Transportation Research Part C 111 (2020) 226–244

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Impact on car following behavior of a forward collision warning system with headway monitoring

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ARTICLE INFO

Keywords:
Forward collision warning
Headway monitoring
Naturalistic driving study
Car-following behavior
Headway time
Reaction time
Vehicle-to-vehicle (V2V) communication

ABSTRACT

Forward collision warning (FCW) systems function by alerting drivers to upcoming hazards ahead and have been shown to help drivers respond more quickly under emergency situations. As FCW directly affects how vehicles interact longitudinally with one another, it may also influence car-following behavior such as reaction time, which has been little researched. To investigate these effects, driving data were collected from the Shanghai Naturalistic Driving Study. Five data-collecting vehicles were equipped with Mobileye® systems, which included an FCW function with headway display and warning system. Participants drove the vehicles for two months, with the Mobileye® system activated the second month only. From the 161,055 km of naturalistic driving data collected from 60 drivers, 3,000 car-following events were selected, and the effects of FCW on car-following headway and reaction time, and on the parameter values of the Gazis-Herman-Rothery (GHR) model were examined. Results showed that (1) drivers tended to maintain shorter headway with FCW enabled, while the proportion of time in short headways did not increase; (2) FCW reduced car-following reaction time when the lead vehicle was accelerating and when the relative speed between the lead and following vehicle was large; and (3) a reduction in the space headway exponent of the GHR was observed when FCW was enabled, indicating that drivers follow more closely with FCW because the system increases drivers' sensitivity to changes in following gaps. Results of this study suggest that an FCW system with a headway monitoring function may increase traffic efficiency and stability without degrading safety.

1. Introduction

A primary aim of forward collision warning (FCW) systems is to reduce rear-end crashes, which account for 20–30% of all crashes, and about 10% of all fatal crashes (Wang et al., 2016a). These in-vehicle FCW systems monitor the roadway ahead and warn the driver when a collision risk reaches a certain threshold. Previous research, which has focused mainly on the effects of FCW on driving behavior in rear-end crash scenarios, has found that FCW can reduce accelerator release time (McGehee et al., 2002) and brake delay time (Soma and Hiramatsu, 1998). However, as FCW directly affects how vehicles interact longitudinally with one another, it may also influence behaviors more specific to car following, behaviors that can be precursors to rear-end collisions and also affect traffic efficiency and stability.

Car following refers to a situation in which a vehicle's speed and longitudinal position are influenced by the vehicle immediately ahead of it, characterized by reaction time and headway (Ranney, 1999; Zhu et al., 2016):

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https://doi.org/10.1016/j.trc.2019.12.015
Received 27 December 2018; Received in revised form 17 December 2019; Accepted 20 December 2019
Available online 06 January 2020
0968-090X/

- Driver reaction time was discussed as early as the 1950s, when the first stimulus-response car-following model was developed (Chandler et al., 1958). In stimulus-response car-following models, the FV observes a change in driving conditions—the stimulus—and responds after a lapse of time, called the reaction time (Gurusinghe et al., 2002). Reaction time is an essential factor contributing to traffic instability and, consequently, is an indispensable element in many car-following models (May, 1990).
- Headway is defined as the elapsed time between the arrival of the lead vehicle (LV) and the following vehicle (FV) at a designated point (Ben-Yaacov et al., 2002). Headway, therefore, relates to the time available for a driver to react, and is a safety measure of car-following behavior (Zhang et al., 1999).

Several studies have investigated the impact of FCW on headway maintenance and have found that FCW does significantly affect headway (Ben-Yaacov et al., 2002) and the time drivers spend in short headways (Shinar and Schechtman, 2002). However, while these studies focused on observable performance changes, they did not explain them: specifically, they did not investigate how FCW influences the internal car-following mechanisms that cannot be observed directly. In particular, little research has been devoted to investigating how FCW might affect car-following reaction time.

Therefore, this study seeks to quantify FCW's impact on the internal mechanisms of reaction time and other parameter values of a fundamental car-following model, and also FCW's impact on the car-following performance measure of headway. Quantification of the internal mechanisms may help explain the headway results.

To address these needs, real-world driving data were collected from the Shanghai Naturalistic Driving Study (SH-NDS). In the SH-NDS, driver behavior was observed as it occurred in the full context of real-world driving, and vehicle kinematic data (e.g., acceleration, velocity, position) were recorded continuously at high resolution. Mobileye® systems were installed in the research vehicles, which included an FCW function. Each participant drove the vehicle for two months, with the Mobileye® system activated for the second month only. The data collection procedure started in December 2012, and by December 2015, driving data had been collected for 60 participants who drove 161,055 km in total. These detailed driving data provide an unprecedented opportunity for investigating the impact of FCW on drivers' car-following behavior.

2. Literature review

2.1. Forward collision warning (FCW) system

Rear-end collisions are a serious highway safety issue. One direct approach to reduce rear-end collisions is to develop an FCW system. These systems use sensors like camera, radar, and lidar to detect slower-moving or stationary vehicles. Once the system determines that a forward collision is going to happen (e.g., with short following distances or large approaching speeds), it will send auditory and/or visionary alerts to the driver so that he or she can take evasive actions to prevent a potential crash.

The warning algorithm is the core of an FCW system. Extensive efforts have been devoted to developing better FCW algorithms, and generally, these algorithms can be divided into two categories: perception-based and kinematic-based (Wang et al., 2016b). Perception-based algorithms trigger warning based on empirical risk indicators such as time headway and time to collision. Once a threshold value is reached, a warning will be signaled. Kinematic-based algorithms determine a minimum theoretical distance to stop safely based on the fundamental laws of motion. Once the following distance is shorter than the safety distance, a warning will be triggered.

2.2. Car-following models

A car-following model describes the movements of a following vehicle (FV) in response to the actions of a lead vehicle (LV). A large number of car-following models have been developed, but most have been based on a stimulus-response framework. This framework assumes that each driver responds to a given stimulus from the vehicle(s) ahead according to the following relationship: response = sensitivity × stimulus. The Gazis-Herman-Rothery (GHR) model, also known as the General Motors (GM) model, is the best-known stimulus-response model and is the result of research spanning from the late 1950s until the middle 1960s (Chandler et al., 1958; Gazis et al., 1961). The GHR assumes that drivers determine their acceleration based on the relative speed and space headway (or following gap); the space headway exponent indicates driver sensitivity to the gaps.

2.3. Impact of FCW on car-following

Several studies have investigated the impact of FCW on car-following behavior, focusing on headway maintenance. Table 1 presents a summary of these studies, which, based on experimental method, can be pooled into two main categories: test track studies and naturalistic driving studies (NDS).

2.3.1. Test track studies

Dingus et al. (1997) conducted three on-road test track studies to see how the FCW's headway monitoring and collision warning systems influenced driver behavior. A total of 108 participants (54 men and 54 women) were recruited. All 108 participants participated in a 40.3-km baseline drive without warning systems, and then a return drive with warning systems. The researchers found that driver headway increased by 0.5 s when an appropriate visual display of headway was presented. Ben-Yaacov et al. (2002) evaluated how an imperfect (with some malfunctions) collision warning system would affect driver headway maintenance. Thirty

Table 1
Results summary for studies of effects of FCW on headway maintenance.

Study	Approach	Vehicle type	Warning mechanism	Headway	Short-headway proportion*
Dingus et al. (1997)	Test track	Light vehicle	● Headway > 1.6 s: green car icon ● Headway between 1.1 s and 1.6 s: orange car icon ● Headway < 1.1 s: red car icon	Increased by 0.5 s	–
Ben-Yaacov et al. (2002)	Test track	Light vehicle	Headway < 1 s: audial warning	Increased	–
Shinar and Schechtman (2002)	NDS	Light vehicle	● Headway between 0.8 s and 1.2 s: red warning light ● Headway between < 0.8 s: red warning light plus audial warning	Increased	Decreased from 25% to 15%
Ervin et al. (2005)	NDS	Light vehicle	Kinematic FCW algorithm: car icon display, with color changing from blue to yellow and eventually to red, and size increasing when rear-end risk increases	Increased on freeway and during daytime	Decreased on freeway
Bao et al. (2012)	NDS	Heavy truck	Audial warning when headway drops to 3 s, 2 s, and 1 s.	Increased by 0.28 s with dense traffic; increased by 0.2 s with wipers on	–
LeBlanc et al. (2013)	NDS	Light vehicle	Headway < 2.5 s: audial and visual warning	Decreased	Increased from 13% to 16%
Kessler et al. (2012)	NDS	Light vehicle and heavy truck	Not reported	Increased	–
Saffarian et al. (2013)	Simulator	Light vehicle	No audial warning, LV acceleration and headway display only	Decreased	No change
Current study	NDS	Light vehicle	● TTC < 2.7 s: audial warning and flashing car icon ● Headway between 0.6 s and 2.5 s: green car icon and headway display ● Headway < 0.6 s: audial warning and red car icon	Decreased by 0.24 s	No change

* Short headways are defined as less than 1 s except in Shinar and Schechtman (2002), who used a 0.8-s threshold.

participants were recruited and were asked to drive four trials. The first trial involved 20 km of driving with the warning system muted; the second trial was a 70-km drive (about 50 min) with the warning system unmuted; the third was another muted baseline drive back to the starting point; the final trial took place 6 months later and was a 20-km drive with the same vehicle and route. It was found that drivers maintained a longer following distance after a short exposure to the system. The major limitations of these two studies are their short experimental durations and artificial driving situations.

2.3.2. Naturalistic driving studies

Data collected by NDS represent real-world driving over longer time spans, and may provide more valid results on FCW's effects. In an NDS conducted by Shinar and Schechtman (2002), 43 drivers drove their cars for 3 weeks without headway feedback and then for approximately 3 more weeks with immediate headway feedback. The results showed that headway feedback reduced the time spent in short headways ($\leq$0.8 s) by approximately 25%, and increased the time spent in safer longer headways ($>$ 1.2 s) by approximately 20%. One limitation of this study is that it has biased subjects because all the drivers were from two Israeli high-technology firms.

Ervin et al. (2005) conducted a 12-month NDS to evaluate an automotive collision avoidance system (ACAS), which included an FCW system and an adaptive cruise control system (ACC). A total of 96 drivers participated in the experiment and drove 137,000 miles in total. The results echoed the above test track studies: they showed that with FCW enabled, headways increased on freeways and during the daytime. One potential limitation of this study is that the experiment was conducted almost 20 years ago (1999–2004).

Using NDS data from the Integrated Vehicle-Based Safety System (IVBSS) program, Bao et al. (2012) and LeBlanc et al. (2013) investigated the effects of an integrated in-vehicle crash warning system on the headway maintenance of heavy trucks and light vehicles, respectively. The results indicated that the warning system led to an increase in headway with heavy truck drivers, but a decrease in headway with light vehicle drivers. In Europe's first large-scale Field Operational Test (euroFOT) project, Kessler et al. (2012) tested several in-vehicle systems in real traffic. They found that for both light vehicles and trucks, the headway increased significantly with the use of ACC and FCW together.

There are several common limitations in the abovementioned studies:

(1) They focused on observable performance (time headway) changes but did not explain what internal car-following mechanisms caused these changes.
(2) They did not investigate how FCW influences the components of car-following models, which are essential for bridging microscopic driving behaviors and macroscopic traffic characteristics.
(3) No study has investigated how FCW might affect car-following reaction time, an essential factor contributing to traffic instability.

Therefore, this study will use naturalistic driving data to (1) investigate FCW's impact on reaction time and car-following model parameter values, and (2) further confirm FCW's effects on headway in order to relate those effects to the system's impact on car-following mechanisms.

3. Data collection and preparation

3.1. Shanghai naturalistic driving study

The data used in this study were collected by the Shanghai Naturalistic Driving Study (SH-NDS) (Zhu et al., 2018a,b) jointly conducted by Tongji University, General Motors (GM), and the Virginia Tech Transportation Institute (VTTI). The three-year data collection procedure started in December 2012 and ended in December 2015. Five GM light vehicles equipped with Strategic Highway Research Program 2 (SHRP2) NextGen data acquisition systems (DAS) were used to collect real-world driving data. The Mobileye® C2-270 active safety system was installed in each test vehicle to evaluate the system's effectiveness.

As shown in Fig. 1, each participant drove his/her assigned vehicle for two months, with the Mobileye® system activated only the second month. Driving data were collected daily from the 60 licensed Shanghai drivers who, altogether, traveled 161,055 km during the study period, with 83,144 km in the Mobileye® system-disabled phase and 77,911 km in the enabled phase.

The 60 participants were randomly sampled from the population of licensed Shanghai drivers; the distributions of gender, age, and driving experience of the sample accord with those of the general Chinese driving population. The general principle for participant inclusion was that they should be non-professional drivers who own vehicles, have driving experience, and have the need to drive daily. The specific inclusion criteria are:

Fig. 1. Flow framework for experiment design.

Table 2
Resolution and accuracy of key data elements.

Data element	Resolution	Error
Timestamp	1 ms	–
Relative speed of radar detected objects	0.1 m/s	< 1.65 m/s
Relative distance of radar detected objects	32 mm	< 0.5 m when distance < 10 m; < 5% when 10 m < distance < 240 m
Relative angle of radar detected objects	1 deg	< 0.5 deg
Subject vehicle speed	0.02 km/h	< 1 km/h

- having at least 2 years of driving experience;
- driving the vehicle for commuting almost every day;
- not being a professional or taxi driver;
- of an age between 25 and 60.

3.2. Data acquisition system

The DAS uses an interface box to collect vehicle controller area network (CAN) data, an accelerometer for longitudinal and lateral acceleration, a radar system that measures relative distances and relative speeds to the LV and vehicles in adjacent lanes, a light meter, a temperature/humidity sensor, and a GPS sensor. The data collection frequency for the accelerometer and radar systems is 50 Hz. The DAS automatically starts when the vehicle's ignition is turned on, and automatically powers down when the ignition is turned off. Table 2 summarizes the resolution and accuracy of the key data elements.

Four synchronized camera views are also included to validate the sensor-based findings (Fitch and Hanowski, 2012). As shown in Fig. 2, the four-camera views monitor the driver's face, the forward roadway, the roadway behind the vehicle, and the driver's hand maneuvers. The frame rate of the videos is 14.98 frames/second.

3.3. Mobileye® active safety system

The Mobileye® C2-270 active safety system includes two subsystems that relate to car following: forward collision warning (FCW) and headway monitoring and warning (HMW). The FCW system alerts drivers to the danger of an impending rear-end collision, while the HMW system helps them maintain a safe following distance from the vehicle ahead by providing visual and audial alerts if the time headway is less than a pre-defined threshold.

Time-to-collision (TTC) and time headway are used by the FCW and HMW systems, respectively, to trigger alerts. TTC is the time that is left until a collision occurs if both vehicles continue on the same course and at the same speed, and is computed as the following gap divided by relative speed. According to Vogel (Vogel, 2003), headway and TTC are independent of each other for vehicles in a car-following situation. A small headway generates a potentially dangerous situation, whereas TTC specifies the actual occurrence of a dangerous situation.

In the FCW, once the TTC drops to 2.7 s, the system emits a series of loud, high-pitched beeps, and displays a red, flashing car icon

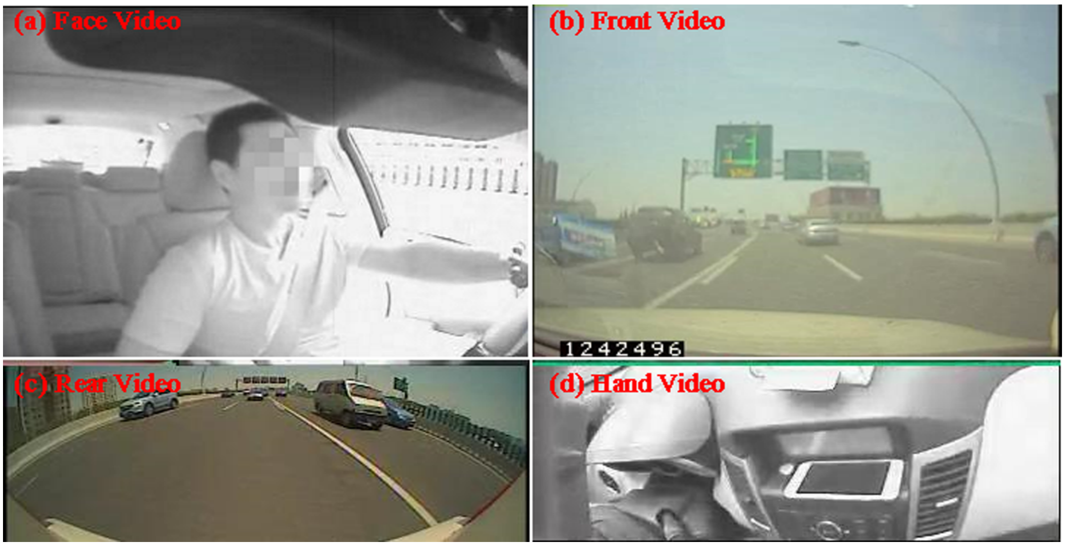

Fig. 2. Four camera views from SH-NDS (Zhu et al., 2018a).

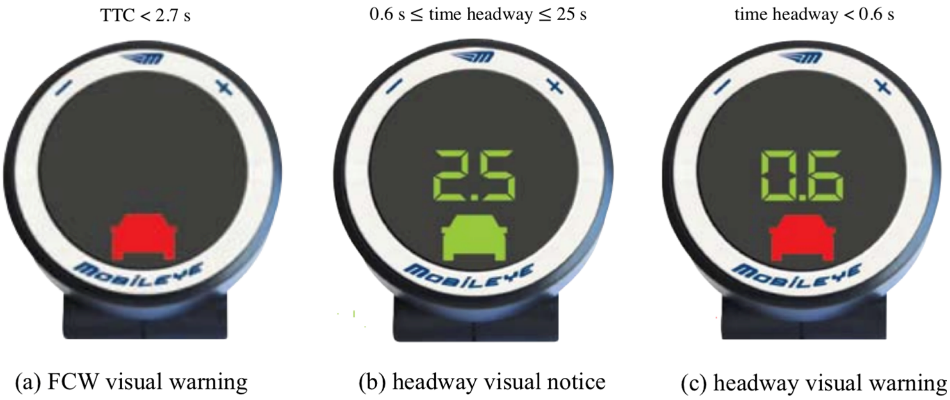

Fig. 3. Visual display of the FCW and HMW systems.

(Fig. 3-a). In the HMW system, the time headway is displayed numerically and is continuously updated (Fig. 3-b) when an LV with headway < 2.5 s is detected. A green car icon is displayed if the headway remains > 0.6 s, but once the headway drops to 0.6 s, a red car icon is displayed (Fig. 3-c) and a single chime is sounded to indicate dangerous tailgating (Mobileye, 2010).

3.4. Car-following periods extraction

As shown in Fig. 4, a car-following period was extracted if the following final criteria were met simultaneously (Chong et al., 2013; LeBlanc et al., 2013; Zhu et al., 2018b; Wang et al., 2018; Zhu et al., 2019):

- Radar target's identification number > 0 and remained constant: this criterion guaranteed that the same LV was being detected;
- Range < 120 m: this criterion eliminated free-flow traffic conditions;
- Lateral distance < 2.5 m: this criterion guaranteed that the following and lead vehicles were driving in the same lane; and
- Duration of car-following period > 15 s: this criterion guaranteed that the car-following persisted long enough to be analyzed.

To ensure the validity of the car-following periods selected for analysis, the results of the automatic extraction process were confirmed by an analyst viewing the video material filtered by the above criteria. A total of 3,000 car-following events were randomly selected and used in this study.

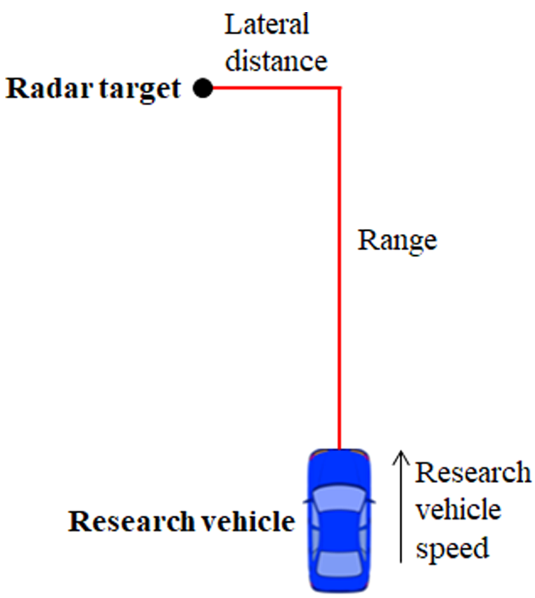

Fig. 4. Radar target's position and motion with respect to the research vehicle.

Table 3
Summary of independent variables.

Variables	Conditions
FCW (Warning condition)	ON, OFF
Roadway	Freeway, surface road
Ambient light	Daytime, nighttime
Weather	Sunny, rainy
Traffic density	Continuous variable
Speed	Continuous variable

4. Methodology

4.1. Independent variables

Table 3 summarizes the independent variables. The key independent variable was FCW, which included *on* and *off* phases depending on the activation of the Mobileye® FCW system. To consider the possible influence of traffic interruption, the roadways were divided into two categories: freeways and surface roads. Freeways refer to roadways with limited access such as urban expressways; arterial, minor arterial, collector, and local roadways were categorized as surface roads. Roadway type, ambient light, and weather information were derived from the front view video by a single analyst to ensure consistency.

Traffic density was measured based on radar data. The radar system can track, at most, eight vehicles simultaneously. Using the position information of radar-detected vehicles, the following distance between each pair of lead and following vehicles can be calculated and averaged, as shown in Fig. 5. The reciprocal of average following distance was taken as traffic density. It should be noted that although this is not a precise calculation of traffic density along a road segment, it well estimates the local traffic density around the subject vehicle. Since vehicles' behaviors are most directly affected by vehicles around them, this estimated local traffic density can well capture how traffic density affects the subject vehicle's behavior.

Road slope was not included as an independent variable because all the car-following events were extracted from trips in Shanghai, for which the vast majority of land area is flat. We also assumed that other road characteristics such as radius, number of lanes, and lane width were distributed consistently across the FCW's *on* and *off* stages because the data from the two stages came from the same group of people who used their vehicles for commuting, that is, they traveled on the same roads daily. Considering the limited number of drivers, we did not include age, gender, and driving experience as independent variables.

Table 4 presents frequency information for the discrete variables and descriptive statistics for the continuous variables. The total number of car-following events that occurred during the FCW's *on* and *off* stages are 1,513 and 1,487, respectively. The road type, ambient light, and weather type distributed unevenly across their levels (e.g., more events on freeways than surface roads), but the distribution patterns were roughly consistent between FCW *on* and *off* stages.

4.2. Dependent variables

To examine the effect of the FCW on car-following, three types of objective measures were used: (1) SPS:refid::e1 time headway, including mean headway and the proportion of time drivers spent in a short time headway zone (i.e., 1 s or less); (2) reaction time; (3) parameters of the GHR car-following model. The basic descriptive statistics for time headway are presented in Table 4.

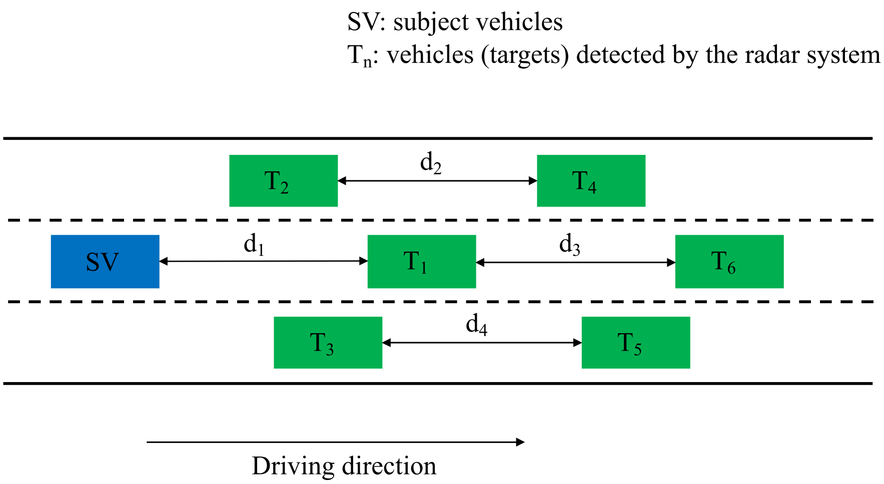

Fig. 5. Traffic density estimation using position information of radar-detected vehicles.

Table 4
Frequency and descriptive statistics of variables.

FCW	Road type		Ambient light		Weather		Traffic density (veh/km/lane)			
	Freeway	Surface road	Daytime	Nighttime	Rainy	Sunny	Mean	Std. Dev.	Min	Max
OFF	999	488	1028	459	415	1072	51.49	25.18	14.12	136.57
ON	963	550	1070	443	476	1037	51.84	25.65	15.45	138.64
All	1962	1038	2098	902	891	2109	51.67	25.41	14.58	139.32

FCW	Travel speed (km/h)				Time headway (s)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
OFF	52.18	20.59	22.03	109.1	1.61	0.77	0.55	4.05
ON	49.95	18.9	22.5	96.68	1.66	0.81	0.52	4.54
All	51.06	19.79	22.42	103.28	1.64	0.79	0.54	4.43

FCW	Distance headway (m)				Short time headway proportion			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
OFF	23.27	15.61	6.23	80.39	0.19	0.32	0	1
ON	22.8	14.3	6.38	74.36	0.16	0.3	0	1
All	23.04	14.96	6.31	78.05	0.18	0.31	0	1

4.2.1. Time headway

Mean time headway for each car-following event was calculated by dividing the following gap by the FV speed. In accord with previous studies, a 1-s threshold was selected for the short time headway zone (Ervin et al., 2005; LeBlanc et al., 2013).

4.2.2. Reaction time

Reaction time was determined by a graphical method of manually comparing the FV acceleration and relative speed (LV speed−FV speed) curves, as proposed by Gurusinghe et al. (2002). Fig. 6 shows a plot of FV acceleration and relative speed in relation to time. For every sharp (local minimum or maximum) change (stimulus) in relative speed, there is a corresponding sharp change (response) in acceleration. The peaks are these points of stimulus and response, and the time between them is reaction time. The stimulus and response peaks were identified manually by an analyst using an interactive plot in which hovering over a point shows its coordinates.

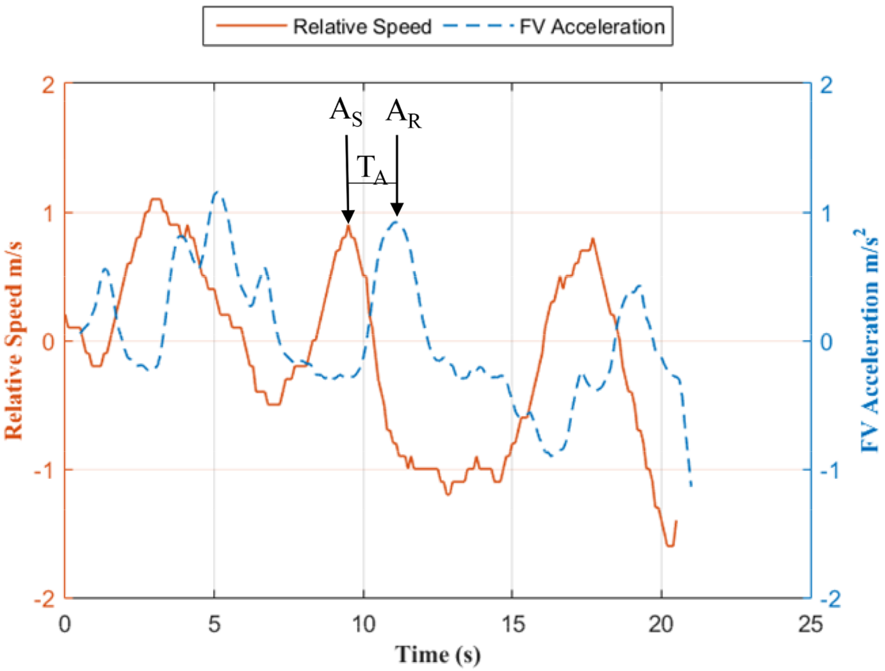

Fig. 6. Determining reaction time through identification of stimulus and response points.

Table 5
Summary of GHR parameters and their bounds.

Parameter (unit)	Short description	Bounds
α^a	Constant sensitivity coefficient	[0 60]
z^b	Speed exponent	[−10 10]
l^b	Space headway exponent	[0 10]
τ_n (s)^a	Reaction time	[0.3 3]

Source: [a]Sangster et al. (2013); [b]Brackstone and McDonald (1999); [c]Saifuzzaman et al. (2015).

For example, in Fig. 6, a peak occurs at point A_S on the relative speed curve. The corresponding peak on the acceleration curve is A_R. The time between A_S and A_R is defined as the reaction time T_A. According to Ozaki (1993), reaction time changes during the process of driving, and may correlate with relative distance, speed, and LV acceleration. Therefore, for every stimulus point, the corresponding relative distance, speed, and LV acceleration were determined in addition to reaction time. They later served as additional independent variables in the analysis of reaction time.

4.2.3. Parameters of the car-following model

Car-following model parameters reveal how drivers use distance and speed information during car-following. Differences in parameters drivers exhibit between the warning and no-warning phases provide complementary information, and thus explanations for the changes in observable performance measures. The Gazis-Herman-Rothery (GHR) model was used in this study because (1) SPS:refid::bib1SPS:refid::e1 it represents the stimulus-response framework, the most widely used framework in car-following modeling, and is the most studied car-following model; and (2) it directly clarifies how drivers adapt their behavior in response to perceptions of distance, speed, and acceleration of the lead vehicle.

The main idea of the GHR model is that the acceleration of the following vehicle is determined by the driver's reaction to the speed and position differences of the vehicle in front, as defined in Eq. (1):

$$a_n(t) = \alpha V_n(t)^z \frac{\Delta V_n(t-\tau_n)}{\Delta X_n(t-\tau_n)^l} \tag{1}$$

where $a\_n(t)$ is the acceleration of the following vehicle at time t, $\Delta V_n(t-\tau_n)$ is the speed difference between the following vehicle and the lead vehicle at time $(t-\tau_n)$, ΔX_n is the space headway between the following and lead vehicle, τ_n denotes reaction time, and α, z, and l are parameters. A summary of the GHR parameters to be estimated can be found in Table 5.

A genetic algorithm (GA) was implemented to find the optimum values of the model parameters by minimizing the difference between the values of simulated and observed following gaps. The GA proceeded as follows:

(1) A population consisting of N individuals was initialized, with each individual representing one parameter set of the GHR model;
(2) With data from the LV serving as externally controlled input, the simulated FV's trajectory was calculated based on the GHR model and its parameters. The simulated trajectory was then compared with the empirically observed trajectory from the SH-NDS data to calculate the simulation error and the fitness of each individual.

The FV's trajectory was simulated as follows: the FV's speed $V_n(t)$ and inter-vehicle spacing $S_{n-1,n}(t)$ were initialized with the empirical SH-NDS data: $V_n(t=0) = V_n^{data}(t=0)$ and $S_{n-1,n}(t=0) = S_{n-1,n}^{data}(t=0)$. After the acceleration $a_n(t)$ was computed by the GHR model, future states of the following vehicle were generated iteratively, based on the state-updating rules defined in Eq. (2).

$$\begin{gathered} V_n(t+1) = V_n(t) + a_n(t)\cdot\Delta T \\ \Delta V_{n-1,n}(t+1) = V_{n-1}(t+1) - V_n(t+1) \\ S_{n-1,n}(t+1) = S_{n-1,n}(t) + \frac{\Delta V_{n-1,n}(t) + \Delta V_{n-1,n}(t+1)}{2}\cdot\Delta T \end{gathered} \tag{2}$$

where ΔT is the simulation time interval, set as 0.1 s in this study, $\Delta V_{n-1,n}(t)$ is the relative speed between a lead and following vehicle, and $V_{n\text{-}1}$ is the velocity of LV, which was externally inputted.

(3) Crossovers between randomly selected individual pairs (parents) and mutations within randomly selected individuals were implemented to produce individuals of the next generation (children); and
(4) Steps 2 and 3 were repeated until the termination criteria were satisfied.

For a detailed description of the model calibration, please refer to Zhu et al. (2018).

4.3. Statistical analysis

In this study, all drivers were involved in multiple car-following events, which is typical of comparative experiments with repeated measures. The term “repeated measures” refers to data with multiple observations of the same sampling unit. Because it is usually reasonable to assume that observations of the same unit are correlated, statistical analysis of repeated measures data must address the issue of covariation between measures of the same unit (Littell et al., 2000). Therefore, a mixed model methodology that permits the covariance structure to be incorporated into the statistical model was applied in this study.

Statistical mixed models affirm that the observed data consists of two parts, fixed effects and random effects. Fixed effects are parameters that do not vary, while random effects are parameters that are themselves random variables. In the presented study, the independent variables described in Section 4.1 and their interaction terms were treated as fixed effects, and the drivers were treated as random effects to account for within-subject covariance of repeated observations of the same driver.

For simplicity, this study only considered random intercepts. Suppose we have N observations, p fixed effects, and q random intercepts, then the mixed model is written as

$$y = X\beta + Z\gamma + \varepsilon \tag{3}$$

where $y \in R^{N\times 1}$ is the dependent variable (e.g., mean time headway), $X \in R^{N\times P}$ is the matrix of the p fixed-effect predictor variables (e.g., FCW state, road type, and weather), $\beta \in R^{p\times 1}$ is the column vector of the fixed-effect regression coefficients, $Z \in R^{N\times q}$ is the design matrix of the q random effects, $\gamma \in R^{q\times 1}$ is the column vector of the q random intercepts, and $\varepsilon \in R^{N\times 1}$ is the unobserved vector of the independent and identically distributed Gaussian random errors.

To better illustrate the concept, we offer an example where the mean time headway is the dependent variable. The following equations show how the vectors and matrices described above look like. With a random intercept setting, Z is a sparse matrix that codes the driver to which a car-following event belongs. Each column of Z is one driver, and each row represents one car-following event. If the event belongs to the driver in that column, the cell will show 1; otherwise, it will show 0.

$$y = \begin{bmatrix} timeheadway \\ 1.3 \\ 1.6 \\ \cdots \\ 1.5 \end{bmatrix}_{N\times 1} \tag{4}$$

$$X = \begin{bmatrix} Fixedintercept & FCW & Roadtype & \cdots & Speed & Density \\ 1 & 1 & 0 & \vdots & 51 & 34 \\ 1 & 0 & 1 & \vdots & 67 & 67 \\ \cdots & \cdots & \cdots & \vdots & \cdots & \cdots \\ 1 & 1 & 1 & \vdots & 42 & 43 \end{bmatrix}_{N\times p} \tag{5}$$

$$\beta = \begin{bmatrix} 0.6 \\ -0.06 \\ 0.04 \\ \cdots \\ -0.003 \\ -0.005 \end{bmatrix}_{p\times 1} \tag{6}$$

$$Z = \begin{bmatrix} Driver_1 & Driver_2 & Driver_3 & \cdots & Driver_{q-1} & Driver_q \\ 1 & 0 & 0 & \vdots & 0 & 0 \\ 0 & 1 & 0 & \vdots & 0 & 0 \\ \cdots & \cdots & \cdots & \vdots & \cdots & \cdots \\ 0 & 0 & 0 & \vdots & 1 & 0 \end{bmatrix}_{N\times q} \tag{7}$$

If we were to estimate random effects γ, it would be a column vector containing q random intercepts. However, in a mixed model, we do not estimate γ specifically. Instead, we assume that γ follows a normal distribution with mean zero and variance σ^2.

$$\gamma \sim N(0,\ \sigma^2) \tag{8}$$

The reason for the mean zero is that we have directly estimated the fixed effects (including the fixed intercept), and the random intercepts are modeled as deviations from the fixed intercept.

To analyze the directions of different fixed effects on the dependent variables, least squares means were used for the discrete independent variables, considering that our data were unbalanced (see Table 4). Balanced data refers to a setting in which all combinations of all factors are sampled equally often. With balanced data, we would be able to use group means to investigate the treatment effect. However, this is not the case when the data are unbalanced: simple averages do not work because all factors do not have an equal chance to affect the response. With least squares means, we can estimate the averages that would have existed if the data had been balanced (Cai, 2014). The estimates indicate the effects of a given factor, with all other factors being equal.

All the analyses were performed using the PROC MIXED procedure in SAS® 9.4. The statistical significance level was set at $\alpha = 0.05$.

Table 6
Significant main effects for mean time headway.

Variables	Statistical results	Conditions with longer headway	Mean headway
FCW	$F(1,42) = 69.48, p < 0.0001$	OFF	1.66 s vs. 1.42 s
Travel speed	$F(1,2764) = 125.12, p < 0.0001$	Higher speed	–
Ambient light	$F(1,47) = 50.18, p < 0.0001$	Nighttime	1.72 s vs.1.36 s
Traffic density	$F(1,2764) = 56.00, p < 0.0001$	Lower traffic density	–

5. Results and analysis

5.1. Mean time headway

The analysis for mean time headway showed significant main effects for FCW, travel speed, ambient light, and traffic density. The directions of these significant main effects are shown in Table 6. Drivers maintained shorter headways in the warning phase (least squares means = 1.42 s) than in the no-warning phase (least squares means = 1.66 s), and the difference was statistically significant ($F(1,42) = 69.48$, $p < 0.0001$). No significant FCW-related interactions were found. The detailed parameter estimation results can be found in the appendix in Table A.1.

5.2. Proportion of time in short headways

The proportion of time in short headways was also analyzed across all six variables (listed in Table 3) and associated interactions. Results showed significant main effects for ambient light and roadway type, and the directions of these effects are shown in Table 7. The effects of FCW were not significant: $F(1,42) = 0.85$, $p = 0.3619$. The short-headway percentage in the warning phase (14.88%) was slightly lower than that of the no-warning phase (15.35%). Table A.2 presents the detailed parameter estimation results for the short-time-headway proportion linear mixed model.

5.3. Reaction time

Reaction time was calculated for the 6,092 pairs of stimulus-response points identified in the FV acceleration and relative speed curves. Besides the variables listed in Table 3, additional variables that may affect reaction time were included as independent variables for the reaction time analysis. These variables were relative speed (LV speed minus FV speed), relative distance, and LV acceleration. The absolute values of relative speed and LV acceleration were used, and two corresponding discrete variables indicating their signs were added.

The results showed that the FCW warning condition did not have a significant effect on reaction time. However, two significant interaction (with the warning condition) effects were observed: Warning Condition×Relative Speed, $F(1, 6018) = 7.60$, $p = 0.0059$, and Warning Condition×Sign of LV Acceleration, $F(1, 91) = 5.76$, $p = 0.0184$. As shown in Fig. 7(a), the reduction in reaction time caused by the FCW increased when relative speed increased, with a 0.22-s reduction in reaction time when relative speed was 2.5 m/s. Fig. 7(b) shows that when the LV is accelerating, the presence of a warning resulted in a 0.07-s decrease in reaction time.

Several independent variables were found to have significant main effects on reaction time, including ambient light, weather, relative speed, and the sign of relative speed. The directions of these effects are shown in Table 8.

5.4. Parameters of the GHR model

As noted in Section 5.1, travel speed, ambient light, and traffic density all had significant effects on headway, and it can be assumed that they may also affect car-following model parameters. To disentangle the effects of the warning condition from these other variables, the car-following events for each driver were grouped into the possible value combinations of all four variables, as shown in Table 9. A total of 179 groups of car-following events, each with a minimum of 10 events, were identified. Speed and density were categorized into two levels, low and high, according to their median values. Parameters of the GHR model, α, z, l, and τ_n (described in Tables 5 and 10), were calibrated independently for each group, and then a linear mixed model was developed for the 4 GHR parameters to test whether the warning condition significantly affected the parameters. In the linear mixed model, warning condition, speed, density, ambient light, and their interaction terms were treated as fixed effects, and drivers were treated as random effects.

Table 7
Significant main effects for proportion of time in short headways.

Variables	Statistical results	Conditions with lower short-headway proportion	Short-headway proportion
Ambient light	$F(1,47) = 8.88, p = 0.0046$	Nighttime	13.95% vs. 16.28%
Roadway type	$F(1,45) = 12.90, p = 0.0008$	Surface road	11.89% vs. 18.34%

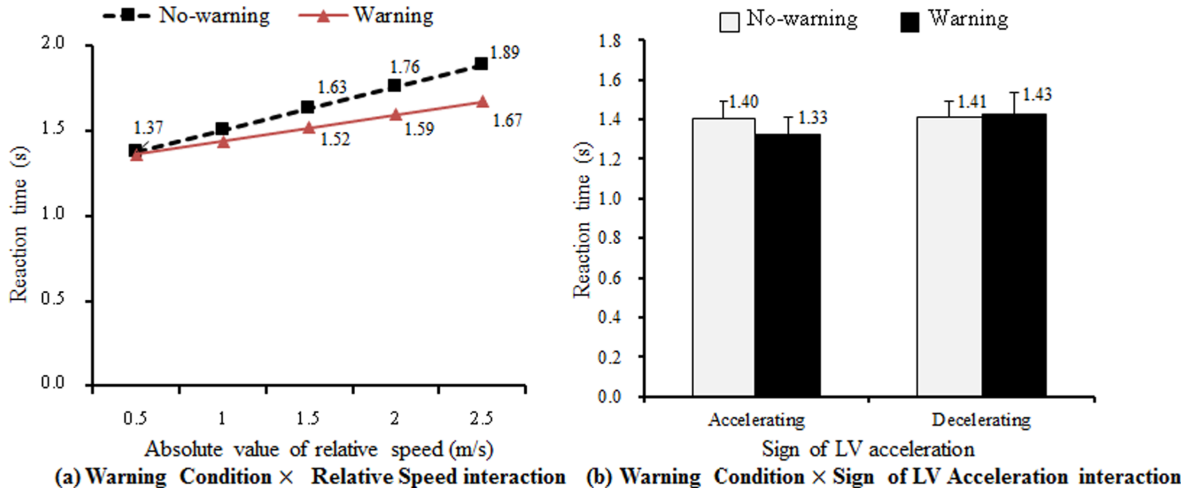

Fig. 7. Reaction time for the two significant FCW interaction effects.

Table 8
Significant main effects for reaction time.

Variables	Statistical results	Conditions with shorter reaction time	Reaction time
Ambient light	$F(1,47) = 9.16, p = 0.0040$	Nighttime	1.34 s vs.1.43 s
Weather	$F(1,40) = 11.36, p = 0.0017$	Sunny	1.35 s vs.1.43 s
Relative speed	$F(1,6018) = 16.82, p < 0.0001$	Lower relative speed	–
Sign of relative speed	$F(1,50) = 7.43, p < 0.0088$	Negative (approaching)	1.36 s vs. 1.42 s

Table 9
Drivers' car-following events in combinations of ambient light, warning condition, travel speed, and traffic density values.

Group ID	Driver ID	Ambient light	Warning condition	Speed	Density	Number of events
1	1	Daytime	No-warning	High	High	13
2	1	Daytime	No-warning	High	Low	16
3	1	Daytime	No-warning	Low	High	18
4	1	Daytime	Warning	High	High	18
5	1	Daytime	Warning	High	Low	12
6	1	Daytime	Warning	Low	High	18
7	1	Nighttime	No-warning	High	High	20
8	1	Nighttime	No-warning	High	Low	24
9	1	Nighttime	No-warning	Low	High	12
174	60	Daytime	Warning	High	Low	10
175	60	Daytime	Warning	Low	High	10
176	60	Daytime	Warning	Low	Low	10
177	60	Nighttime	Warning	High	Low	17
178	60	Nighttime	Warning	Low	High	18
179	60	Nighttime	Warning	Low	Low	10

Table 10
Summary of the effects of the warning condition on GHR parameters and calibration errors.

Parameter (unit)	Short description	No-warning	Warning	Statistical results
α	Constant sensitivity coefficient	30.8968	25.9432	$F(1,123) = 1.22, p = 0.2716$
z	Speed exponent	0.4561	0.1660	$F(1,123) = 2.46, p = 0.1195$
l	Space headway exponent	1.6640	1.2454	**$F(1,123) = 4.68, p = 0.0324$**
τ_n (s)	Reaction time	1.3829	1.4423	$F(1,123) = 0.80, p = 0.3726$
RMSPE	Calibration error	0.1531	0.1430	$F(1,123) = 1.03, p = 0.3112$

5.4.1. Parameter differences between warning and no-warning

Table 10 summarizes the effects of the warning condition on the GHR parameters and the calibration errors. The calibration errors from the warning and no-warning phases were not significantly different. This indicates that the car-following behaviors were

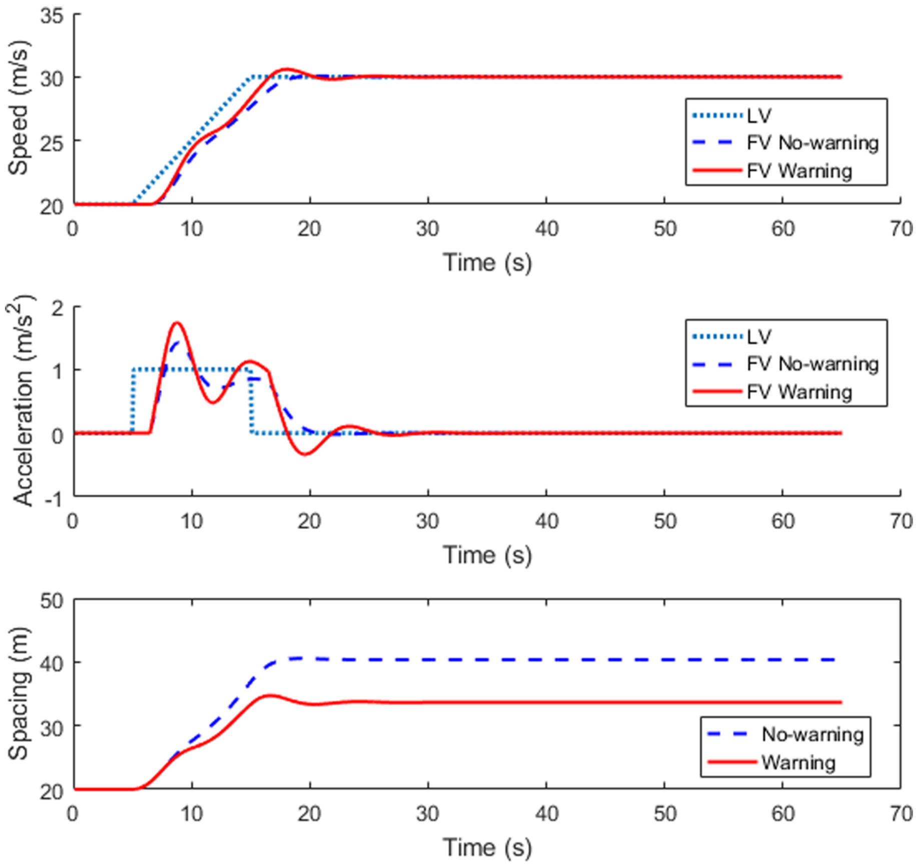

Fig. 8. Effects of FCW as simulated by average GHR model parameters in warning and no-warning phases.

modeled at an equal level of accuracy in the warning and no-warning phases, hence the comparison of model parameters is rational. The FCW had no significant effects on the GHR parameters, other than on the space headway exponent l. The FCW warning caused a 0.4186 reduction in the space headway exponent.

5.4.2. Scenario simulation

According to the acceleration function of the GHR model specified in Eq. (1), reduction in the space headway exponent causes drivers to be more sensitive to the following gap and perform larger accelerations under the same space headway condition. To further illustrate the effects of the FCW on car-following behavior, the response of the GHR model to a simple scenario was simulated. The simulation, consisting of a ramped increase in LV speed, shows the car-following behavior as captured by the model, thus excluding unpredictable and/or time-variant behavior as may be present in the original data.

As shown in Fig. 8, the simulation began with the FV and LV driving at the same speed (20 m/s), with a space headway of 20 m. When travel time reached 5 s, the LV accelerated with a constant 1 m/s^2 acceleration rate for 10 s; then the LV kept a constant speed of 30 m/s. Fig. 8 shows the predicted effect of the warning by simulating the average model parameters on the FV in the warning and no-warning phases. As can be seen, the FV maintained shorter following distances and made larger accelerations and decelerations in the warning phase as compared to the no-warning phase.

5.4.3. Fundamental diagram comparison

To provide a more insightful interpretation of driver behavioral differences between the warning and no-warning phases, fundamental diagrams that describe homogeneous and equilibrium traffic were constructed in order to analyze the effects on the GHR model parameters. The relationship between speed and space headway at a steady-state condition can be found in Leutzbach (1988): if $z \neq 1$ and $l \neq 1$:

$$v_e = \begin{cases} (v_{des}^{1-z} - \alpha s_e^{1-l})^{\frac{1}{1-z}} & z > 1 \\ (\alpha s_{jam}^{1-l} - \alpha s_e^{1-l})^{\frac{1}{1-z}} & z < 1 \end{cases} \tag{9}$$

where s_e and v_e are equilibrium space headway and speed, respectively; v_{des} is the desired speed of drivers, specified here as 120 km/h according to speed limits in Shanghai; s_{jam} is the standstill space headway, fixed here at 8.09 m according to real-world data; and α, z

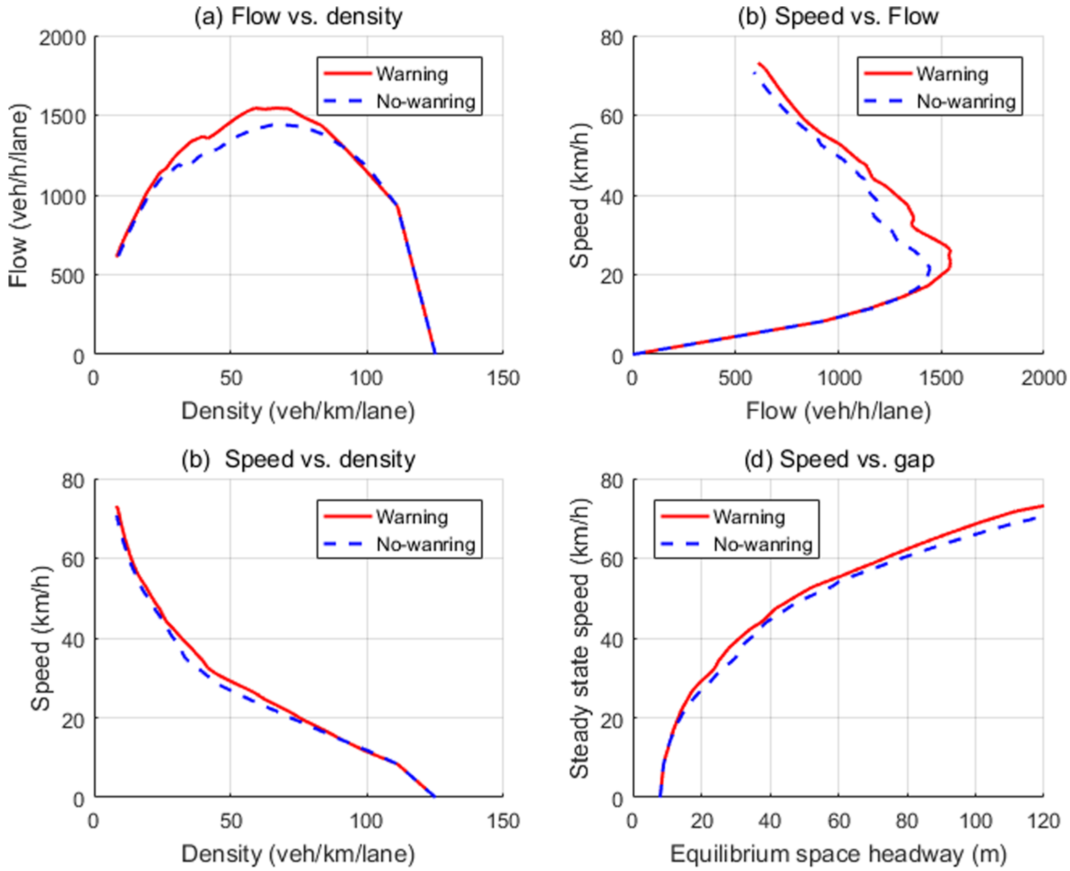

Fig. 9. Fundamental diagrams of the warning and no-warning phases derived from the GHR model.

and l are the constant sensitivity coefficient, speed exponent, and space headway exponent, respectively.

Each of the 179 groups of car-following events had a unique set of GHR parameters that corresponded to a particular speed-headway relationship. Therefore, for the same equilibrium space headway, different equilibrium speeds were able to be derived using the GHR parameters of the different event groups. The mean value of these equilibrium speeds was used as the aggregated equilibrium speed. Translation from the microscopic space headway s into density ρ is given by:

$$\rho = \frac{1}{s} \tag{10}$$

where l is the vehicle length, fixed here to 5 m. The flow Q is derived by:

$$Q = \frac{v}{s} \tag{11}$$

Fundamental diagrams were plotted, as shown in Fig. 9. The results of the warning and no-warning phases are aggregated and presented as red solid lines and blue dashed lines, respectively. Under the same steady-state speed, the warning phase exhibited a slightly shorter space headway than the no-warning phase (Fig. 9-d). As a result, the activation of the FCW can be said to have increased traffic capacity (Fig. 9-a).

6. Summary and discussion

This study has investigated how an FCW system with a headway monitoring function can affect the time headway and reaction time during car following, and offers an explanation of the performance changes by examining the changes in parameters of a fundamental car-following model.

6.1. Headway

Employment of the FCW system with a headway monitoring function resulted in a decrease in headway time, while the proportion of time drivers spent in short headways (< 1 s) was not affected, indicating that the FCW may increase traffic efficiency without degrading safety. The results of this study concur with results of a similar simulator study conducted by Saffarian et al. (2013), which investigated the effects of a car-following assistance system displaying LV acceleration and time headway. Saffarian et al. found that the system reduced both the mean and standard deviation of the time headway but did not increase the occurrence of potentially unsafe headways of less than 1 s.

The parameter estimations of the GHR car-following model provide complementary information to the changes in time headway. For example, a reduction in the space headway exponent was observed when the FCW was enabled. As illustrated by the simulation, this reduction in the space headway exponent suggests that when drivers are alerted by a warning system, they become more sensitive to the following gap and feel able to make larger accelerations under the same space headway. These changes are easy to understand: the numerically displayed and continuously updated time headway provided by the FCW system assists drivers' naturally more limited distance estimation capability, and the enhanced capability influences their behavior.

The amount of change in mean time headway was 0.24 s in our study, which is at the same level of magnitude with previous studies' results (0.2–0.5 s) as summarized in Table 1 in the literature review above. The fact that the magnitude of change is relatively small may indicate support for the findings of Ervin et al. (2005) that adaptive cruise control (ACC) impacts are substantially more marked and robust across driving conditions than those of FCW. That is, human driver behaviors are not as easily influenced by an advisory system such as FCW as they are by a control assistance system such as ACC. The small amount of change additionally suggests that a higher penetration rate is needed for an assistance system to greatly influence driver behavior.

The results of this study did not always concur with those of similar studies conducted with test tracks, driving simulators and NDS. Table 1 above summarizes the results of these studies, which differ as to the size and even direction of FCW effects. These contradictory effects could be caused by the following factors:

(1) The warning logics and modalities of the FCW systems differed. For example, in our study, the FCW gave visual and audial warnings when the time headway decreased to 0.6 s or less, while in Shinar and Schechtman (2002), a visual-only warning was issued when time headway dropped to 1.2 s.
(2) Drivers' behavior in natural driving situations might differ from their behavior in controlled experimental situations. In controlled test track studies, drivers are aware that they are being observed and thus may pay more attention to the warning.
(3) Drivers from different countries or operating different vehicle types might vary in driving behavior. For example, Bao et al. (2012) and LeBlanc et al. (2013) reached different conclusions: when FCW was enabled, headway increased with heavy trucks while it decreased with light vehicles. LeBlanc et al. explained that the difference might be due to truck drivers' professional status leading them to be generally more conservative.

6.2. Reaction time

Driver reaction time has a substantial influence on traffic flow stability; specifically, traffic stability increases with a decrease in reaction time (Treiber et al., 2006). The current study found that the presence of warnings resulted in a 0.22 s decrease in reaction time when the absolute values of relative speed reached 2.5 m/s (i.e., when the FV was rapidly approaching or falling back from the LV); warnings resulted in a 0.07 s decrease when the LV was accelerating. These results suggest that the FCW system could be beneficial to traffic stability.

According to Olson (2002), driver reaction time consists of four components: detection, estimation, decision, and movement. In the car-following process, the detection interval starts when the relative speed and/or relative distance changes, and ends when the driver becomes consciously aware that the relative motion state has changed. Having become aware, the driver then estimates the relative distance or relative speed. With this estimation completed, the driver must decide what action, if any, is appropriate. The typical response action is a change of speed and/or direction. Last, in the movement interval, the driver lands his or her foot on the

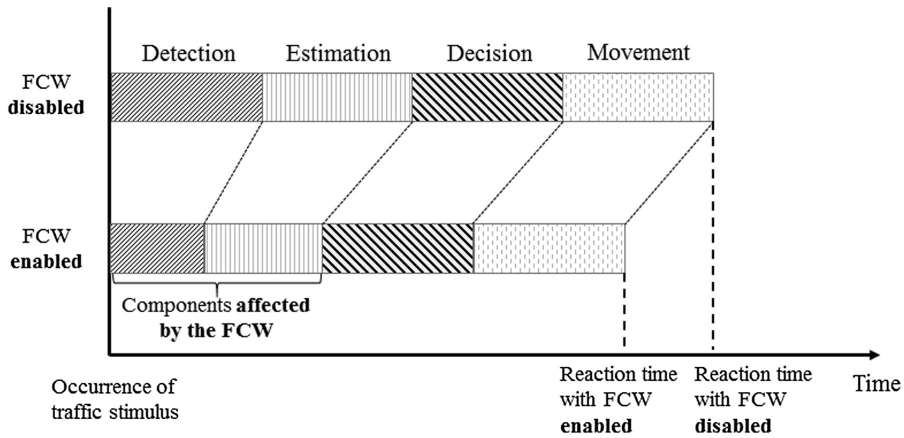

Fig. 10. Reaction time with FCW disabled and enabled.

brake pedal or adjusts the steering wheel.

As shown in Fig. 10, the FCW system may shorten both the detection and estimation intervals of car-following reaction time, and thus shorten its total length. The likely reason is similar to the reason for changes in headway behavior: the continuously updated time headway provided by the FCW assists drivers' observations and estimations of distance and speed changes, permitting drivers to react more quickly.

This study found that ambient light, weather, relative speed, and the sign of relative speed also affected reaction time. It was surprising to find that drivers had shorter reaction times in nighttime driving. A possible explanation is that the drivers may be more cautious in nighttime driving, pay more attention to the driving task, and thus respond more quickly.

The mean and median values of the reaction times in this study were 1.31 s and 1.10 s respectively, which are slightly lower than the 1.5 s mean value reported by Gurusinghe et al. (2002). Although several methods (Taylor et al., 2015; Ma and Andréasson, 2006) have been proposed to automatically calculate the instantaneous reaction time during car-following, this study chose to extract the reaction time manually, in consideration of accuracy. A method that is both efficient and accurate could be developed in future work.

6.3. Implications for car-following modeling in the V2V environment

With the development of vehicle-to-vehicle (V2V) communication technologies, more and more advisory messages enter drivers' daily lives, many of which pertain to the measures of speed and headway between two consecutive vehicles. Such messages, which help a vehicle to collect its neighbor's kinetic information and provide the vehicle with warnings as they are needed, may have a significant impact on driving behavior. The emerging V2V technology thus creates a challenge for engineers who want to incorporate V2V influence into traditional car-following models. The results of this study provide meaningful insights toward meeting this challenge.

This study showed that use of the FCW system resulted in a reduction in the space headway exponent of the GHR model. Therefore, a straightforward way to incorporate the FCW into the GHR model may be to add a parameter k to represent the impact of V2V communication on driver reaction to the space headway, as shown in Eq. (12).

$$a_n(t) = \alpha V_n(t)^z \frac{\Delta V_n(t-\tau_n)}{\Delta X_n(t-\tau_n)^{(l-k)}} \tag{12}$$

where all things hold the same as Eq. (1), except that an additional parameter k is added. This illustrates one of the possible adaptations to the model. Future studies are needed to test the effectiveness of this adaptation and to find better ways of modeling car-following behavior with V2V communication.

7. Conclusion

This study used high-validity naturalistic driving data to investigate the impact of an FCW system on car-following headway, reaction time and other internal mechanisms. Employment of the FCW system resulted in a reduction in headway and a conditional reduction in reaction time, while the occurrence of potentially unsafe short headways (< 1 s) was not increased. Indeed, examining the changes in parameters of the GHR car-following model suggested that drivers follow more closely with the FCW because the system helps them become more sensitive to the changes in the following gap.

The major implications derived from this study are:

- An FCW system with a headway monitoring function may increase both traffic efficiency and stability without degrading safety. Therefore, active safety systems (such as FCW) and V2V communication technologies are recommended for future transport systems.
- Providing time headway feedback to drivers may help them respond more quickly by assisting them in observing and estimating the changes in distance and speed.
- The FCW system indeed resulted in differences in the internal car-following mechanisms, justifying the need to incorporate the impacts of emerging driving assistance systems and V2V technologies into traffic flow modeling. Future studies are needed to determine how to better model these impacts.

CRediT authorship contribution statement

Meixin Zhu: Writing - original draft, Software, Methodology. **Xuesong Wang:** Conceptualization, Supervision, Data curation. **Jingyun Hu:** Investigation, Visualization, Writing - review & editing.

Acknowledgments

This study was jointly sponsored by the Chinese National Science Foundation (51878498), and the Science and Technology Commission of Shanghai Municipality (18DZ1200200).

Appendix. Parameter estimates for the liner mixed model

This appendix presents the results of the parameter estimations for the linear models used in the mean time headway and short time headway-proportion analyses. The results of the linear models used in analyzing reaction times and car-following model parameters are not presented because of the abundance of parameters and limited space (see Tables A1 and A2).

Table A1
Parameter estimation results for the mean-time headway linear mixed model.

Effect	FCW	Light	Roadway	Weather	Estimate	Std. Dev.
Intercept					2.9272	0.1431
Speed					0.01184	0.009207
FCW	ON				−0.1355	0.1165
FCW	OFF				0	.
Light		Nighttime			0.2101	0.1256
Light		Daytime			0	.
Roadway			Freeway		−0.891	0.1364
Roadway			Surface road		0	.
Weather				Rainy	0.2199	0.1994
Weather				Sunny	0	.
Density					−0.0016	0.001456
Speed*FCW	ON				−0.00133	0.005479
Speed*FCW	OFF				0	.
FCW*Light	ON	Nighttime			−0.00321	0.04854
FCW*Light	ON	Daytime			0	.
FCW*Light	OFF	Nighttime			0	.
FCW*Light	OFF	Daytime			0	.
FCW*Roadway	ON		Freeway		−0.03837	0.05297
FCW*Roadway	ON		Surface road		0	.
FCW*Roadway	OFF		Freeway		0	.
FCW*Roadway	OFF		Surface road		0	.
FCW*Weather	ON			Rainy	−0.1344	0.07788
FCW*Weather	ON			Sunny	0	.
FCW*Weather	OFF			Rainy	0	.
FCW*Weather	OFF			Sunny	0	.
Density*FCW	ON				−0.00157	0.001082
Density*FCW	OFF				0	.
Speed*Light		Nighttime			−0.00066	0.006098
Speed*Light		Daytime			0	.
Speed*Roadway			Freeway		0.02671	0.007632
Speed*Roadway			Surface road		0	.
Speed*Weather				Rainy	0.007898	0.008952
Speed*Weather				Sunny	0	.
Speed*Density					−0.00199	0.000105
Light*Roadway		Nighttime	Freeway		−0.06202	0.05904
Light*Roadway		Nighttime	Surface road		0	.
Light*Roadway		Daytime	Freeway		0	.
Light*Roadway		Daytime	Surface road		0	.
Light*Weather		Nighttime		Rainy	0.01235	0.09473
Light*Weather		Nighttime		Sunny	0	.
Light*Weather		Daytime		Rainy	0	.
Light*Weather		Daytime		Sunny	0	.
Density*Light		Nighttime			−0.00095	0.001109
Density*Light		Daytime			0	.
Roadway*Weather			Freeway	Rainy	−0.1589	0.09218
Roadway*Weather			Freeway	Sunny	0	.
Roadway*Weather			Surface road	Rainy	0	.
Roadway*Weather			Surface road	Sunny	0	.
Density*Roadway			Freeway		0.006351	0.001118
Density*Roadway			Surface road		0	.
Density*Weather				Rainy	−0.00135	0.002003
Density*Weather				Sunny	0	.
Random intercept variance		0.3271				
Null Model Likelihood Ratio Test		Chi-Square = 61.92 ($p < 0.001$)				
Final Log likelihood		5080.3				

Table A2
Parameter estimation results for the short time headway-proportion linear mixed model.

Effect	FCW	Light	Roadway	Weather	Estimate	Std. Dev.
Intercept					−0.2257	0.05385
Speed					−0.00925	0.003463
FCW	ON				0.01906	0.04383
FCW	OFF				0	.
Light		Nighttime			−0.1442	0.04724
Light		Daytime			0	.
Roadway			Freeway		0.1253	0.05131
Roadway			Surface road		0	.
Weather				Rainy	0.02157	0.075
Weather				Sunny	0	.
Density					−0.00079	0.000547
Speed*FCW	ON				−0.00085	0.002061
Speed*FCW	OFF				0	.
FCW*Light	ON	Nighttime			0.003913	0.01826
FCW*Light	ON	Daytime			0	.
FCW*Light	OFF	Nighttime			0	.
FCW*Light	OFF	Daytime			0	.
FCW*Roadway	ON		Freeway		−0.00769	0.01992
FCW*Roadway	ON		Surface road		0	.
FCW*Roadway	OFF		Freeway		0	.
FCW*Roadway	OFF		Surface road		0	.
FCW*Weather	ON			Rainy	0.01108	0.02929
FCW*Weather	ON			Sunny	0	.
FCW*Weather	OFF			Rainy	0	.
FCW*Weather	OFF			Sunny	0	.
Density*FCW	ON				−0.00024	0.000407
Density*FCW	OFF				0	.
Speed*Light		Nighttime			−0.00285	0.002293
Speed*Light		Daytime			0	.
Speed*Roadway			Freeway		0.005278	0.00287
Speed*Roadway			Surface road		0	.
Speed*Weather				Rainy	−0.00237	0.003367
Speed*Weather				Sunny	0	.
Speed*Density					0.000846	0.000039
Light*Roadway		Nighttime	Freeway		0.007391	0.0222
Light*Roadway		Nighttime	Surface road		0	.
Light*Roadway		Daytime	Freeway		0	.
Light*Roadway		Daytime	Surface road		0	.
Light*Weather		Nighttime		Rainy	−0.02298	0.03562
Light*Weather		Nighttime		Sunny	0	.
Light*Weather		Daytime		Rainy	0	.
Light*Weather		Daytime		Sunny	0	.
Density*Light		Nighttime			−0.0023	0.000417
Density*Light		Daytime			0	.
Roadway*Weather			Freeway	Rainy	0.02522	0.03467
Roadway*Weather			Freeway	Sunny	0	.
Roadway*Weather			Surface road	Rainy	0	.
Roadway*Weather			Surface road	Sunny	0	.
Density*Roadway			Freeway		0.001901	0.000421
Density*Roadway			Surface road		0	.
Density*Weather				Rainy	−0.0004	0.000753
Density*Weather				Sunny	0	.
Random intercept variance		0.04625				
Null Model Likelihood Ratio Test		Chi-Square = 75.85 ($p < 0.001$)				
Final Log likelihood		−403.6				

References

Bao, S., LeBlanc, D.J., Sayer, J.R., Flannagan, C., 2012. Heavy-truck drivers' following behavior with intervention of an integrated, in-vehicle crash warning system: a field evaluation. Hum. Factors: J. Hum. Factors Ergonomics Soc. 54 (5), 687–697.

Ben-Yaacov, A., Maltz, M., Shinar, D., 2002. Effects of an in-vehicle collision avoidance warning system on short- and long-term driving performance. Hum. Factors: J. Hum. Factors Ergonomics Soc. 44 (2), 335–342.

Brackstone, M., McDonald, M., 1999. Car-following: a historical review. Transportation Res. F: Traffic Psychol. Behav. 2 (4), 181–196.

Cai, W., 2014. Making Comparisons Fair: How LS-Means Unify the Analysis of Linear Models. SAS Institute Inc., Paper, SA, pp. S060–S2014.

Chandler, R.E., Herman, R., Montroll, W., 1958. Traffic dynamics: studies in car-following. Oper. Res. 6, 165–184.

Chong, L., Abbas, M.M., Flintsch, A.M., Higgs, B., 2013. A rule-based neural network approach to model driver naturalistic behavior in traffic. Transportation Res. Part

C: Emerging Technol. 1 (32), 207–223.
Dingus, T.A., McGehee, D.V., Manakkal, N., Jahns, S.K., Carney, C., Hankey, J.M., 1997. Human factors field evaluation of automotive headway maintenance/collision warning devices. Hum. Factors: J. Hum. Factors Ergonomics Soc. 39 (2), 216–229.
Ervin, R., Sayer, J., LeBlanc, D., Bogard, S., Mefford, M., Hagan, M., Winkler, C. 2005. Automotive Collision Avoidance System Field Operational Test Report Methodology and Results. Publication DOT HS 809 886. NHTSA, U. S. Department of Transportation.
Fitch, G.M., Hanowski, R.J., 2012. Handbook of Intelligent Vehicles: Using Naturalistic Driving Research to Design, Test and Evaluate Driver Assistance Systems. Springer, London, pp. 559–580.
Gazis, D.C., Herman, R., Rothery, R.W., 1961. Nonlinear follow-the leader models of traffic flow. Oper. Res. 9, 545–567.
Gurusinghe, G.S., Nakatsuji, T., Azuta, Y., Ranjitkar, P., Tanaboriboon, Y., 2002. Multiple car-following data with real-time kinematic global positioning system. Transportation Res. Rec.: J. Transportation Res. Board 1802, 166–180.
Kessler, C., Etemad, A., Alessandretti, G., Heinig, K., Selpi, R., Brouwer, A., Cserpinszky, W., Hagleitner, Benmimoun, M., 2012. European Large-scale Field Operational Tests on In-vehicle Systems Deliverable D11.3. Final Report. Publication ICT-2-6.2. ICT for Cooperative Systems Large-scale Integrating Project, EuroFOT Consortium.
LeBlanc, D., Bao, S., Sayer, J., Bogard, S., 2013. Longitudinal driving behavior with integrated crash-warning system: evaluation from naturalistic driving data. Transportation Res. Rec.: J. Transportation Res. Board 2365, 17–21.
Leutzbach, W., 1988. Introduction to the Theory of Traffic Flow. Springer-Verlag, Berlin.
Littell, R.C., Pendergast, J., Natarajan, R., 2000. Tutorial in biostatistics: modelling covariance structure in the analysis of repeated measures data. Statistics Med. 19 (13), 1793–1819.
Ma, X.L., Andréasson, I., 2006. Driver reaction time estimation from real car following data and application in GM-type model evaluation. Transportation Res. Rec.: J. Transportation Res. Board 1965, 130–141.
May, A.D., 1990. Traffic Flow Fundamentals. Prentice Hall, Eaglewood Cliffs, New Jersey.
McGehee, D., Brown, T., Lee, J., Wilson, T., 2002. Effect of warning timing on collision avoidance behavior in a stationary lead vehicle scenario. Transportation Res. Rec.: J. Transportation Res. Board 1803, 1–6.
Mobileye, 2010. C2-270 Collision Prevention System User Manual. http://www.c2sec.com.sg/Files/Mobileye%20C2-270%20UserManual.pdf.
Olson, P.L., 2002. Human Factors in Traffic Safety: Driver Perception-response Time. Lawyers & Judges Publishing Company, Tucson, pp. 43–76.
Ozaki, H., 1993. Reaction and anticipation in car-following behavior. In: Daganzo, C.F. (Ed.), Transportation and Traffic Theory. Elsevier Science Publishers, Amsterdam, Netherlands, pp. 349–362.
Ranney, T.A., 1999. Psychological factors that influence car-following and car-following model development. Transportation Res. Part F: Traffic Psychol. Behav. 2 (4), 213–219.
Saffarian, M., De Winter, J., Happee, R., 2013. Enhancing driver car-following performance with a distance and acceleration display. IEEE Trans. Hum.-Mach. Syst. 43 (1), 8–16.
Saifuzzaman, M., Zheng, Z., Haque, M., Washington, S., 2015. Revisiting the task-capability interface model for incorporating human factors into car-following models. Transportation Res. Part B: Methodological 82, 1–19.
Sangster, J., Rakha, H., Du, J., 2013. Application of naturalistic driving data to modeling of driver car-following behavior. Transportation Res. Rec.: J. Transportation Res. Board 2390, 20–33.
Shinar, D., Schechtman, E., 2002. Headway feedback improves intervehicular distance: a field study. Hum. Factors: J. Hum. Factors Ergonomics Soc. 44 (3), 474–481.
Soma, H., Hiramatsu, K., 1998. Driving simulator experiment on drivers' behaviour and effectiveness of danger warning against emergency braking of leading vehicle. In: 16th International Technical Conference on the Enhanced Safety of Vehicles, pp. 467–475.
Taylor, J., Zhou, X.S., Rouphail, N.M., Porter, R.J., 2015. Method for investigating intradriver heterogeneity using vehicle trajectory data: a dynamic time warping approach. Transportation Res. Part B: Methodological 73, 59–80.
Treiber, M., Kesting, A., Helbing, D., 2006. Delays, inaccuracies and anticipation in microscopic traffic models. Phys. A 360 (1), 71–88.
Vogel, K., 2003. A comparison of headway and time to collision as safety indicators. Accid. Anal. Prev. 35 (3), 427–433.
Wang, X., Zhu, M., Chen, M., Tremont, P., 2016a. Drivers' rear end collision avoidance behaviors under different levels of situational urgency. Transport. Res. Part C: Emerging Technol. 1 (71), 419–433.
Wang, X., Chen, M., Zhu, M., Tremont, P., 2016b. Development of a kinematic-based forward collision warning algorithm using an advanced driving simulator. IEEE Trans. Intell. Transp. Syst. 17 (9), 2583–2591.
IEEE Trans. Intell. Transport. Syst. 19 (3), 910–920. https://doi.org/10.1109/TITS.2017.2706963.
Zhang, G.H., Wang, Y.H., Wei, H., Chen, Y.Y., 1999. Examining headway distribution models using urban freeway loop event data. Transportation Res. Rec.: J. Transportation Res. Board 2007, 141–149.
Zhu, M., Wang, X., Wang, X., 2016. Car-following headways in different driving situations: a naturalistic driving study. CICTP 2016, 1419–1428.
Zhu, M., Wang, X., Wang, Y., 2018a. Human-like autonomous car-following model with deep reinforcement learning. Transportation Res. Part C: Emerging Technol. 1 (97), 348–368.
Zhu, M., Wang, X., Tarko, A., Fang, S., 2018b. Modeling car-following behavior on urban expressways in Shanghai: A naturalistic driving study. Transportation Res. Part C: Emerging Technol. 93, 425–445.
Zhu, M., Wang, Y., Pu, Z., Hu, J., Wang, X., Ke, R., 2019. Safe, efficient, and comfortable velocity control based on reinforcement learning for autonomous driving. arXiv preprint arXiv:1902.00089.