AN EXPLORATION OF CUT-IN BEHAVIOR AND GAP ACCEPTANCE USING SHANGHAI NATURALISTIC DRIVING DATA

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ABSTRACT

Cut-in maneuvers are dangerous lane changes that may result in traffic conflicts or crashes. The maneuvers affect the safety gap between vehicles and may adversely affect automated vehicle operations and safety. To comprehensively explore cut-in behavior, 4,734 cut-in events in China were extracted from the Shanghai Naturalistic Driving Study. The data were used to analyze the characteristics of cut-in behavior, including purposes, turn signal usage, duration and urgency. Cut-in duration and gap acceptance distributions were quantified and an exploratory gap model was developed to promote a broader understanding of cut-in behavior in Shanghai. The results showed that 1) cut-in behavior is relatively dangerous and risky with smaller time to collision than normal lane change, and more than 50% of cut-ins are motivated by a slow preceding vehicle; 2) almost half of Chinese drivers did not use a turn signal when cutting-in, which is indicative of poor driving habits and an aggressive driving style; 3) unlike a typical lane change, cut-ins have a shorter duration as well as a smaller lag gap. A lognormal distribution and Generalized Extreme Value distribution produced the best fit for the cut-in duration and lag gap respectively; 4) road type, relative speed, and following vehicle's acceleration are important factors that might influence drivers' lag gap acceptance. This paper extends the exploration and development of lane change theory and its applications. The results indicate social norms and behavior are influenced by culture and other countries should consider calibrating assumptions about cut-in behavior based on local data sources.

Keywords: Cut-in Behavior, Gap Acceptance, Naturalistic Driving Study, Driving Style, Duration Distribution, Lag Gap Model

1 INTRODUCTION

Lane change maneuvers, which refers to a vehicle moving into the space between a lead and following vehicle in the target adjacent lane, are very common on the road. Cut-ins are atypical and potentially dangerous lane changes. They are often so abrupt that following vehicle cannot react to it properly in time to avoid severe traffic conflicts even crashes. Improper lane changes, including unsafe cut-ins and overtaking account for 4.9% of all crashes in China in the year 2015 (*1*). It is reported that unsafe lane change and lane merge maneuvers account for approximately 5% of all crashes and as high as 7% of all crash fatalities in the U.S. (*2*). Therefore, an exploration of cut-in behavior can help researchers to develop preventive countermeasures to proactively address safety concerns (*3*).

Cut-ins are dangerous because they affect the safety gap between vehicles. This effect on the safety gap additionally causes interference to advanced driver assistance systems (ADAS) and automated vehicles (*4-5*). A following vehicle equipped with ADAS, or with partially automated driving (NHTSA's Level 2) must adjust themselves accordingly in an abrupt cut-in, resulting in the hard braking and unnecessary acceleration that contribute to not only wasted fuel and emissions but also traffic waves (i.e., one car braking so others must also brake) which further worsen the situation (*6*). Cut-in behavior is one reason why these advanced technologies need to be tested in various complicated situations before going into mass production (*7*).

Since the first lane change model was proposed by Gipps in 1986 (*8*), researchers in developed countries have devoted substantial effort to investigating lane change characteristics and their modeling. Several comprehensive examinations of lane change behavior have been conducted in the U.S. since the 1990s (*9-10*), which have provided insight into the behaviors and parameters associated with lane change (*9*). These in-depth results were well applied to driving simulation systems, which are commonly used to study lane change. Although China's traffic systems have developed rapidly during recent years, few studies of driving behaviors have analyzed cut-in behavior in China due to a lack of effective data collection technology. Therefore, most driving simulation models are based on experiments conducted in western countries, where driving styles, types of vehicles, and traffic regulations, as well as cultural environments are all different from developing countries (*11*). Chinese drivers, i.e., face a challenging driving environment of omnipresent pedestrians, electric bikes, and bicycles, aggressive driving, and, indeed, frequent cut-ins. Thus, an exploration of cut-in behavior is significantly necessary for traffic safety in China, and it can also enable traffic simulation technologies, in general, to be more effective and robust.

To better address this need, real-world driving data were collected in the Naturalistic Driving Study (NDS) conducted in Shanghai, China. Typically, NDS offers a new and complementary approach, to existing methods for understanding driving behavior in normal, impaired and safety-critical situations (*12*). The Shanghai NDS data collection started in December 2012 and ended in December 2015. During the study period, 60 licensed drivers totally travelled about 161,055 km (*13*). Using such large quantities of driving data, we can make a thorough exploration of cut-in behavior overall. More specifically, this study aims to fill the gap of cut-in behavior research in China, and the results will provide an important reference for active vehicle safety. Additionally, this study conducts a comparative analysis of Chinese and U.S. cut-in behavior, which will advance the development of lane change theory and its applications.

The balance of this paper is organized as follows. The next section provides a review of various cut-in related studies, and then the Shanghai NDS data are described and the cut-in events extraction method is introduced. The core section presents characteristics and quantitative analysis of cut-in behavior in detail, and a cut-in gap acceptance model is developed. The final section is devoted to a summary and further discussion.

2 LITERATURE REVIEW

This section focuses on a brief overview of lane change and cut-in behavior studies, and some cut-in related models.

2.1 Lane Change and Cut-in Characteristics Analyses

Characteristics analyses are the foundations of microscopic traffic simulation. CORSIM (*14*), MITSIM (*15*) and SITRAS (*16*) are several micro-simulators that implement lane change behavior analyses. Most previous research has been devoted to characterizing lane change behavior generally, with few studies focused on cut-in characteristics specifically. Olsen et al. (*9*) conducted a comprehensive examination of naturalistic lane changes in the U.S., including frequency, duration, urgency, and severity of lane change in relation to maneuver type, direction, and other classification variables. Next Generation Simulation (NGSIM) data are frequently used to explore lane change behavior, e.g., Thiemann et al. (*18*) calculated lane change duration, time gaps and time to collision (TTC); and Toledo and Zohar (*19*) investigated duration. To better understand lane change behavior in China, lane change frequency, turn signal usage, and rear mirror usage were explored by Dang et al. (*20*) and Wang et al. (*21*), using real vehicle experimental data and naturalistic driving data, respectively.

When drivers decide to cut-in, they must consider the possibility, necessity and desirability of the maneuver (*8*). As a cut-in is a type of lane change, it can be classified along with other lane changes as either mandatory or discretionary, a classification of lane change proposed by Yang and Koutsopoulos (*15*) in MITSIM. Their classification 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 the driver perceives that driving conditions in the target lane are better, e.g., to maintain a desired speed, but a lane change is not required (*17*).

Turn signal usage is a very important characteristic of lane changes and, therefore, of cut-ins. Using a turn signal when changing lanes is a statutory law in many countries, as by using a turn signal, the intention of the lane changer is delivered to surrounding vehicles and a safer environment is thus created (*20*). A turn signal used properly enhances the flow of traffic and prevents near-crash situations (*22*). Olsen (*9*) and Ponziani (*22*) found that crash rates resulting from neglected turn signal use when changing lanes causes more crashes than distracted driving.

Duration, another crucial characteristic of lane change, starts with the vehicle initiating movement in its original lane, and ends with it stabilized in the target lane. Duration has a significant effect on simulation outputs; e.g., the acceleration behavior of the lane changing vehicle and other vehicles around it may be affected during the execution of lane changes (*19*). Because of its importance, duration has been well studied, with results ranging from 1-16 s (*19*, *23-24*). Few studies, however, focus specifically on the duration of cut-ins.

Time to collision (TTC) is an additional valuable lane change characteristic, particularly useful for evaluating the functions of ADAS. TTC is the time it would take for vehicles to collide if the following vehicle does not make an adjustment maneuver; i.e., TTC equals the range between the lane changer and the following vehicle divided by their relative speed. Olsen et al. (*9*) divided lane change into a 4-point scale that indicates how soon a lane change is needed, based on TTC with the closest vehicle ahead. Talmadge (*25*) concluded TTC seems a likely candidate to activate warnings for drivers in Crash Avoidance Systems.

2.2 Modeling Gap Acceptance

Gap acceptance is also a crucial characteristic of lane change, but because it is a decisive element in lane change analysis, models are developed for its analysis and it is addressed separately in this study. Drivers considering a cut-in assess whether the gaps between their own vehicle and the lead vehicle (LV) in the target lane, as well as the gap to the following vehicle (FV), are sufficient to execute lane change. The longitudinal distance between the LV and cut-in vehicle (CV) is defined as the lead gap. Similar to lead gap, lag gap is the distance between the FV and CV (*17*).

Choudhury (*26*) and Toledo et al. (*17*) modeled lane-changing 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. In the Toledo et al. model, critical gaps are assumed to follow lognormal distributions to ensure that they are always non-negative. Mandatory and discretionary lane changes differ with respect to gap acceptance. Lee et al. (*27*) 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 (*28-29*), i.e., a gap is more acceptable if the target lane speed is higher than the original lane. In mandatory lane changes, the situation is more urgent, so the driver has fewer choices than for discretionary changes, and the acceptable gap is therefore smaller. Ahmed et al. (*30*) developed a forcing merging (mandatory lane changing) model and found that in heavily congested traffic where gaps larger than the minimum acceptable length are hard to find, drivers change lanes either through the FV's courtesy yielding or through the CV forcing the FV to slow down.

In summary, a number of characteristics analyses have been conducted, and models have been proposed and developed for lane change. However, few researchers have comprehensively studied cut-ins, or have provided data or evidence to offer insight into cut-in behavior. Moreover, studies specifically on Chinese drivers are limited.

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 SARP2 NextGen Data Acquisition Systems (DAS) were used to collect real-world driving data. The three-year data collection procedure started in December 2012 and ended in December 2015. Driving data were collected daily from 60 licensed Chinese drivers who, altogether, travelled 161,055 km during the study period (*12-13*).

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 (LV) and vehicles in the adjacent lanes, a light meter, a temperature/humidity sensor, a GPS sensor for location, and four synchronized camera views to validate the sensor-based findings. As shown in Figure 1, the four camera views monitor the driver's face (1a), the forward roadway (1b), the rear, or roadway behind the vehicle (1c), and the driver's hand maneuvers (1d) (*13*).

(a) Driver's face (b) Forward roadway

(c) Rear (d) Driver's hand

FIGURE 1 Four camera views for the SH-NDS.

3.2 Cut-in Events Extraction

In this study, the NDS vehicles, those that are equipped with DAS, are generally referred to as FV, as they provide the perspective of the following vehicle. As illustrated in Figure 2, they record the fundamental information (e.g., velocity and position) of lane changing vehicles near them, from the position of the FV. If the longitudinal distance between the two vehicles is sufficiently large (criteria is discussed below), there is no significant impact on the FV, and thus the information was not extracted. Information was extracted only when the distance was insufficient; vehicles changing lanes in this condition were designated as cut-in (CV).

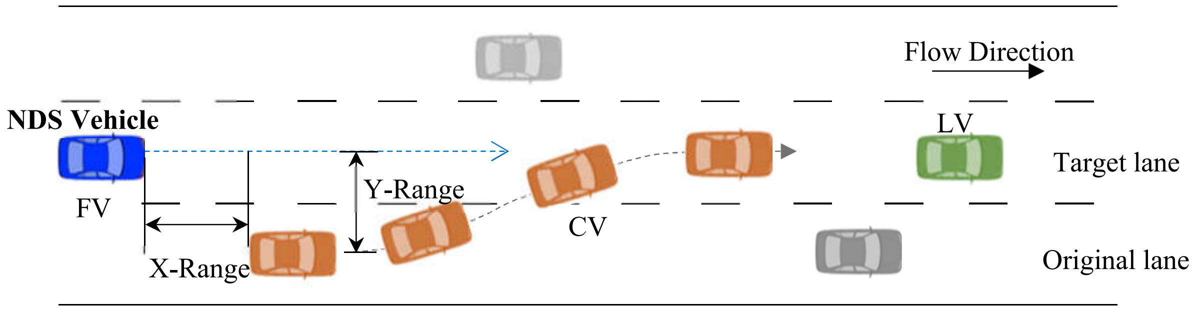

FIGURE 2 Radar target's (CV) position and motion in a cut-in scenario.

Figure 3 illustrates the key time points in an example of cut-in data extracted from the DAS. The CV, before cut-in is initiated, is about 4 m laterally from NDS vehicle. At the onset of cut-in, the CV's Y-Range (its lateral position in relation to the FV) is about 3.5 m, as the CV is still in its own lane but has initiated movement. The initiate point is thus the last peak (local maximum) of the Y-Range, as determined by a built-in function of MATLAB. In just over 3 s, it crosses over into the adjacent target lane, continually decreasing the Y-Range. 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 will cross the lane. This is the cross lane point. In about 1.5 s from the cross lane position, the CV becomes T0, or tangent zero. The Y-Range at this point, marked by the red vertical, is very small, approaching zero. In this position, the CV has become stable in the adjacent target lane. The first zero value of Y-Range after the CV becomes T0 is defined as the end of cutting behavior, or stabilization. From this point, the CV has completely stabilized its movement in the target lane.

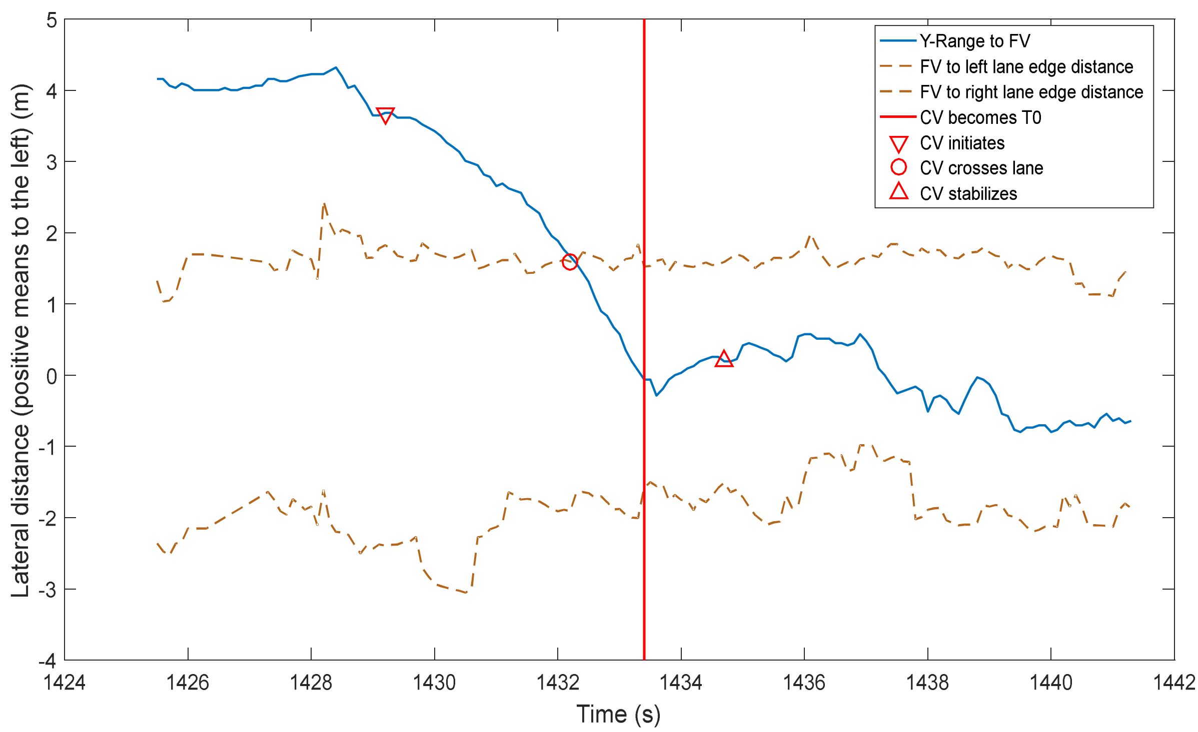

FIGURE 3 Y-Range time points of cut-in sequence: initiate, cross lane and stabilize.

Prior to automatic extraction, we viewed videos and analyzed 100 random cut-in events by hand, making statistical analysis to obtain criteria for the range of variables that would be extracted, e.g., lateral distance before cut-in > 2.2 m and <1.2 m, after completion. An event was extracted if the following criteria were met simultaneously:

- Y-Range (lateral distance) > 2.2 m when the CV initiates its movement toward the lane of the FV, and < 1.2 m when the CV is stable in the target lane. Together, these criteria guarantee the CV changes its lane.
- Maximum lateral acceleration of FV < 0.07 g, and lane offset < 1.7 m. These criteria guarantee the FV doesn't 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 lane change has no effect on the FV. Based on our 100 observations, we defined the maximum X-Range < 75 m in this study.
- The velocity of both FV and CV > 1 m/s. This criterion ensures the two vehicles are always in motion.

Events that met the above criteria were automatically extracted. Results were validated by the forward roadway camera video recording; road type was identified during validation.

We obtained 4,347 cut-in events, which were recorded by 51 of the 60 NDS drivers. 926 events were on surface roads, 2,589 events were on expressways, and 1219 events were on freeways.

4 CUT-IN BEHAVIOR CHARACTERISTICS ANALYSES

The four parts of our cut-in behavior analysis are presented in this section. First, we identified the purposes, or CV drivers' motives for cutting-in. Then turn signal usage was observed, which can reflect drivers' safety awareness. With the aim of exploring cut-in execution characteristics, we quantified cut-in duration and its distribution. Finally, we calculated TTC (time to collision) to classify urgency of cut-in behavior.

4.1 Cut-in Purposes

4.1.1 Purposes

Following Yang and Koutsopoulos (*15*), we classified cut-in purposes as either mandatory or discretionary. The main purposes for mandatory cut-ins are entering an intersection area in situations where a car must change lanes in order to be in the correct lane for a turn, entering or exiting a limited-access expressway/freeway, and avoiding work zone or other obstacles. Purposes for discretionary cut-ins include avoiding traveling behind slow preceding vehicles, and changing to fast or slow lanes in order to maintain a desired speed. Cut-ins without any clear purpose were considered discretionary in this study. The 4,734 cut-in events were identified and coded through watching forward roadway videos. The results, classified by road type, are shown in Table 1.

TABLE 1 Cut-in Purposes for Different Road Types

Road Type	Classification	Purposes (percent)		
Surface Road	Mandatory	1: 31.4%	2: 13.9%	3: 2.7%
	Discretionary	4: 39.5%	5: 8.8%	6: 3.7%
Freeway	Mandatory	1: 0 %	2: 10.5%	3: 1.2%
	Discretionary	4: 63.9%	5: 18.0%	6: 6.4%
Expressway	Mandatory	1: 0 %	2: 17.3%	3: 1.7%
	Discretionary	4: 63.4%	5: 14.9%	6: 2.7%

Mandatory:

Purpose 1 - Entering intersection area;

Purpose 2 - Entering or exiting a limited-access road;

Purpose 3 - Avoid work zone or other obstacles;

Discretionary:

Purpose 4 - Avoid slow preceding vehicle;

Purpose 5 - Change to fast/slow lane;

Purpose 6 - No clear purpose.

As shown in Table 1, avoiding a slow preceding vehicle is, by far, the main purpose (Purpose 4) of cut-in behavior on all road types, and accounted for 50.9% of cut-in behavior overall. This is similar to results in Olsen's U.S. lane change study, in which a slow vehicle ahead accounted for the largest number of lane changes, 37.24% on interstates and highways (*9*). It is reasonable to assume that most drivers pursue the shortest travelling time and comfortable driving experience, so a larger driving space and faster speed are their preferences.

Purpose 2 is most common on expressways, as drivers have to merge onto ramps when entering and exiting expressways. Purpose 5 is basically observed on freeways, where drivers are often required to choose the correct lane according to their speed. Purpose 1 is drivers' main motive on surface roads where there are frequent intersections; cut-in maneuvers are likely to be executed by drivers who realize they are in the wrong lane when they intend to turn left or right. Particularly notable, however, is that a considerable number of cut-ins (232 events) occurred without any apparent definite purpose (Purpose 6), more, in fact, than avoiding obstacles (Purpose 3).

4.1.2 Single/Multiple Lane Cut-ins Classified by Purpose

When cutting-in, some drivers move laterally a single lane, while others cross multiple (two or more) lanes, a choice that varies according to purpose and road type. We counted the proportion of single and multiple lane cut-ins according to road type. The results are in Table 2.

TABLE 2 Single/Multiple Lane Cut-in for Different Road Types

Road Type	Classification	Single Lane Cut-in	Multiple Lane Cut-in
Surface Road	Mandatory	73.7%	27.3%
	Discretionary	99.2%	0.8%
Freeway	Mandatory	55.9%	44.1%
	Discretionary	95.7%	4.3%
Expressway	Mandatory	61.6%	38.4%
	Discretionary	95.2%	4.8%

As shown in Table 2, more than 95% discretionary cut-ins are single lane. When drivers execute discretionary cut-ins, they want to keep desired speed, in most cases, single lane change can attain this goal. But for mandatory cut-ins, the situations are more urgent, i.e., drivers realize they must exit the freeway when they are in the left-most lane or they need to turn left/right when entering intersection area. According to our observation, driving in the wrong lane, hesitating to enter or exit and avoiding obstacles are main reasons for multiple lane cut-in, which accounts for a certain percentage of mandatory cut-ins. Especially on freeways and expressways, the percentage is up to 44.1% and 38.4%. The results are higher than that in the U.S. In Goswami's study (*31*), there are 20.0% multiple lane changes in the on-ramp or off-ramp areas. From this comparison we can find that Chinese drivers are slightly more aggressive as they execute more multiple lane cut-in, which is rather dangerous to surrounding vehicles.

4.2 Turn Signal Usage

Turn signal usage was also analyzed on different road types, which was observed by watching the videos. As shown in Table 3, the usage percentages are below 50% other than on the expressway, where turn signal usage percentage is 53.3%. Although Chinese traffic law requires use of turn signals, the overall turn signal usage on all road types is just 50.2%. This suggests that Chinese drivers may have a limited safety awareness, which adds to the risk difference between cut-in and normal lane change behavior.

TABLE 3 Turn Signal Usage for Different Road Types and Comparative Analysis

Road Type	Used Frequency	Not Used Frequency	Usage Percentage
Surface Road	439	487	47.4%
Freeway	1381	1208	53.3%
Expressway	555	664	45.5%
All Road Types	2375	2359	50.2%
Turn Signal Usage Comparative Analysis			
Lee & Olsen'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%

Lee and Olsen (*9*), used here for comparative analysis, do not explicitly differentiate between normal lane change and cut-in behavior, but both categories displayed in Table 3, *forced* and *urgent*, meet the definition of cut-in as more urgent than normal lane change. In their study, turn signal usage for lane changes (LC) on interstates and freeways was 44.0%

when situations were forced (TTC $\leq$ 3 s), but 53.3% when the situations were somewhat less urgent (5.5 s $\geq$TTC > 3 s). Our results are similar to urgent LC situations in the U.S. However, in normal lane change situations, Dang's study indicates that turn signal usage for Chinese driver's is 65% on highways (*20*), which is higher than the 50.2% freeway cut-in usage in our study. This difference can be explained by following reasons: 1) drivers are not aware of the real situation, and think they are safe when they are not; the lack of a direct and immediate cause-effect makes many drivers think that neglecting turn signal usage is not dangerous; 2) driver skill level varies, and some drivers are challenged by simply getting the vehicle from point A to point B; because cut-ins by definition have some degree of urgency, using a turn signal just does not come to mind (*22*); 3) simple carelessness, again due to urgency, some cut-ins are very quickly executed, so using turn signal is forgotten.

4.3 Cut-in Duration and Distribution Selection

Cut-in duration is defined roughly the same as lane change duration, i.e., the time span from the lane changer's initiation of lateral movement to stabilization in the target lane. Therefore, the duration in Figure 3 above is about 5.7 s. For all 4,734 events, the duration varies from 0.7 s to 12.3 s, its mean is 3.82 s and standard deviation is 2.28 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.

Statistics software provides strong analysis of existing data in a perspective view. We explored 8 possible distribution alternatives in MATLAB Distribution Fitting. According to the duration histogram, lognormal is the best fit to our duration data. This result is similar to the results of Toledo (*19*) and Hetrick (*24*), who, to explore normal lane change distribution (lognormal distribution), selected proper probability density functions (PDF) to fit to lane change duration. 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*).

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

We obtained the results that μ = 1.174 and σ = 0.517, which are slightly different from Toledo's (19). In his results, 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 μ = 1.376 and σ = 0.550. Cut-in maneuvers differ from normal lane change in their shorter duration (3.82 s on average).

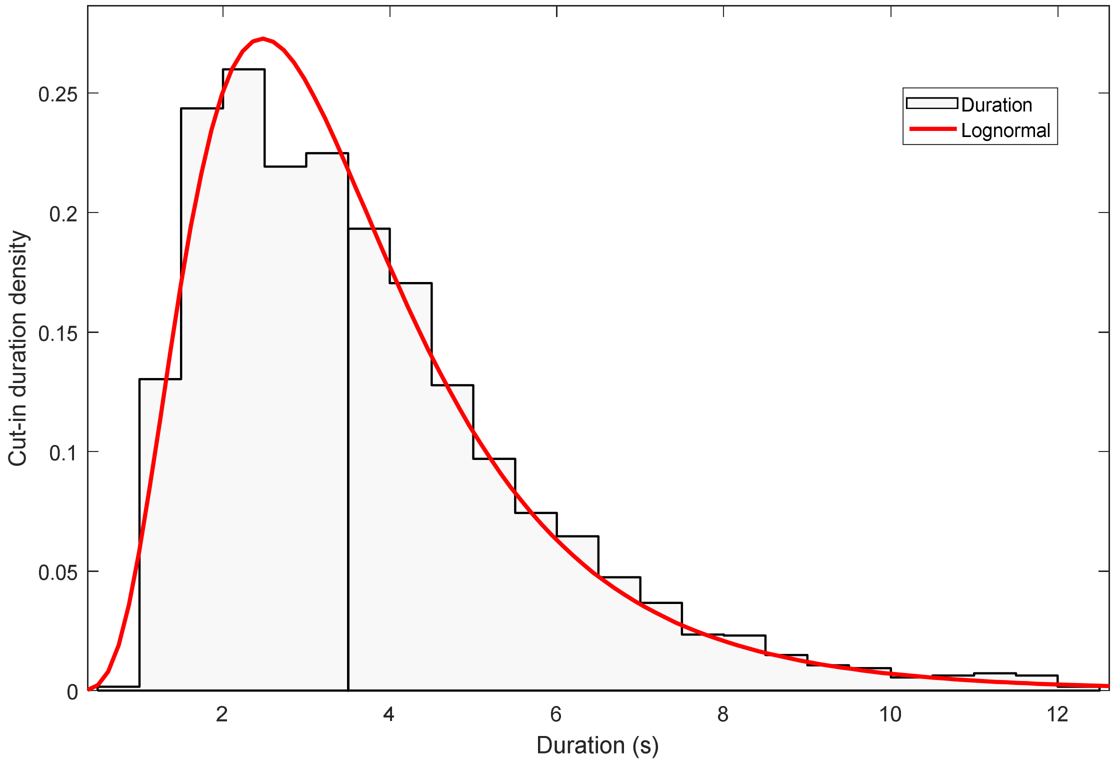

FIGURE 4 Distribution best fits to cut-in duration (lognormal).

4.4 Cut-in Urgency Based On TTC

TTC is used extensively to evaluate level of safety, which is essential to calculate rear-end conflict, the most common cut-in risk. Olsen et al. (*9*) classified urgency of normal lane change in a 4-point rating scale (1 = not urgent, 4 = critical) that indicated how soon the lane change was needed, need being based on TTC with the closest vehicle ahead or behind. We adopted the same cut-in urgency rating scale, 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). Note that only positive TTC makes sense, as TTC equals the range between CV and FV divided by their relative speed. In order to compare cut-ins with normal lane changes, the mean of TTC during cut-ins was calculated. Results of our classification of cut-in urgency based on TTC for different road types are in Table 3.

TABLE 3 Cut-in Urgency Based on TTC (positive) for Different Road Types

Urgency / Road Type	1	PCT	2	PCT	3	PCT	4	PCT
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	1096	79.7%	215	15.6%	60	4.4%	3	0.3%
All Road Types	2008	79.4%	397	15.7%	118	4.7%	5	0.2%
Olsen's LC study	2945	91.2%	269	8.3%	14	0.5%	0	0%

Note: PCT means percentage on the corresponding road.

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 percentages but 1 (non-urgent) were higher than those in Olsen's normal lane change study, which indicates cut-in behavior is relatively more dangerous than normal lane change. Because of the shorter TTC, cut-ins can have negative impact on traffic safety.

Freeways and expressways had lower percentages of urgencies of 2 and 3 than on surface roads. A reasonable explanation is that surface roads may have higher-risk influences on cut-in behavior, such as lower absolute speed, more frequent mandatory cut-ins (refer to Figure 1 above), and shorter distance ranges, both laterally and longitudinally, between the CV and FV.

5 MODELING CUT-IN GAP ACCEPTANCE

Modeling gap acceptance contains two aspects, one to explore gap distribution, and the other to quantify the influencing factors of gap acceptance. As discussed earlier, drivers considering a cut-in consider safety as well as speed and convenience. Determining whether or not a target gap is safe enough to accept is the most 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. The lag gap, however, is their primary concern. Because CV drivers depend on mirrors to determine lag gap, they know their perception of that gap is not as reliable as it is for lead gap (*17*). Therefore, this study limits the modeling of cut-in gap acceptance to lag gap.

5.1 Lag Gap Distribution

Lag gap refers specifically to the longitudinal distance between the CV and FV when the CV initiates its movement. As drivers start to execute cut-in, it is assumed that they accept an available gap by comparing it to their own critical gap. Therefore, lag gap is considered as deterministic; and unlike duration, the correlation test results showed a significant relationship between lag gap and road types (*P-Value* < 0.0001).

Since the expressway had the largest sample size in our study (2589 events), we used more than 10 distributions (including normal, lognormal, gamma, generalized extreme value, etc.) to fit the cut-in lag gap on that road type. In a previous lane change study, Bham (*32*) fitted a Gamma distribution to lag gap acceptance data, but as our results of cut-ins on the expressway differed from Bham's, we fitted a Generalized Extreme Value (GEV) distribution. GEV tends to be a better fit when the lag gap is shorter than 20 m. As mentioned above, cut-ins often occur when situations are urgent or the CV otherwise moves unpredictably; thus CV drivers' critical accepted gap will be shorter than that for normal lane change. As shown in Figure 5, this study's expressway lag gap, from 8 m to 16 m, has a higher density proportion than fits to Gamma distribution.

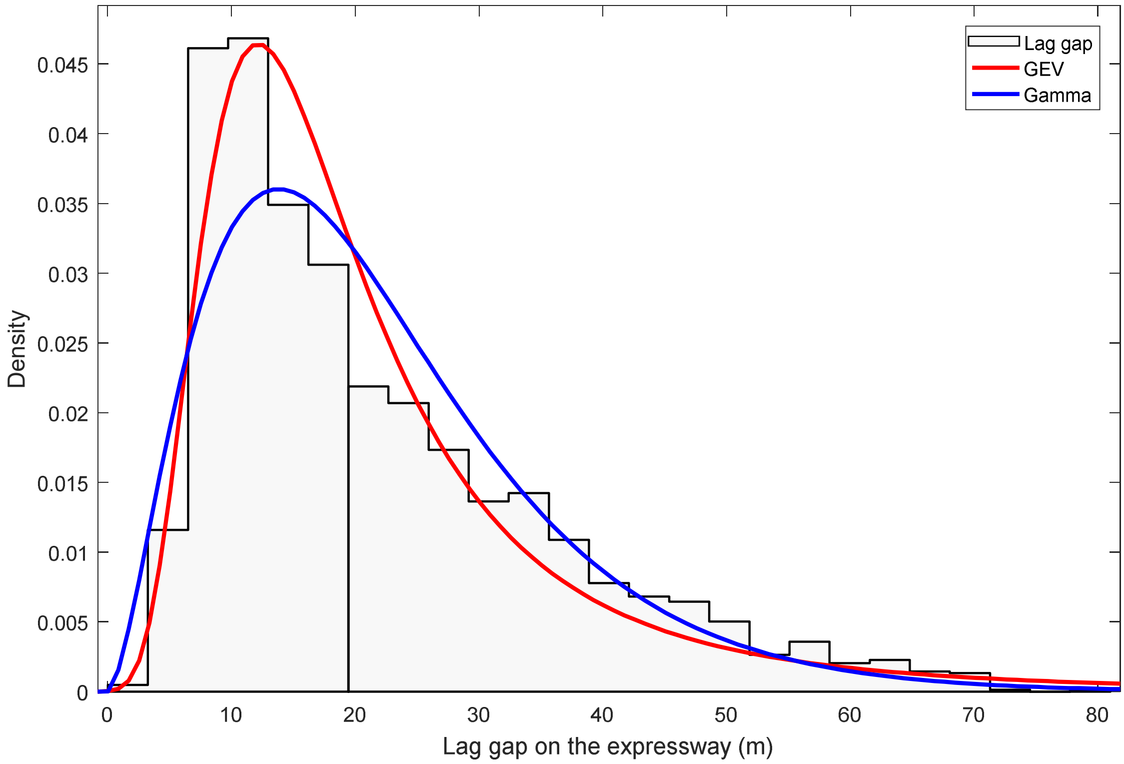

FIGURE 5 Distribution best fits to lag gap on the expressway.

Similarly, GEV distribution fitted best to the lag gap on surface roads and freeways. That smaller lag gaps are more frequent in cut-ins confirms that cut-in behavior is atypical lane change. Although cut-ins did not in most cases lead to crashes or near crashes in this study, unsafe lane changing has been connected with crash occurrence in previous studies. Thus, it remains important to explore the factors that influence drivers' gap acceptance.

5.2 An Exploratory Lag Gap Regression Model

The multiple regression model is the most widely used method for empirical analysis. Having obtained the gap and other related variables, we were able to explore the influencing factors of the cut-in lag gap using a multiple regression model. In order to ensure that gaps are always non-negative, we calculated the natural logarithm (ln) of lag gap. The equation is given by:

$$\ln G_n = \beta_0 + \beta_n x_n + \varepsilon \quad (3)$$

where G_n is the lag gap for each cut-in event, β_0 is a constant, x_n is vector of explanatory variables, β_n are corresponding parameters and ε is the error term.

As road type, relative speed and FV acceleration have been shown to be related to gap acceptance (*17*), we chose these three explanatory variables to analyze their influence on lag gap acceptance. Road type is described as a dummy variable (Road1, Road2), i.e., Road1 = 0 and Road2 = 0 for surface roads, Road1 = 1 and Road2 = 0 for freeways, while Road1 = 0 and Road2 = 1 for expressways. Relative speed, named RelSpd in Equation (4), with a unit of m/s, is defined as the difference between the speed of CV and the speed of FV (FV speed minus CV speed). FV's longitudinal acceleration is designated as FVAcc, with a unit of m/s^2. Speed and acceleration information were initially recorded by the data acquisition system (DAS). All variables in Equation (4) are for the onset, or initiation, of cut-in. Therefore, Equation (3) can be rewritten as Equation (4):

$$\ln\left(G_{n,\ lag}\right) = \beta_0 + \beta_1 \times Road1 + \beta_2 \times Road2 + \beta_3 \times RelSpd + \beta_4 \times FVAccel + \varepsilon_n \qquad (4)$$

TABLE 4 Estimation Results of Cut-in Lag Gap Model

Variable	Coefficient	Std. Error	t-Statistic	Pr > |t|
Constant	2.8486	0.0202	140.71	<0.0001
Road1	0.1782	0.0270	6.61	<0.0001
Road2	0.0568	0.0236	2.41	0.0162
RelSpd	0.0453	0.0034	13.37	<0.0001
FVAcc	0.0437	0.0114	3.83	0.0001

As shown in Table 4, all variables are significant at the 95% confidence level (*P-Value* < 0.05 is significant). The size of the acceptable cut-in lag gap increases with the increase in relative speed between FV and CV, i.e., faster the speed of the FV in comparison to the CV, the larger the lag gap must be for the CV to attempt the cut-in. Similar to the effect of relative speed, when the FV accelerates, the cut-in lag gap will increase. The positive coefficients of relative speed and FV acceleration implies that because drivers are more cautious when the FV accelerates and closes in to them, the cut-in lag gap must become larger.

Absolute speed, as well as relative speed, affects lag gap acceptance. The lag gap on the freeway is the largest (Road 1 coefficient of 0.1782), followed by the expressway (Road 2 coefficient of 0.0568) and finally on the surface road. The probable reason is that the speed limit varies from 30 km/h to 80 km/h on surface roads, from 60 km/h to 80 km/h on expressways, and from 80 km/h to 120 km/h on freeways. As few drivers take the risk of entering small lag gaps when FV speed is high, the minimum perceived safe gap between vehicles must therefore be larger at higher speeds.

These results indicate that road type, relative speed and FV acceleration are important factors that may influence CV gap acceptance, supporting earlier findings for lane change gap acceptance.

6 SUMMARY AND CONCLUSION

This study explored drivers' cut-in behavior in Shanghai, China. A methodology to extract cut-in events was proposed and 4,734 events were used to acquire a broad view of Chinese driving behavior. Cut-in characteristics, including drivers' purposes, turn signal usage, duration, and urgency were analyzed comprehensively. A regression model of gap acceptance that considered road type, relative speed, and the following vehicle's acceleration was developed to capture the influencing factors of cut-in behavior.

The first important characteristic of cut-in behavior is the primary motive, or purpose. More than half of cut-ins are correlated with a slow preceding vehicle, which suggests drivers are motivated to maintain a desired speed. Moreover, discretionary cut-ins are more common on freeways and expressways than they are on surface roads, which suggests that drivers have more freedom when cutting-in on such roads, perhaps because they are larger, faster, and have limited access. It is worth mentioning that some Chinese drivers cut-in without any clearly observable intention (i.e., 4.2% 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 next 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.

Almost half of Chinese drivers do not use a turn signal when cutting-in, which may further indicate bad driving habits and aggressive driving style. According to a 1992 study by Daimler-Benz, if passenger car drivers have 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% rear-end collisions (*33*). Therefore, the use of turn signals is not only a responsible safety precaution for the drivers themselves, but also shows respect for others' safety, especially occupants of following vehicles. This low percentage of turn signal usage, combined with the high rate of cut-in behavior, especially cut-ins without clear intention, indicates a need for strengthened safety education in China, as well as greater attention from traffic police.

Quantifying cut-in duration and lag gap is an important issue related to driving behavior and traffic safety. Among several distributions, a lognormal distribution produced the best fit for cut-in duration data, and Generalized Extreme Value (GEV) distribution produced a best fit for lag gap data. Unlike typical lane changes, cut-ins have shorter durations as well as smaller lag gaps, both of which increase the riskiness of cut-in behavior. This suggests that drivers' perceive an urgency in performing this maneuver, so it is unsurprising that through calculating time to collision of cut-ins (TTC), we find that cut-in behavior has a significantly higher degree of urgency than normal lane change. Because drivers tend to execute cut-in maneuvers hastily, they are more accepting of gaps that would be normally rejected and ignore the potentially dangerous impact on following vehicles.

A regression lag gap model that considers road type, relative speed and following vehicle's acceleration can capture crucial factors that influence drivers' gap acceptance. However, while our model shows significant results, the R-square is only 0.1963, which means missing variables account for the limited goodness of fit. Gap acceptance cannot be easily predicted because drivers' decision-making processes are complicated, depending on driver psychology and driving style as well as the performance capabilities of the vehicle (*17, 34*). In addition, weather, light condition, traffic density and cut-in vehicle type may result in different accepted gaps. Nevertheless, our model has good explanatory capability and highlights the influencing factors that may affect the cut-in decision-making process.

In summary, this paper extends the exploration and development of lane change theory and its applications. The results indicate that current assumptions about cut-in behavior in developed countries do not directly transfer to the Shanghai condition. More broadly, social norms and behavior are influenced by culture and other countries should consider calibrating assumptions about cut-in behavior based on local data sources.

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