, and ends with its stabilization in the target lane. Duration has a significant effect on simulation outputs, e.g., on the acceleration behavior of the lane changing vehicle and the response of other adjacent vehicles during the execution of the lane change (Toledo and Zohar, 2007). In application, connected and autonomous vehicles (CAVs) can learn to perform lane changes in a human-like manner by controlling the duration, and they can learn to respond more effectively to the lane change behavior of human-driven vehicles (Bascunana, 1995). Because of its importance, duration has been well studied, with results ranging from 1 to 16 s (Hetrick, 1997; Chovan et al., 1994; Toledo and Zohar, 2007). Few studies, however, have focused specifically on the duration of cut-ins.

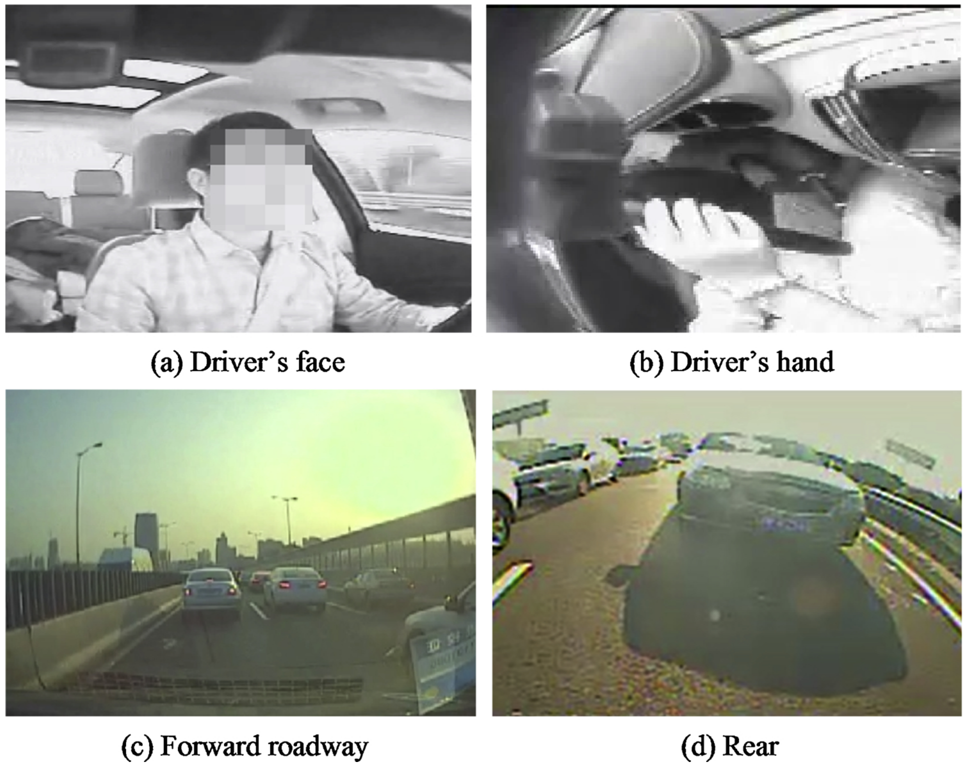
Time to collision (TTC) is also an important characteristic, particularly useful for evaluating the functions of advanced driver assistance systems (ADAS). TTC is the time it would take for vehicles to collide if the following vehicle does not perform an avoidance maneuver; i.e., TTC equals the distance between the lane changer and the following vehicle divided by their relative speed. Talmadge et al. (1997) concluded TTC seems a likely candidate to activate warnings for drivers from crash avoidance systems, and Olsen et al. (2002) divided lane changing into a 4-point scale that indicates how soon a lane change is needed, based on TTC with the closest vehicle ahead.

2.2. Cut-in gap acceptance

Gap acceptance is a key aspect of driver decision-making, and is a decisive element in lane change analysis. Drivers considering a lane change decide whether to accept an available gap, i.e., they assess whether the longitudinal gaps between their own vehicle and the vehicles in the target lane are sufficient. The target gap is separated into the lead gap, which is the longitudinal distance between the lead vehicle (LV) in the target lane and the lane changing vehicle (CV); and the lag gap, the distance between the following vehicle (FV) and the CV (Toledo et al., 2003).

Toledo et al. (2003) and Choudhury and Farheen (2005) modeled lane change gap acceptance by assuming an available gap was acceptable if it was greater than the critical gap, that is, the smallest gap that a driver perceives will ensure successful lane change. Lee et al. (2016) found that when drivers consider executing discretionary lane changes, both relative velocity and relative lead gap are the main criteria, and have similar positive influences on the choice to change lanes; i.e., as either relative velocity or relative lead gap increases, lane changing becomes more likely. Some simulation models have found that gap acceptance is also affected by speed differences between the target lane and the original lane (Laval and Daganzo, 2005), i.e., a gap is more acceptable if the target lane speed is higher than the original lane. Gap acceptance differs for mandatory lane changes, in which the situation is more urgent. Because the driver has fewer choices than for discretionary lane changes, the acceptable gap is smaller.

In summary, while a number of lane change behavior analyses have been conducted, and models have been proposed and developed, few researchers have carried out comprehensive and integrated studies of cut-in characteristics, especially of gap acceptance. Further, few have provided evidence using real-world data to examine the multiple



(a) Driver's face (b) Driver's hand

(c) Forward roadway (d) Rear

Fig. 1. Four camera views for the SH-NDS DAS.

variables that affect cut-in maneuvers, and fewer still have given attention specifically to Chinese drivers' cut-in behavior.

3. Data preparation

3.1. Shanghai naturalistic driving study

The data used in this paper were collected in the Shanghai Naturalistic Driving Study (SH-NDS) jointly conducted by Tongji University, General Motors (GM), and the Virginia Tech Transportation Institute (VTTI). Five GM light vehicles equipped with SHRP2 NextGen Data Acquisition Systems (DAS) were used to collect real-world driving data. The DAS includes an interface box to collect vehicle controller area network (CAN) data, an accelerometer for longitudinal and lateral acceleration, a radar system that measures range and range rate to the lead vehicle in front (LV) and those in the adjacent lanes, a light meter, a temperature/humidity sensor, a GPS sensor for location, and four synchronized cameras that can be used to validate the sensor-based findings (Regan et al., 2012; Zhu et al., 2017). As shown in Fig. 1, the four camera views monitor the driver's face (1a), the driver's hand maneuvers (1b), the forward roadway (1c), and the rear, or roadway behind the vehicle (1d).

3.2. Cut-in events extraction

This study focuses on cut-in maneuvers from the lanes adjacent to the DAS-equipped NDS vehicles, which function as the following vehicle (FV); that is, they provide the perspective of the FV when another vehicle is changing lanes (CV) into the gap in front of it. Based on the fundamental information (e.g., position, velocity and acceleration) of lane changing vehicles recorded by NDS FV vehicles, the general cut-in characteristics, CV gap acceptance, and FV responses (e.g., braking, speed variation and drivers' other maneuvers) were comprehensively explored. A typical cut-in scenario is illustrated in Fig. 2.

An extraction algorithm was developed to obtain cut-in events, and the results were then manually validated by observing the videos from the forward roadway camera. As shown in Fig. 3, the LV vehicle directly in the front of the NDS vehicle in the target lane is designated as in the T0 position. If the NDS's radar records a change in the position of a vehicle from the adjacent lane, from which it moves to the T0 position, it is determined to be a CV intending to execute a lane change (i.e., in Fig. 3, the red car was T0 at first, and then the blue car moved into the FV's current lane; the blue car is designated as the new T0). If the lane change meets the X-Range critical condition below, it is determined to be a cut-in maneuver.

To develop the extraction algorithm, an empirical analysis was conducted to identify threshold values for detecting cut-in events from the NDS data. As part of the analysis, 500 random cut-in events were manually observed, and the criteria for extracting cut-in events based on several relevant variables were derived. These extraction criteria are given below:

- Y-Range (lateral distance) is less than 2.2 m, to show the CV has initiated its movement toward the lane of the FV; the Y-Range is less than 1.2 m to ensure the CV is stable in the target lane. Together, these criteria guarantee the CV changes its lane.
- Maximum lateral acceleration of FV is less than 0.07 g, and lane offset is less than 1.0 m. These criteria guarantee the FV does not move in a lateral direction.
- The critical condition is that the X-Range (longitudinal distance from CV to FV) should not be so large that the cut-in has no effect on the FV. Based on the 500 observations, this study defined the maximum X-Range to be 75 m.
- The velocity of both FV and CV should be more than 1 m/s. This criterion ensures that the two vehicles are always in motion.

Fig. 4 illustrates the critical time points (i.e. A, B, and C) utilized in the DAS cut-in data extraction process. At the onset of the cut-in, the CV's Y-Range (i.e., its lateral distance in relation to the FV) is about 3.5 m, as the CV is still in its own lane but has just initiated the movement. The *initiation point* (i.e. A in Fig. 4) is defined as the last peak (also known as the local maximum) of the Y-Range determined by

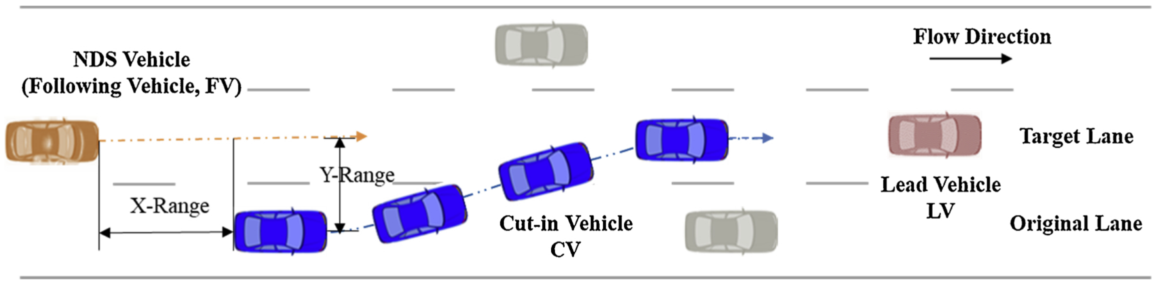


Fig. 2. Radar target's (CV) position and motion during a cut-in scenario.

Fig. 3. Radar target T0 change, detecting a cut-in of the blue car from adjacent lane (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

a built-in function of MATLAB, *findpeaks*. When the CV's Y-Range has decreased to less than the distance between the lane edge and the FV, it can be assumed that the CV has crossed its lane. This is the *cross-lane point* (i.e. B in Fig. 4) of the cut-in. In about 1.5 s from the cross-lane position, the CV becomes T0. The Y-Range at this point, marked by the red vertical, is very small and approaching zero. The first zero value of Y-Range after the CV becomes T0 is defined as the end of cut-in behavior, or *stabilization* (i.e. C in Fig. 4). From this point, the CV has completely stabilized its movement within the target lane. Note that the cut-in duration is defined as the time required for the CV to travel from A to C. Therefore, the duration in Fig. 4 is about 5.5 s.

The number of cut-in events obtained was 5608, each event validated by the forward roadway camera video recording. Roadway type, weather and light conditions, turn signal usage, and CV and LV types were also identified during validation.

The 5608 lane change events occurred on three road types with different speed limits: 1038 occurred on surface roads with speed limits ranging from 30 km/h to 80 km/h, 2901 on expressways with a speed limit range of 60 km/h to 80 km/h, and 1669 on freeways with speed limits ranging from 80 km/h to 120 km/h.

4. Cut-in behavior characteristics

Four characteristics of cut-in behavior are presented in this section. First, motivations are identified, followed by observations on turn signal usage, which can reflect drivers' safety awareness. The execution characteristics of duration and distribution are quantified, and, finally, urgency is classified through TTC (time to collision) and the FV's response.

4.1. Cut-in motivations

4.1.1. Mandatory and discretionary

Following Yang and Koutsopoulos (1996), cut-in motivations were

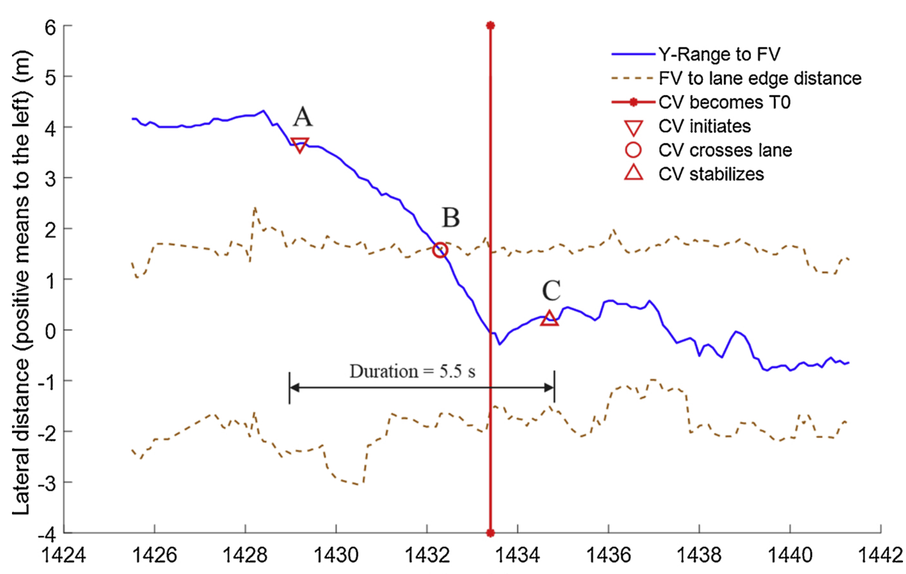


Fig. 4. Y-Range time points of cut-in sequence: initiate, cross-lane and stabilize.

Table 1
Cut-in motivations for different road types.

Road Type	Classification	Motivation ID: (percent)		
Surface Road	Mandatory	1: 34.4	2: 11.3	3: 3.2
	Discretionary	4: 40.2	5: 8.2	6: 2.7
Freeway	Mandatory	1: 0	2: 10.9	3: 1.3
	Discretionary	4: 63.8	5: 17.8	6: 6.2
Expressway	Mandatory	1: 0	2: 17.2	3: 1.8
	Discretionary	4: 64.0	5: 14.4	6: 2.6

classified as either mandatory or discretionary. Mandatory cut-ins have three primary motivations: approaching an intersection in situations where the vehicle must change lanes to be in the correct lane to turn (motivation ID = 1, as shown in Table 1), entering or exiting a limited-access roadway (motivation ID = 2), and avoiding a work zone or other obstacle (motivation ID = 3). Motivations for discretionary cut-ins include avoiding traveling behind a slow lead vehicle (motivation ID = 4) and changing to a fast or slow lane to maintain a desired speed (motivation ID = 5). Cut-ins without any clear motivation were considered discretionary in this study (motivation ID = 6). Briefly, the motivations and their classifications are:

1 (M): approaching intersection
2 (M): entering/exiting roadway
3 (M): avoiding obstacle
4 (D): avoiding slow lead vehicle
5 (D): preferring fast/slow lane
6 (D): undetermined

The 5608 cut-in events were identified and coded through watching videos from the forward roadway cameras. The results, classified by road type, are shown in Table 1.

As shown in Table 1, avoiding following a slow lead vehicle is, by far, the main motivation (ID = 4) for cut-in behavior on all road types. It accounted for 52.8% of all cut-in behavior, and 63.8% and 64% on freeways and expressways, respectively. One of the possible explanations is that the speed limits are higher on freeways and expressways, the presence of a slow lead vehicle would likely influence the speed and position of a vehicle behind it. CV drivers tend to change lanes in this situation to maintain their current speed by passing (Hetrick, 1997). These figures are higher than the 37.24% on interstates and highways found by Olsen et al. (2002) in their U.S. study of general lane changes. It is reasonable to assume that most Chinese drivers execute cut-in maneuvers to pursue the shortest travelling time and comfortable driving experience, so a larger driving space and faster speed are generally preferable.

Some differences between road types have obvious explanations. For example, the mandatory Motivation 2 is most common on expressways, where drivers have to merge onto ramps when entering and exiting, whereas Motivation 1 is drivers' main motive on surface roads where there are frequent intersections. Discretionary Motivation 5 is mostly observed on freeways, where drivers are often required to choose the correct lane according to their speed. Notable, however, is that a considerable number of cut-ins (207 events) occurred without any apparent definite purpose (Motivation 6), more, in fact, than occurred when drivers maneuvered to avoid obstacles (Motivation 3). The percentage of discretionary Motivation 6 is considerably higher on freeways (6.2%), which can be attributed to the faster speed and more available lanes.

4.1.2. Single and multiple lanes

When cutting in, some drivers move laterally a single lane, while others cross two or more lanes, a choice that varies according to motivation and road type. The proportion of single and multiple lane cut-ins according to road type is shown in Table 2.

Table 2
Single/multiple lane cut-in for different road types.

Road Type	Motivation	Single Lane Cut-in	Multiple Lane Cut-in
Surface Road	Mandatory	74.8%	25.2%
	Discretionary	99.1%	0.9%
Freeway	Mandatory	56.2%	43.8%
	Discretionary	96.2%	3.8%
Expressway	Mandatory	61.9%	38.1%
	Discretionary	95.7%	4.3%

As shown in Table 2, more than 95% of discretionary cut-ins on all road types are single lane. When drivers execute discretionary cut-ins, they want to maintain a desired speed, and in most cases, a single lane change can attain this goal. Multiple lane cut-ins have a much greater frequency of mandatory motivation, where the situations are more urgent, e.g., drivers are avoiding obstacles, or they are in the leftmost lane of the road when they realize they must presently exit the freeway or turn at an intersection. In contrast with the under-5% figures for multiple-lane discretionary cut-ins, a minimum of 25.2% (for surface roads) of mandatory cut-ins are executed across multiple lanes. The proportion is even higher on freeways and expressways, at 43.8 and 38.1, respectively, and are roughly double the 20.0% figure for multiple lane changes in U.S. on-ramp and off-ramp areas observed by Goswami and Bham (2006). This comparison may indicate that Chinese drivers are slightly more aggressive as they execute multiple lane cut-in more frequently, which is rather dangerous for surrounding vehicles.

4.2. Urgency and TTC

Time to collision (TTC) is used extensively to evaluate safety as it is essential for calculating rear-end conflict. Rear-end conflict is the most common cut-in risk (Hu et al., 2017), but its avoidance is also a common reason to change lanes. Olsen et al. (2002) and Lee et al. (2004) used TTC to classify the urgency of lane changes on a 4-point rating scale (1 = not urgent, 4 = critical). Based on TTC with the closest vehicle ahead or behind, the urgency level indicates how soon a lane change is needed. This study adopted the same scale to rate cut-in urgency, i.e., 1 = non-urgent (TTC > 5.5 s), 2 = urgent (5.5 s ≥ TTC > 3 s), 3 = forced (3 s ≥ TTC > 1 s), and 4 = critical or near crash (1 s ≥ TTC). To compare cut-ins with all lane changes, the mean cut-in TTC was calculated. Results of our TTC classification of cut-in urgency for different road types are in presented Table 3.

As shown in Table 3, 79.4% of cut-ins on all road types were rated with an urgency of 1, i.e., non-urgent; 15.7% were rated with an urgency of 2, and 4.7% were rated with an urgency of 3, i.e., forced. All levels but 1 (non-urgent) had higher percentages than those in the Olsen et al. (2002) and Lee et al. (2004) all lane change study, which indicates cut-in behavior is comparatively more dangerous than other lane changes. Because urgency is based on time to collision, the shorter TTC demonstrates that cut-ins can have a negative impact on traffic safety.

Table 3
Cut-in urgency based on TTC for different road types.

Urgency / Road Type	1 Non-Urgent	%	2 Urgent	%	3 Forced	%	4 Critical	%
Surface Road	398	72.2	113	20.5	39	7.1	1	0.2
Freeway	514	85.2	69	11.4	19	3.2	1	0.2
Expressway	1,096	79.7	215	15.6	60	4.4	3	0.3
All Road Types	2,008	79.4	397	15.7	118	4.7	5	0.2
All Lane Changes (Olsen et al.)	2,945	91.2	269	8.3	14	0.5	0	0

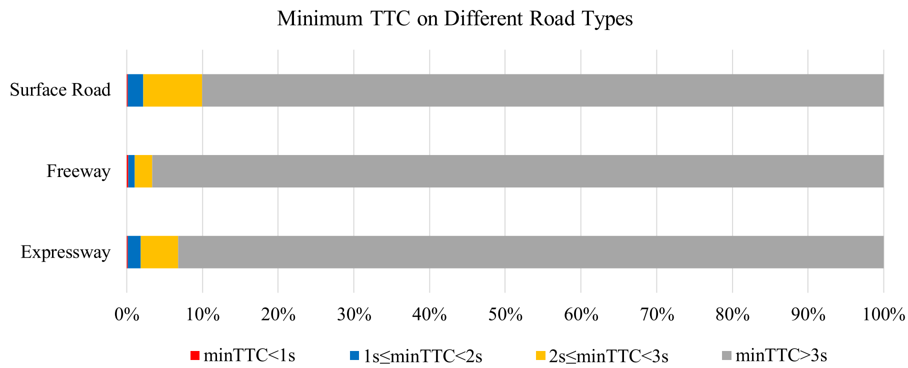


Fig. 5. Minimum TTC on different road types.

Freeways and expressways showed lower percentages of level 2 and 3 urgency than surface roads, which indicates cut-ins on surface roads are more dangerous. A reasonable explanation is that surface roads may have more influences on cut-in behavior, such as pedestrians, electric bikes and bicycles, unlimited access, lower absolute speeds, more frequent mandatory cut-in situations, and shorter distance ranges, both laterally and longitudinally, between the CV and FV.

Minimum TTC, i.e., the minimum positive value of TTC during the cut-in process, was calculated to verify the urgency of cut-ins on different types of roads. As shown in Fig. 5, the proportion of minimum TTC less than 3 s (forced and critical near crash) on surface roads was 9.9%, considerably larger than its proportion on freeways and expressways. Although most cut-ins have limited impact on following vehicles (minimum TTC > 3 s), those with small TTC values, reaching almost 10% on surface roads, are high-risk and cannot be ignored. While none of this study's cut-in events resulted in a crash, the abruptness of low TTC cut-ins puts heavy pressure on FV drivers to make appropriate decisions and maintain steady control of the vehicle once they recognize the intention of a lane changing vehicle. On the other hand, the absence of crashes suggests that because most drivers can handle urgent cut-in scenarios well, ADAS and CAV can learn some valuable skills from human drivers.

4.3. Turn signal usage

Turn signal usage was observed on different road types by watching the forward roadway videos. Although Chinese traffic law requires use of turn signals when changing lanes, Table 4 shows that the usage percentages are below 50% on every road type. The 48.7% overall figure is similar to the U.S. proportion of turn signal usage for urgent and forced lane changes, which are both included in our definition of cut-in. Olsen et al. (2002), found that U.S. drivers used turn signals for 53.3% of urgent lane changes (5.5 s ≥ TTC > 3 s) and 44.0% of forced lane changes (TTC ≤ 3 s) on interstates and freeways, and this study found 48.6% usage on expressway cut-ins and 49.3% usage on freeways. Only small differences were observed between road types, but it is perhaps surprising that turn signal usage was lowest on surface roads where lane changing is more frequent.

Table 4
Turn signal usage for different road types.

Road Type	Used (# of events)	Not Used (# of events)	Usage Percentage
Surface Road	489	549	47.1
Freeway	811	858	49.3
Expressway	1,432	1,469	48.6
All Road Types	2,732	2,876	48.7
Comparisons			
Olsen et al.'s study on interstates and freeways, U.S. (**forced** LC situations)			44.0
Lee & Olsen's study on interstates and freeways, U.S. (**urgent** LC situations)			53.3
Dang's study on highways, China (normal LC situations)			65.0

In general, low turn signal usage can be explained the lack of a direct and immediate cause-effect relationship between not using a turn signal and an unsafe consequence, which can make drivers think that neglecting the turn signal is not dangerous; that is, drivers can think they are safe when they are not if they do not accurately perceive their risk exposure (Lee et al., 2004). Urgency appears to lower the frequency of turn signal usage, however. Because drivers vary in their skill level and familiarity with a particular road, a driver may be challenged by simply getting the vehicle from point A to point B; this situation can create an urgency in which using a turn signal does not come to mind (Ponziani, 2012). Likewise, urgency might contribute to mere carelessness. Cut-ins are the most urgent of lane changes. Turn signal usage by Chinese drivers for overall lane changing has been found to be 65% on highways (Dang et al., 2014), considerably higher than the 49.3% freeway cut-in usage observed in this study. Considering that usage may be even higher when turns are anticipated, or less urgent than for lane changes, we observed 50 surface road trips from the SH-NDS database, and found that turn signal use for normal left or right turns was 78%. Observing signal use for 22 intersections in Canada, Faw (2013) found a very large range, 54% to 95% depending on driver population, location, and traffic conditions, but the overall turn signal use rate was 76%, similar to the Shanghai proportion.

4.4. Cut-in duration and distribution selection

As illustrated in Fig. 4 above, cut-in duration is defined in the same way as lane change duration, i.e., the time span from the lane changer's initiation of lateral movement to stabilization in the target lane. For the 5608 cut-in events, the duration varies from 0.7 s to 12.4 s, with a mean of 3.91 s and standard deviation of 2.34 s A correlation test was conducted to analyze the relationship between road type and cut-in duration. As results showed there was no significant relationship between the two variables (P-Value = 0.3451), it can be assumed that cut-in duration does not differ significantly on different types of road. Previous studies on lane change duration in general show a range of 1–16 s, however, so it becomes clear that cut-in maneuvers have shorter duration.

Duration distribution is one of the most important parameters used in microscopic traffic simulation. There are 8 possible distribution alternatives: including exponential, gamma, normal, lognormal, logistic, loglogistic, Laplace and Pearson 5 distribution. This study's distribution fitting was performed using @RISK (Palisade, 2017) with Akaike Information Criterion (AIC) as the criterion for goodness of fit; according to fitting results, lognormal is the best fit to our duration data (as shown below in Fig. 6). Toledo and Zohar (2007) and Hetrick (1997) also found lognormal distribution the best fit for exploring normal lane change distribution, in their case by using proper probability density

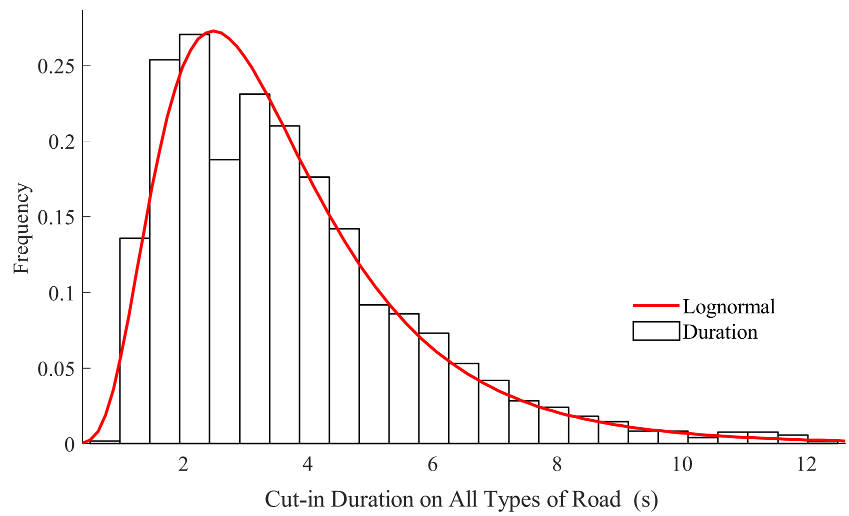


Fig. 6. Distribution of best fits to cut-in duration (lognormal).

functions (PDF) to fit the data. The PDF of lognormal distribution is shown below:

$$f(x|\mu,\sigma)=\frac{1}{x\sigma\sqrt{2\pi}}\exp\left\{\frac{-(\ln x-\mu)^2}{2\sigma^2}\right\} \tag{1}$$

where, μ and σ are the lognormal mean value and variance, respectively, which can be calculated by sample mean (m) and sample variance (var).

$$\mu=\ln\left(\frac{m^2}{\sqrt{var+m^2}}\right)\sigma=\sqrt{\ln\left(\frac{var}{m^2+1}\right)} \tag{2}$$

This study's results showed that $\mu = 1.174$ and $\sigma = 0.517$, which differ slightly from the results of Toledo and Zohar (2007). In their study, a total of 1790 successful lane changes (on average, in the range of 5 to 6 s) were identified, and lognormal distribution was recommended with two parameters $\mu = 1.376$ and $\sigma = 0.550$. Cut-in maneuvers differ from normal lane change in their shorter duration, which average 3.91 s.

4.5. Impact on the following vehicle

One way the impact of lane change on the FV can be analyzed is through the FV driver's braking response. The Data Acquisition System (DAS) in an NDS FV vehicle records the braking timestamp for the brake pedal position variable. Statistical results showed that 44.0% of FV drivers brake when the CV initiates its movement but before it crosses the lane line, while only 14.1% of drivers brake after the CV crosses into the target lane, and 41.9% do not brake at all. This finding indicates that most braking behavior occurred when cut-ins were at the initial stage, when a warning to the driver could improve the FV's safety. As most forward collision warning (FCW) systems only focus on the lead vehicle in the FV's current lane, the FCW cannot fully meet safety needs, suggesting a tremendous need to optimize current FCW functions. For example, the FCW should be capable of perceiving complex interactions between its vehicle and vehicles in adjacent lanes, which may intend to execute cut-in or other disruptive maneuvers.

To understand the impact of cut-ins on FV lateral and longitudinal movements, acceleration and deceleration behavior was assessed. In Fig. 7(a) positive lateral acceleration denotes movement to the right from the sensor position, while negative acceleration denotes movement to the left. The larger proportion of negative lateral acceleration values indicates the FV was more likely to be affected by cut-ins coming from the right. This seems reasonable, as in right-side driving countries such as China, a CV would be most likely to make discretionary cut-ins to the left to avoid slower traffic.

Longitudinal deceleration reflects urgent operation of the FV. As shown in Fig. 7(b), a majority of the longitudinal deceleration ranged from $-3\,\mathrm{m/s^2}$ to $0\,\mathrm{m/s^2}$, indicating that, in most braking-required events, the FV driver took steps to maintain a safe distance by braking before the CV entered into its lane. However, a number of drivers braked more urgently in order to yield quickly to the CV to avoid a collision. The maximum longitudinal deceleration observed was as high as $-6\,\mathrm{m/s^2}$, which probably had a negative influence on traffic flow. Previous studies (Zheng, 2014) have demonstrated that lane changes are linked to stop-and-go oscillations, and are responsible for transforming subtle oscillations into substantial disturbances.

As much as cut-ins can disrupt traffic flow and safety, however, this evidence of human drivers' ability to react to complex interactions between vehicles, i.e., predict danger and adopt safe, suitable, and timely strategies, suggests that ADAS and CAVs can learn a similar response (Casner et al., 2016). For example, an SAE Level 3 (as defined by the Society of Automotive Engineers) autonomous vehicle should be able to make appropriate decisions and maintain steady control of the vehicle when it recognizes the surrounding vehicles' intentions.

5. Modeling cut-in gap acceptance

5.1. Cut-in gap acceptance characteristics

Gap acceptance is a particularly important characteristic of cut-in behavior. A driver considering a cut-in considers safety as well as speed and convenience; determining whether or not a target gap is safe enough to accept is a vital element of the cut-in decision-making process. CV drivers assess the gaps between their own vehicle and both the LV and the FV, i.e., the lead gap and lag gap, respectively. When drivers start to execute cut-ins, it can be assumed that they have accepted an available gap by comparing it to their own critical gap, the smallest gap that they perceive will ensure a successful lane change. This study extracted the gap size from the data based on when the CV driver began to move into the target lane, i.e., the initiation point. Gap size was defined in terms of time rather than space, using the second as the unit of measure. Time gaps are a function of spatial distance and speed: because the CV is concerned with having sufficient time, which is influenced by current speed that can vary, time gaps are more generalizable representations (Bham, 2009).

As shown in Table 5, the minimum lead and lag gaps were smaller on freeways than on surface roads and expressways. The maximum lead gaps show no significant difference by road type; however, the maximum lag gap is again smaller on freeways, likely due to the higher

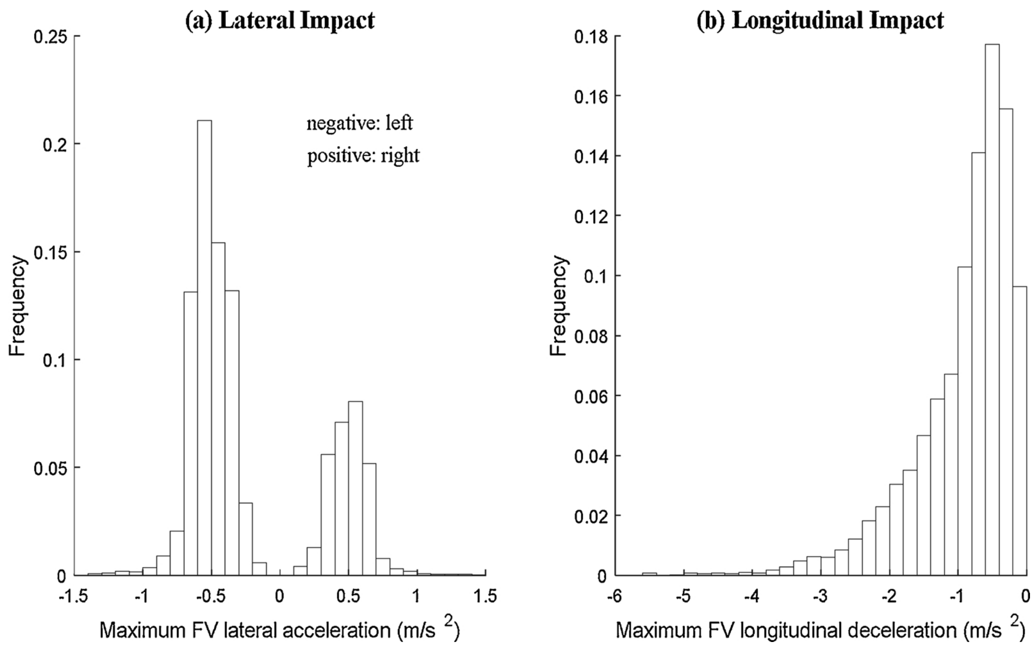


Fig. 7. Cut-in impact on following vehicle: (a) Lateral; (b) Longitudinal.

speed limits on freeways.

The averaged lead and lag gaps on surface roads are largest, followed by expressways and then freeways; a statistically significant difference between the averaged values (P-Value < 0.05) was confirmed by T-test. The standard deviations of lead and lag gaps are largest on surface roads, which can likely be attributed to inconsistency resulting from interactions with buses, bicycles, pedestrians and other road users.

Gap acceptance is also influenced by motivation. As shown by the mean values in Table 5, drivers accepted smaller gaps for mandatory cut-ins than for discretionary cut-ins. These smaller gaps are consistent with the definition of mandatory cut-ins, which are executed in more urgent situations, e.g., to avoid an obstacle or make a needed turn. These results suggests that, for applications such as ADAS, simulated gap acceptance thresholds should be set to accommodate different motivations.

5.2. Three-level mixed-effects linear regression model

Because it is assumed that gap acceptance depends on the specific driving scenario, gap acceptance is often modeled as a random variable to capture the variation in driver behavior and environment. For instance, a driver avoiding an obstacle may accept a short minimum gap, whereas a driver who intends to enter a fast lane for speed preference may wait for a larger gap. A gap acceptance model should therefore be capable of cut-in decision-making mechanism.

The mixed-effects linear regression model is a widely used method for empirical analysis that addresses this need. The model can be used to analyze unbalanced longitudinal data, where individuals may be measured at different time points, or even at different numbers of time points. For instance, lead gaps are nested within motivations (mandatory and discretionary) and motivations are further nested within road type. Moreover, lead gaps within mandatory cut-ins may have some similarities, i.e., within-cluster correlation. On the other hand, there might be variation between lead gaps due to different motivations and/or road types, i.e., between-cluster variation. Therefore, a statistical model is needed that can jointly control both within- and between-cluster variations. In this hierarchical model, a specific available gap is assumed to be influenced by variables from all three levels (Deligianni et al., 2017).

Formally, a three-level mixed-effects model can be written as:

$$y_{jk} = X_{jk}\beta + Z_{jk}^{(3)}u_k^{(3)} + Z_{jk}^{(2)}u_k^{(2)} + \varepsilon_{jk} \tag{3}$$

For $i = 1, \ldots, n_{jk}$ first-level observations nested within $j = 1, \ldots, M_k$ second-level groups, which are nested within $k = 1, \ldots, M$ third-level groups, Groups j, k consist of n_{jk} observations, so y_{jk}, X_{jk}, and ε_{jk} each have row dimension n_{jk}. $Z_{jk}^{(3)}$ is the $n_{jk} \times q_3$ design matrix for the third-level random effects $u_k^{(3)}$, and $Z_{jk}^{(2)}$ is the $n_{jk} \times q_2$ design matrix for the

Table 5
Descriptive statistics of lead and lag gap (unit: s).

Statistics	Gap	Road Type			Motivation	
		Surface Roads	Expressways	Freeways	Mandatory	Discretionary
Sample Size	Lead	834	2,262	1,120	859	3,357
	Lag	1038	2,901	1,669	1,209	4,399
Min	Lead	0.16	0.14	0.13	0.13	0.14
	Lag	0.17	0.15	0.12	0.12	0.15
Max	Lead	5.91	5.98	5.95	5.98	5.98
	Lag	5.96	5.77	5.59	5.59	5.76
Mean	Lead	1.82	1.49	1.42	1.45	1.68
	Lag	1.81	1.38	1.25	1.57	1.71
Std. Dev	Lead	1.16	0.90	0.91	1.18	0.95
	Lag	1.07	0.86	0.88	1.02	0.86

Table 6
Three-level mixed-effects linear regression models for lead and lag gaps.

Dependent variable	Lead Gap Model			Lag Gap Model		
Fixed effect	Coefficient	t-stat	Pr > |t|	Coefficient	t-stat	Pr > |t|
Traffic density:						
High	−0.2348	−2.61	0.009	−0.2349	−3.45	0.001
Medium	−0.1465	−2.62	0.009	−0.2341	−5.51	0.000
Low (Reference)						
Weather condition:						
Rainy	0.1286	2.26	0.024	0.1142	2.64	0.008
Sunny (Reference)						
Light condition:						
Nighttime	0.1960	4.86	0.000	0.0823	2.69	0.007
Daytime (Reference)						
CV type:						
Heavy vehicle	0.3214	3.50	0.000	–	–	–
Light vehicle (Reference)						
CV acceleration	0.1082	5.14	0.000	−0.0564	−3.53	0.000
Relative speed ($V_{LV} - V_{LCV}$)	0.0386	4.85	0.000	−0.0331	−5.12	0.000
LV acceleration	−0.0792	−4.60	0.000	–	–	–
Relative speed ($V_{FV} - V_{LCV}$)	−0.0831	−8.22	0.000	0.0647	8.84	0.000
FV acceleration	−0.0723	−3.21	0.001	0.0509	3.01	0.000
Intercept	2.3842	15.21	0.000	0.1094	12.66	0.000
Random effect parameters	Estimate	95% Conf. Interval		Estimate	95% Conf. Interval	
Variance of cut-in motivation	0.0578	[0.0043, 0.7708]		0.0964	[0.0271, 0.3433]	
Reference: Discretionary						
Variance of road type	0.1038	[0.0408, 0.2642]		0.7593	[0.0319, 0.1806]	
Reference: Surface Roads						
Variance of Residual	1.0578			0.8852		
LR test vs. linear regression	$\chi^2 = 22.92$, Prob $> \chi^2 = 0.0000$			$\chi^2 = 56.37$, Prob $> \chi^2 = 0.0000$		
Statistics						
Number of observations	4216			5608		
Number of groups	6			6		
Log-likelihood	−5464.3586			−6918.8843		

second-level random effects $u_{jk}^{(2)}$. Furthermore, assume that

$$u_k^{(3)} \sim N(0, \sum 3) u_{jk}^{(2)} \sim N(0, \sum 2) \varepsilon_{jk} \sim N(0, \sigma_\varepsilon^2 I) \tag{4}$$

and that $u_k^{(3)}$, $u_{jk}^{(2)}$, and ε_{jk} are independent (Stata, 2013).

In this gap acceptance model, first-level refers to event observations (i.e., lead and lag gaps), second-level refers to motivation (mandatory or discretionary), and third-level refers to road type. Therefore, to accommodate both lead gaps and lag gaps, event observations were divided into six groups. The independent variables are listed in Table 6, and include traffic and environmental factors (e.g., traffic density, weather and light conditions), vehicle type (e.g., heavy or light vehicles), and kinematic parameters (e.g., relative speed, acceleration). The dependent variable is the lead or lag gap for event *i*, motivation *j* and roadway *k*. Parameters of all components were estimated using Stata® 13 (Stata, 2013).

Traffic density was determined by analyzing DAS and forward video data, and was divided into three states of high, medium, and low density. The inter-vehicle spacing is large in the low-density state, which is defined by this study as traffic moving at a relatively fast speed (more than two thirds of the speed limit) with 1˜2 vehicles traveling in the proximity and same direction as the NDS following vehicle. Medium density is defined as traffic moving at moderate speed (one to two thirds of the speed limit) with 3˜5 vehicles in proximity to the FV, and high density is indicated by slow speeds (less than one third of the speed limit) with more than 5 vehicles in proximity. Cut-in vehicle type is separated into heavy (e.g., large passenger vehicles and large trucks) and light vehicles (e.g., small passenger vehicles and small trucks).

The estimation results of the proposed three-level mixed-effects models for lead and lag gap are shown in Table 6. As expected, both random effects parameters associated with cut-in motivation and road type were significant (the 95% confidence interval does not include zero). These results confirm our assumption that lead and lag gaps vary with motivation as well as road type, and demonstrate that the three-level model can capture these characteristics of gap acceptance.

All independent variables were significant at the 95% confidence level (P-Value < 0.05 indicating the coefficient is significant). These environmental conditions, vehicle type, and kinematic parameters are the most important factors influencing the cut-in vehicle's gap acceptance (Toledo et al., 2003; Choudhury and Farheen, 2005). Results show that acceptable lead and lag gaps decreased with the increase in traffic density (note the negative coefficients). It seems reasonable that heavy traffic with short headways results in frequent interactions between vehicles, situations in which drivers have to accept smaller gaps rather than waiting for better opportunities. Bad weather (e.g., rainy days) and the lack of sunlight (i.e., nighttime) led to larger cut-in gaps, as shown by their positive coefficients. Drivers cutting in to the adjacent lane in these unfavorable conditions appear to be less willing to take risks by accepting insufficient headways, even when faced with urgent situations.

Acceptable lead gaps are significantly affected by the type of vehicle cutting in. The positive coefficient for heavy vehicles indicates these drivers are more cautious; they seem aware that their vehicle needs more time to execute a cut-in that will avoid a rear-end crash with the lead vehicle. Unlike lead gap, lag gap is not significantly impacted by the CV type, possibly because drivers may be more concerned with the scenario in front than to the rear.

The kinematic parameters are critical elements in cut-in gap acceptance. CV acceleration (unit: m/s^2) has different effects on lead gap and lag gap, i.e., the size of the acceptable lead gap increases with an increase in CV acceleration, while the lag gap decreases. The CV has likely begun to accelerate for the purpose of creating a sufficient lag gap in which to execute the cut-in, but then the driver's attention shifts to the road ahead (as seems the case in CV type influencing lead but not lag gap). It makes sense that the CV's increasing speed intensifies the driver's need for a larger space in front, while the same acceleration naturally reduces the lag gap as the driver moves away from the FV.

Relative speed (unit: m/s) has similar opposing effects on lead and lag gaps. Relative speed, which refers to LV/FV speed minus CV speed, is a more revealing parameter than absolute speed because it can eliminate the effect of speed difference based on road type. Results showed that the higher the LV speed in comparison to the CV, the lead gap increased as the lag gap decreased. However, when the FV's speed increased in comparison to the CV, the lead gap decreased while the lag gap increased. As few drivers risk entering a gap that appears to be closing due to a fast FV, the minimum safe gap between those vehicles must be perceived as larger. Supporting this interpretation, the LV and FV acceleration variables affect gap acceptance similar to the effect of relative speed; that is, LV acceleration increased the lead gap while FV acceleration increased the lag gap. These results are consistent with Toledo et al. (2003), who found that the CV's critical gap depends on its relative speed to the lead and following vehicles.

6. Summary and conclusion

This study explored drivers' cut-in behavior in Shanghai, China, by developing an innovative algorithm to extract 5608 cut-in events from the Shanghai Naturalistic Driving Study database. Cut-in characteristics, including duration, drivers' motivations, turn signal usage, and urgency were analyzed comprehensively to acquire a broad view of Chinese driving behavior.

Almost half of Chinese drivers do not use a turn signal when cutting-in. Although this proportion is similar to that of U.S. drivers, according to a 1992 study by Daimler-Benz, if a passenger car driver has 0.5 s additional warning time, about 60% of rear-end collisions can be prevented; and an extra full second of warning time can prevent about 90% (National Transportation Safety Board, 2001). The use of turn signals provides this warning, making it not only a responsible safety precaution for drivers themselves, but also a sign of respect for others' safety, especially occupants of following vehicles. Shanghai traffic police reported in 2016 that improper lane changes, especially without using turn signal, accounted for almost 50% of all traffic violations, which our figures confirm. Since 2016, Shanghai has launched a campaign to enforce traffic violations. As Faw (2013) notes, we might have no technological means of ensuring appropriate turn signal use, so gaining a clear understanding of why drivers do or do not use their turn signals remains a valuable pursuit. One intervention that might raise the rate of turn signal use is to post reminders such as "Signal before lane changing" on some of the many variable highway signs. Traffic police should issue tickets or citations to drivers who do not signal when cutting in. In addition, strengthened driver education would emphasize the essential role that signaling plays in promoting safety, both for individual drivers and for the larger community of road users.

A lognormal distribution produced the best fit for cut-in duration data. Cut-ins have shorter duration than other lane changes, which is likely the result their significantly higher degree of urgency, as demonstrated by our time to collision (TTC) calculations. The shorter duration and TTC increase the cut-in's riskiness: because drivers tend to execute cut-in maneuvers hastily, they are more accepting of gaps that may normally be rejected; additionally, their attention to the lag gap decreases, leading them to be less aware of the potentially dangerous impact on following vehicles. Quantifying cut-in duration is important to microsimulation as well. Current microsimulations generally consider lane change duration as near-instantaneous or assign it a constant value, yet duration has considerable range, which can have strong impact on the simulated scenario.

This study's descriptive statistics confirmed that a driver's decision to cut in is influenced by road type and motivation. With the aim of identifying the variables influencing the cut-in decision-making process, two three-level mixed-effects linear models were developed to capture the characteristics of lead and lag gap acceptance. The models demonstrated that traffic density, weather, light conditions, CV vehicle type, relative speed to LV/FV and acceleration of CV, LV and FV all had significant effects on the decision to cut in to an adjacent lane. Because the models offer general insight into driver decision-making when interacting with multiple vehicles, they can assist the evaluation and improvement of active safety functions in driving simulators and connected and autonomous vehicles (CAV). One of the most important applications of the findings is that gap acceptance thresholds should be set according to a variety of conditions. More specifically, road type and motivation parameters can be used to simulate cut-in trajectories in different scenarios.

Motivation has significant influence on cut-in behavior. More than half of cut-ins are correlated with a slow preceding vehicle, which confirms the common understanding that drivers are motivated to maintain a desired speed. These discretionary cut-ins are more common on freeways and expressways than they are on surface roads, which suggests that these roads may give drivers more opportunity to cut in because they are larger, faster, and have limited access. It is worth mentioning that a relatively large number of Chinese drivers cut-in without any clearly observable intention (3.7% of cut-in events in this study). Generally speaking, drivers of following vehicles can often anticipate cut-ins when, for example, they see a particularly slow vehicle in the adjacent lane. However, because it is much more difficult to predict cut-in maneuvers without clear intention, these cut-ins may have a particularly negative influence on traffic flow and safety. When this apparently random cut-in behavior is considered along with Chinese drivers' shorter headway, the low percentage of turn signal usage, and the overall high rate of lane change behavior (Wang and Li, 2016), the possibility that these behaviors indicate poor driving habits and an aggressive driving style warrants further research.

This paper also addressed the impact of cut-ins on the following vehicle by analyzing its braking response and acceleration behavior. The finding that 44.0% of FV drivers decelerate to yield to a CV when it initiates cut-in movement from an adjacent lane indicates that advanced driver assistance systems, such as forward collision warning, must consider the movement of vehicles in adjacent lanes as well as those the driver's own lane. On the positive side, this study found that human drivers were able to avoid crashes in a variety of complicated cut-in interactions, which supports suggestions that human drivers' decision-making processes could be employed as a set of guidelines for vehicle automation systems to ensure that they act in a manner consistent with human-driven vehicles (Radlmayr et al., 2018). Future CAVs control systems, for example, can incorporate these findings in anticipating and responding to cut-in vehicles.

Since the cut-in process is complex, future study should address other variables, such as roadway geometry, vehicle performance capabilities, and the influence of driver psychology on decision-making and driving style. Nevertheless, this paper extends the exploration and development of lane change theory, methodology, and applications, to focus on the more dangerous cut-ins, and can provide a valuable reference for further research.

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