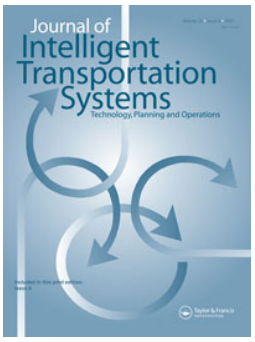

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A Bayesian regression analysis of truck drivers' use of cooperative adaptive cruise control (CACC) for platooning on California highways

Shiyan Yang[a], Steven E. Shladover[a], Xiao-Yun Lu[a], Hani Ramezani[a], Aravind Kailas[b], and Osman D. Altan[c,d]

[a]Partners for Advanced Transportation Technology (PATH), Institute of Transportation Studies, University of California, Berkeley, Richmond, CA, USA; [b]Volvo Group North America, Costa Mesa, CA, USA; [c]FHWA, Washington D.C., USA; [d]Global Smart System, LLC, Troy, MI, USA

ABSTRACT

Cooperative Adaptive Cruise Control (CACC), as an advanced version of adaptive cruise control (ACC), automates brake and engine controls based on the information received from wireless V2V communications and remote sensors, enabling smaller vehicle-following time gaps. It can improve the safety of vehicle platooning and increase fuel savings. As an extension of our previous investigation of truck drivers' acceptance of CACC, this case study investigates factors affecting the use of CACC for truck platooning. Nine commercial fleet drivers were recruited to operate two following trucks in a CACC-enabled string on freeways in Northern California. We analyzed the usage of CACC time gaps and its correlation with truck drivers' stated preferences for these time gaps, and we found that the highest preferred Gap 3 (1.2 s) was used the most. Moreover, a Bayesian regression model was built to show that truck drivers are more likely to disengage CACC when driving in low-speed traffic or on downgrades where this CACC could not provide sufficient braking. In high-speed traffic or on upgrades, truck drivers are more likely to engage CACC, particularly at Gap 3. Truck position, however, does not affect truck drivers' time gap selection. The findings encourage the adoption of CACC in the trucking industry through implementing driver-preferred time gaps and responsive braking systems, and operating on routes with minimal interference to truck speeds.

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KEYWORDS
Bayesian regression model; CACC; time gap selection; traffic density; truck platooning

Introduction

Cooperative adaptive cruise control (CACC) is an extension of adaptive cruise control (ACC) by incorporating dedicated short-range communications (DSRC) to enable wireless vehicle-to-vehicle (V2V) communications. The CACC at SAE Level 1 can automate the longitudinal control of the following vehicle(s) based on other vehicle's information (e.g., velocity, acceleration) transmitted through V2V wireless communications and remote sensors (e.g., radar and lidar). It can maintain a desired time gap between the vehicles in a string to avoid human delays in speed control, therefore enabling safe but smaller time gaps between these vehicles (Shladover et al., 2015). Due to the smaller following time gaps, increase in CACC market penetration rate is expected to generate macro-level benefits on transportation corridors, such as reducing fuel consumption and emissions (Browand et al., 2004; McAuliffe et al., 2018), improving traffic flow stability (Liu et al., 2018; van Arem et al., 2006), and relieving traffic congestion (Arnaout & Arnaout, 2014; Lunge & Borkar, 2015; Ramezani et al., 2018).

Apart from the technical maturity, drivers' acceptance of CACC is another critical factor that can affect the market penetration rate of this technology. Although CACC is designed to support drivers' longitudinal control and reduce driver stress, fatigue, and judgment errors, it may also have negative effects, such as performance degradation, overreliance, and distraction (Dey et al., 2016). For example, in the interviews of some truck drivers who did not have prior direct experience with CACC, these drivers expressed negative opinions (e.g., low expectance of safety benefits, less interest in driving, and fear of causing crashes; Neubauer et al., 2019) or reluctant

CONTACT Shiyan Yang dgysy501@gmail.com Partners for Advanced Transportation Technology (PATH), Institute of Transportation Studies, University of California, Berkeley, Richmond Field Station Building 452, Richmond, CA 94804, USA; Seeing Machines, 80 Mildura St, Canberra, ACT 2612, Australia

attitudes (e.g., lack of trust, fear of job redundancy, and interference with job satisfaction and pleasure; Bhoopalam et al., 2021) toward using CACC. However, Castritus Dietz et al. (2020) found that gaining extensive experience with truck platooning on highways clearly increased truck drivers' acceptance of such technology, suggesting that truck drivers without on-road experience with CACC could be biased negatively toward this technology. Therefore, it is necessary to investigate truck drivers' acceptance and actual usage of CACC in on-road settings to support more objective decisions about the deployment of this technology.

Although multiple truck platooning projects demonstrated CACC's technical capacities (e.g., SARTRE, GCDC, Energy ITS, and European Truck Platooning Challenge; Bergenhem et al., 2012), only limited on-road studies investigated truck drivers' experience with specific CACC time gaps. Previously, we found the highest preference for the medium time gap settings (1.2 s and 1.5 s) from the truck drivers, because of their intention to avoid the blockage of their road view (by the trailer of the preceding truck) at small time gaps and cut-in vehicles at the longest time gap (Yang et al., 2018). Another study on German highways, however, found that truck drivers quickly adapted to the short space gap (15 m) in a level-2 two-truck platoon despite their initial concerns (Castritius, Hecht, et al., 2020). Also, passenger car drivers felt comfortable with the short time gap (< 1 s) in a CACC-enabled two-vehicle string (Nowakowski et al., 2010). Since drivers may prefer to different gaps in different scenarios, we need to study their gap selections for truck platooning in public traffic. This type of empirical study has been rare.

Nevertheless, abundant studies about the use of ACC may shed light on the use of CACC by truck drivers. Drivers, in general, would like to use shorter ACC time gaps (less than 1.3 s; Marsden et al., 2001), but their selection of ACC time gaps can also be influenced by a range of driver factors, including age, experience and knowledge. For example, younger drivers prefer shorter ACC time gaps (Marsden et al., 2001); drivers who have more experience with ACC are more aware of its limitations (Larsson, 2012) and use the shortest time gap more often (Pereira et al., 2015); drivers who are unaware or unsure of ACC limitations are more likely to use ACC on curvy roads or when tired (Dickie & Boyle, 2009); and bus drivers under distraction should use longer ACC time gaps to remain safe (Lin et al., 2009). In addition to these driver factors, driving environments, such as high-speed road and low-density traffic, can encourage the use of ACC (Strand et al., 2011) with pleasure (de Winter et al., 2017). However, drivers can be discouraged by the technical problems of ACC, including occasional clumsiness, hard braking caused by vehicle cut-ins, and unexpected disengagements and accelerations (de Winter et al., 2017). All these factors may also influence truck driver's actual use of CACC for platooning.

This paper, based on the same case study investigating truck drivers' acceptance of CACC (Yang et al., 2018), aims to analyze the factors that affect truck drivers' actual use of CACC in truck platooning on public highways. Commercial fleet drivers were recruited to operate three Class 8 Volvo trucks equipped with CACC on public highways in Northern California. They were allowed to select any time gaps in the test drive, and they were responsible for steering wheel control during the engagement of CACC. The analysis of their usage of CACC was used to answer several research questions.

1. Whether some CACC time gaps were used more than others for truck platooning during the test drive? If so, which time gap was used the most?
2. Whether truck drivers' usage of CACC time gaps was associated with their stated preference for these time gaps?
3. How do factors such as truck speed, traffic density, road grade, and truck position affect the use of CACC for truck platooning on highways?

Since these factors may encourage or discourage the use of CACC for truck platooning on highways, understanding their impacts provides valuable insight into the design and implementation of CACC systems for appropriate contexts and sets reasonable expectations for the CACC-related benefits on the trucking industry and traffic environments.

Method

The on-road experiment was described in Yang et al. (2018) and is summarized here. This study was approved by the Committee for Protection of Human Subjects at the University of California, Berkeley.

Participants

Nine professional male fleet truck drivers from the U.S. (7) and Canada (2) participated in this on-road experiment. We were only able to recruit nine

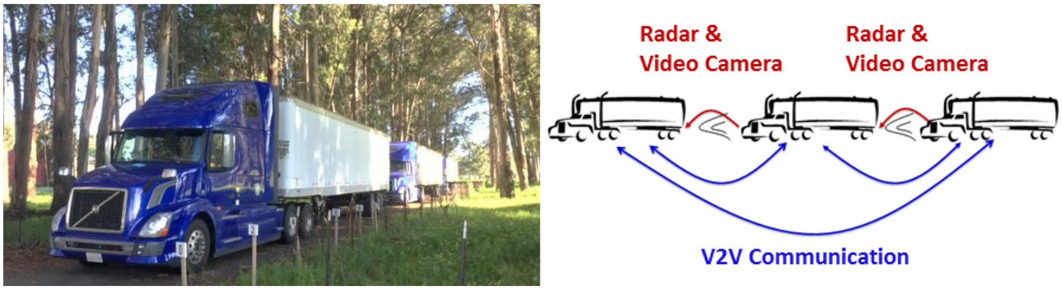

Figure 1. The Volvo Class 8 trucks (left) and the V2V communication system (right).

Figure 2. The CACC control stalk (left), truck cabin interior with the CACC user interface and emergency disengage button (middle), and the CACC user interface layout (right).

Table 1. The time gaps and corresponding distances in CACC and ACC Modes.

Time gap	CACC time gap (s)	Following distance (m) at 55 mph (88.5 km/h)	ACC time gap (s)	Following distance (m) at 55 mph (88.5 km/h)
1	0.6	14.8	1.1	27.0
2	0.9	22.1	1.3	32.0
3	1.2	29.5	1.5	36.9
4	1.5	36.9	1.7	41.8
5	1.8	44.3	1.9	46.7

participants because of the shortage of truck drivers in the U.S. and the limited flexibility of their working hours. These truck drivers were relatively senior (mean age = 48, SD = 12.6) and had relatively long careers as commercial vehicle operators (mean years = 21.1, SD = 14.1), but they only had very limited prior experience with ACC (1.4/7), collision warning systems (2.1/7), and truck platooning (0.7/7) according to the background questionnaires (0 indicates "Not Familiar at All" while 7 indicates "Very familiar" in the Likert-type scale; Yang et al., 2018).

Test trucks and CACC system

Three Volvo Class 8 trucks (see Figure 1 left) with empty trailers were used in the study. All trucks were equipped with CACC systems so that they can exchange control-related messages with each other via the DSRC-based V2V communication (See Figure 1 right).

The CACC system can be engaged, disengaged, and resumed using a control stalk behind the left side of the steering wheel (see Figure 2 left). It can also be ceased by pressing a red emergency disengage button (see Figure 2 middle) or pressing the brake pedal. The CACC user interface installed on the top of the truck instrument panel (see Figure 2 middle) presented elementary status information about the other trucks in the string and was used to select the time gap and driving mode (see Figure 2 right). The details of using the control stalk, emergency disengage button, and CACC user interface can be found in Yang et al. (2018).

Time gap setting

When the V2V communication signal was not available for an extended time (20 s or more), the control mode switched automatically from CACC to ACC. The time gap settings for CACC and ACC modes are listed in Table 1, and they were chosen to match some of the CACC time gaps tested on passenger cars in previous studies (Nowakowski et al., 2010). The ACC time gaps listed in Table 1 were modified and still much smaller than default ACC time gaps in the production vehicles. For example, the shortest default

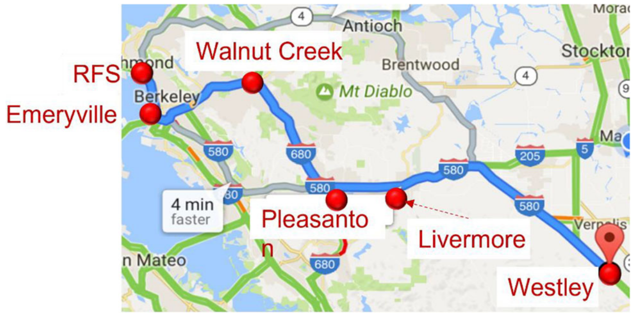

Figure 3. The test route between RFS and Westley. The red dots indicate the cities along the test route.

ACC time gap for the Volvo trucks was set by the manufacturer as 2.0 s.

The experiments had to comply with all applicable traffic laws based on the requirements from the project sponsors and the Institutional Review Board. This meant that the driving speeds should not exceed 55 mph (~90 km/h), which is the maximum legal speed for trucks in California.

Test route

The test route consisted of state and interstate freeways (dual carriageway highways with access limited to dedicated entrance/exit ramps) in Northern California. It started from the UC Berkeley Richmond Field Station (RFS) in Richmond, via I-580 (to Emeryville), SR 24 (to Walnut Creek), I-680 (to Pleasanton), I-580 (passing Livermore and merging into I-5) and ended around Westley on I-5 (see Figure 3).

After arriving at Westley, the drivers took a short break at a parking area near a truck stop and then returned to RFS via the same route. The trucks usually took more than 3 hours between 10:00 AM and 2:30 PM to complete a round trip between Richmond and Westley without heavy traffic delay.

Experimental procedure

Participants received the study introduction, signed the consent form, and finished the background questionnaire at UC Berkeley RFS. Then they were instructed to establish familiarity with the controls and time gaps of CACC on the highway between Emeryville and Walnut Creek (SR 24). After passing Walnut Creek, they could choose CACC time gaps for truck platooning until arrival at Westley. Due to safety concern, participants were instructed by the experimenters to do coordinated lane changes using the voice radio communication. To ensure a clear space in the destination lane for all the trucks, the driver of the last truck was instructed to deactivate CACC and start changing lane to block any other vehicles approaching from behind, so that the other two trucks could complete their lane changes unimpeded. After a short break at Westley, participants drove back to Walnut Creek in a different following truck and returned to RFS to complete the post-experiment questionnaire (see Figure 4).

Data analysis

A PC-104 computer stored inside the truck cab was used to record the vehicle and driver behavior data from 100 channels at a sampling rate of 50 Hz. Among these channels, we only analyzed driving mode (i.e., manual, ACC, CACC), CACC time gap, vehicle speed, road grade, and GPS data collected during the outward trip (from Walnut Creek to Westly) and return trip (from Westly to Walnut Creek; see Figure 4), after excluding the familiarization stage of CACC between RFS and Walnut Creek. Road grade is expressed as the ratio of the vertical elevation difference (m) to the horizontal distance (100 m) traveled. For example, road grade 5% means 5 m of elevation change over 100 m distance traveled.

The data collected in each trip was divided into consecutive 1-min epochs. We calculated the most frequent driving mode, and the road grade, truck speed, and GPS coordinates averaged over each epoch. If the most frequent driving mode was CACC, we calculated the dominant CACC time gap during the 1-min epoch. The traffic density in each epoch was estimated by "occupancy", retrieved from the Caltrans Performance Measurement System (PeMS; https://pems.dot.ca.gov/). Occupancy is defined as the fraction of time (0 ~ 100%) over a given period that the inductive loop detector detects a vehicle above, which is related to the number of vehicles passing the detector over this period and average vehicle speed (Jia et al., 2001). It is recorded at each detector station on the highway. The occupancy corresponding to each epoch was retrieved from the closest detector station (to the average GPS coordinates of this epoch) over a 5-min period that overlaps with this epoch. The data processing was completed in Python 3.7.

All epochs were localized on the map using the "3 D map" function in Microsoft Excel (see Figure 5). 57 ACC epochs (due to V2V communication faults preventing CACC operation) and 24 epochs with low vehicle speed (<20 km/h) were removed, and the remaining 1,128 epochs were used for analysis. For each participant, the number of epochs using Gaps 1 ~ 5 was normalized by the total number of epochs (excluding manual epochs) to estimate the "epoch percentage", which was compared

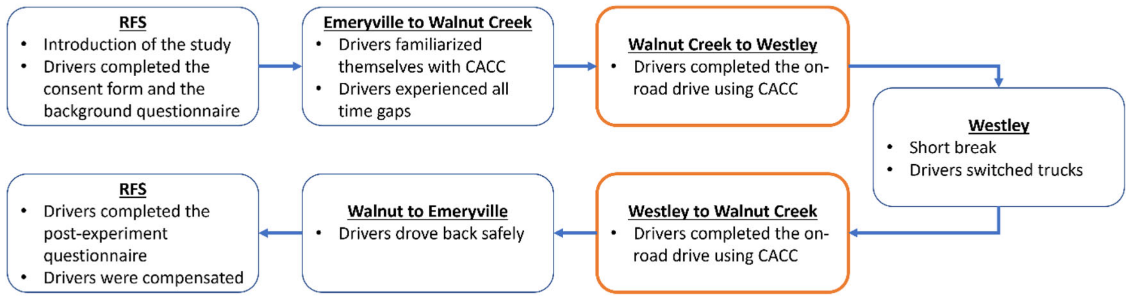

Figure 4. The flow chart of the experimental procedure. Only the data collected in the orange sections were processed and analyzed.

among Gaps $1\sim5$ by the Kruskal-Wallis test with the Dunn test (Dinno, 2017), showing the mostly used time gap. Also, the correlation between the epoch percentage and the driver's preference for time gaps was analyzed by Spearman's coefficient.

A multi-level Bayesian regression model (BRM) was used to analyze the effects on the use of CACC. The BRM estimates the posterior distributions of the effects (parameters), which include the population-level effect (assumed to be the same across observations) and group-level effect (assumed to vary across the grouping variables). They are equivalent with the fixed effect and random effect in the frequentist model (Bürkner, 2018). The population-level effects are indicated by the coefficients in Equation (1), including the effects of truck speed (β_{speed}), occupancy ($\beta_{occupancy}$), road grade (β_{grade}), and truck position ($\beta_{position}$), and the group-level effect is indicated by the coefficient of the participant ID (u_{pid}). These parameters are linearly combined with the independent variables to generate the linear predictor η (see Equation (1)), which relates to the mean (μ) of the probability distribution function of the response variable (y) via the logit function (see Equation (2)). The response variable is the use of CACC in each epoch, belonging to one of the six categories: manual driving (indicating zero use of CACC) or using Gaps $1\sim5$. It follows a categorical distribution (see Equation (3)), in which the mean (μ_j) represents the probability of the j^{th} category, with the sum of the probabilities of all categories as 1 (see Equation (4)).

$$\boldsymbol{\eta_j} = \beta_{\ intercept} + \beta_{speed}\boldsymbol{X}_{speed} + \beta_{occupancy}\boldsymbol{X}_{occupancy} + \beta_{\ grade}\boldsymbol{X}_{grade} + \beta_{\ position}\boldsymbol{X}_{position} + u_{pid}\boldsymbol{Z}_{pid} \quad (1)$$

$$logit(\mu_{i,j}) = \eta_{i,j} \quad (2)$$

$$y_{i,j} \sim Categorical(\mu_{i,j}) \quad (3)$$

$$\sum_j \mu_{i,j} = 1 \quad (4)$$

, where **X** and **Z** are the vectors of the variables observed in all epochs. $\boldsymbol{X}_{speed}$ is the truck speed (km/h); $\boldsymbol{X}_{occupancy}$ is the occupancy (%); $\boldsymbol{X}_{grade}$ is the road grade (%;- downhill, + uphill); $\boldsymbol{X}_{position}$ is the truck position (2nd or 3rd); and $\boldsymbol{Z}_{pid}$ is the participants' ID ($1\sim9$). i means the ith observation (1, 2, …, 1128) and j means the jth category of the response variable.

The posterior distributions of the population-level effects (β) were estimated by the NUTS (No-U-Turn Sampler) sampling algorithm (a variant of Hamiltonian Monte Carlo; Hoffman & Gelman, 2014) using R package "brms" (Bayesian regression models using Stan; Bürkner, 2018). The default improper flat prior was chosen as the prior of all β parameters. The NUTS algorithm approximated the posterior distribution of every β using four Markov chains with 2000 samples per chain. The first 1000 samples were used to tune the parameters of the NUTS sampling algorithm, and the total 4000 remaining samples were used to estimate the posterior distribution of each β. Every β was summarized using the mean ("Estimate") and the standard deviation ("Est. Error") of the posterior distribution with two-sided 95% credible intervals ("Lower 95% CI" and "Upper 95% CI"; see Table 2). The Bayesian credible interval is the interval that has a 95% probability to contain the true value of a parameter. The prediction accuracy of the fitted BRM was estimated by the efficient approximate leave-one-out cross-validation (LOO) using Pareto smoothed importance sampling (PSIS; Vehtari et al., 2017). The statistical analyses were completed in R 4.0.5.

Results

CACC use and preference

The epochs of each trip were depicted as colored dots on the map based on GPS coordinates, and color-coded (Manual = black, ACC = purple, CACC Gap 1 = dark red, Gap 2 = red, Gap 3 = green, Gap 4 = blue, and Gap 5 = dark blue; see Figure 5). Participants P1 and P2, P3 and P4, P5 and P6, and P7 and P8 were paired to drive the second and third

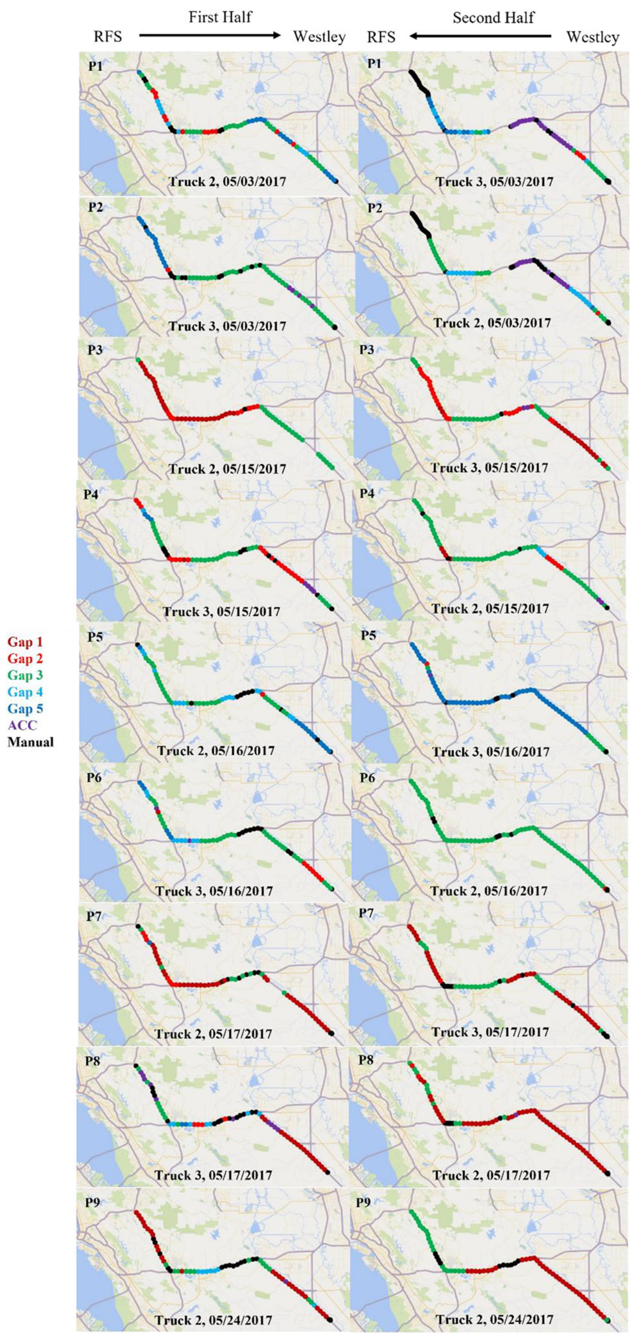

Figure 5. The epochs of each test drive on the map. Since GPS on the third truck failed on 05/03/2017, the coordinates of its epochs were estimated using the second truck's GPS coordinates based on synchronized timestamps from both trucks.

trucks on the same trips, whereas P9 did not have a teammate and only drove the second truck.

The CACC usage was significantly different among the time gaps, according to the KW test on epoch percentage ($\chi^2 = 13.6$, df = 4, p = .001). The Dunn test showed that participants used Gap 3 (mean = 43.3%, median = 40.0%) significantly more than other time gaps (Gap 1: mean = 26.0%, median = 4.5%, p = .009; Gap 2: mean = 10.3%, median = 7.1%, p=.003; Gap 4: mean = 8.0%, median = 7.1%, p<.001; Gap 5: mean = 12.5%, median = 2.7%, p = .001).

Participants ranked their preference for CACC time gaps in the post-experiment questionnaire (Yang et al., 2018). The percentage of the time gap usages negatively correlated with the ranking order of the time gaps: the Spearman correlation coefficient was −0.63 with a 95% confidence interval (−0.83, −0.36). Since smaller ranking orders indicate higher preferences, participants had lower usages of their less preferred time gaps (see Figure 6).

Bayesian regression analysis

We validated the prediction accuracy of the fitted BRM according to Pareto k estimates using "LOO". 99.8% of the (1,126) observations were good (k in (-∞, 0.5]) and 0.2% (2) observations were OK (k in (0.5, 0.7]).

The BRM offered by "brms" needs a reference category of the response variable, which was the manual (m) category here. If an independent variable shows a positive effect ($+\beta$) on Gap i, this variable, when it increases (as a continuous variable) or changes from the reference level (as a categorical variable), leads to a higher probability of using Gap i than driving manually (reference category), and vice versa.

The parameters β, however, did not quantify the direct effects of the population-level variables on the response variable. We used brms to calculate the "conditional effect" of each population-level variable on the response variable, with all other variables fixed, either at a value (e.g., occupancy = 0, road grade = 0, and speed = 90 km/h), or the reference level (e.g., truck position = 2; see Figures 7–10).

Truck speed

When the truck speed increases, there is a 95% probability for participants to reduce manual driving and increasingly use CACC at all time gaps (see Table 2). The BRM predicts that the probability of manual driving decreases from 100% to 7.8% when the truck speed increases from 20 km/h to 90 km/h (conditioning on occupancy = 0, truck position = 2, road grade = 0). Also, Gap 3 is most likely to be used (mean probability = 54.4%) and Gap 1 the next (mean probability = 22.1%) when driving at the speed of 90 km/h on a flat road without traffic (see Figure 7).

Table 2. Summary of the posterior probability distribution of the coefficients (effects).

	Effect	Parameter	Estimate	Est. error	Lower 95% CI	Upper 95% CI
Population level	$Intercept_1$	$\beta_{intercept,1}$	−12.3	2.37	−17.19	−7.82
	$Intercept_2$	$\beta_{intercept,2}$	−8.02	1.67	−11.48	−4.96
	$Intercept_3$	$\beta_{intercept,3}$	−10.45	1.45	−13.36	−7.71
	$Intercept_4$	$\beta_{intercept,4}$	−18.74	3.23	−25.47	−12.98
	$Intercept_5$	$\beta_{intercept,5}$	−18.8	2.94	−24.98	−13.46
	$Speed_1$*	$\beta_{speed,\ 1}$	0.14	0.02	0.10	0.19
	$Speed_2$*	$\beta_{speed,\ 2}$	0.09	0.02	0.06	0.12
	$Speed_3$*	$\beta_{speed,\ 3}$	0.14	0.02	0.11	0.17
	$Speed_4$*	$\beta_{speed,\ 4}$	0.20	0.04	0.14	0.27
	$Speed_5$*	$\beta_{speed,\ 5}$	0.19	0.03	0.13	0.25
	$Occupancy_1$	$\beta_{occupancy,\ 1}$	−6.95	4.52	−15.92	1.77
	$Occupancy_2$	$\beta_{occupancy,\ 2}$	−0.26	5.03	−10.31	9.53
	$Occupancy_3$	$\beta_{occupancy,\ 3}$	5.97	3.65	−0.90	13.38
	$Occupancy_4$*	$\beta_{occupancy,\ 4}$	16.39	4.83	7.19	26.03
	$Occupancy_5$*	$\beta_{occupancy,\ 5}$	11.58	4.87	2.14	21.09
	Road $Grade_1$*	$\beta_{grade,\ 1}$	0.78	0.12	0.56	1.02
	Road $Grade_2$*	$\beta_{grade,\ 2}$	0.53	0.13	0.28	0.79
	Road $Grade_3$*	$\beta_{grade,\ 3}$	0.57	0.10	0.38	0.76
	Road $Grade_4$*	$\beta_{grade,4}$	0.78	0.14	0.51	1.07
	Road $Grade_5$*	$\beta_{grade,\ 5}$	0.52	0.14	0.26	0.79
	$3rdPosition_1$*	$\beta_{position,\ 1}$	−1.4	0.30	−1.98	−0.84
	$3rdPosition_2$	$\beta_{position,\ 2}$	0.07	0.31	−0.56	0.67
	$3rdPosition_3$*	$\beta_{position,\ 3}$	−0.64	0.24	−1.12	−0.18
	$3rdPosition_4$	$\beta_{position,\ 4}$	−0.68	0.35	−1.37	0.03
	$3rdPosition_5$*	$\beta_{position,\ 5}$	1.58	0.35	0.91	2.27
Group level	SD ($Intercept_1$)*	$\sigma_{pid,\ 1}$	3.91	1.31	2.16	7.18
	SD ($Intercept_2$)*	$\sigma_{pid,\ 2}$	2.38	0.79	1.29	4.35
	SD ($Intercept_3$)*	$\sigma_{pid,3}$	1.34	0.45	0.70	2.44
	SD ($Intercept_4$)*	$\sigma_{pid,4}$	1.20	0.54	0.48	2.55
	SD ($Intercept_5$)*	$\sigma_{pid,5}$	2.32	0.79	1.21	4.20

Note. The symbol * indicates a 95% (or higher) probability for the effect to occur.

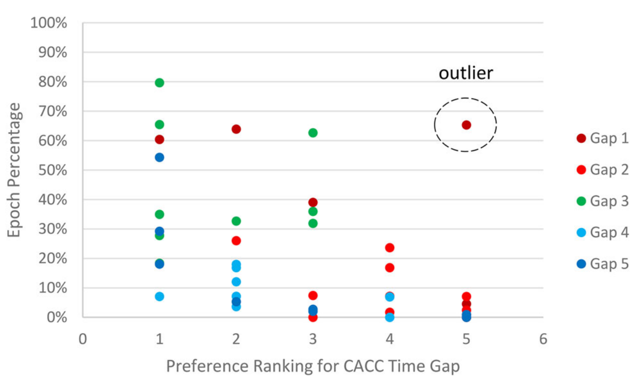

Figure 6. The correlation between the usage and preference ranking of the time gaps.

Occupancy

There is a 95% probability that participants use Gaps 4 and 5 more often than driving manually on highways with increasing occupancy (see Table 2). When the occupancy increases from 0 to 0.25, the BRM predicts that the probability of choosing manual driving mode is stable at mean probability of 1.7% ~7.8%, while the mean probability of using Gap 3 and 4 is 44.7% and 44.1%, respectively, dominating the CACC use (conditioning on speed = 90km/h, truck position = 2, road grade = 0; see Figure 8).

Road grade

When the road grade changes from negative (downhill) to positive (uphill), there is a 95% probability for participants to switch from manual driving mode to CACC mode (see Table 2). Participants are more likely to drive manually on downgrades (road grade between −5.0 and −2.5), but use CACC, especially at Gaps 1 and 3, on the flat or uphill roads (see Figure 9). For example, if driving the second truck at speed of 90 km/h on a flat road without traffic, the truck driver is expected to select Gaps 1 and 3 with a mean probability of 22.2% and 54.4%, respectively.

Truck position

There is a 95% probability for participants to reduce the use of Gaps 1 and 3 and increase the use of Gap 5, to some extent, in the third truck (see Table 2). Even though the mean probability of choosing Gap 5 is increased to 11.3% in the third truck (from 1.6% in the second truck), Gap 3 is still the most selected option among all, with a mean probability = 46.5% conditioning on speed = 90 km/h, occupancy = 0, road grade = 0 (see Figure 10).

Discussion

CACC represents a promising technical approach to automate the time gap control in truck platooning to promote safety and fuel efficiency. Truck drivers with on-road experience using CACC have shown positive attitudes toward this technology (Castritius, Hecht,

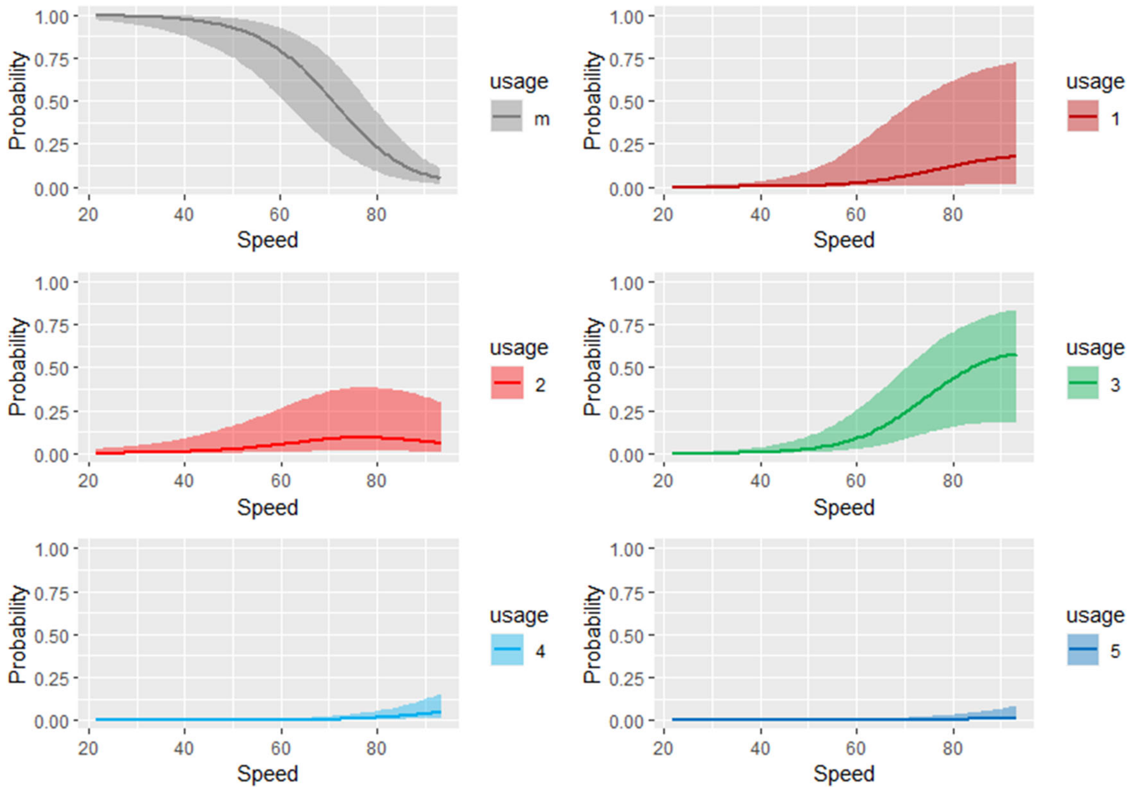

Figure 7. The conditional effect of truck speed on the use of CACC when other variables are fixed (occupancy = 0, truck position = 2, road grade = 0). The solid lines indicate the mean probability and the colored areas represent the 95% credible interval. “m” represents manual mode and the numbers 1 ∼ 5 represent Gaps 1 ∼ 5.

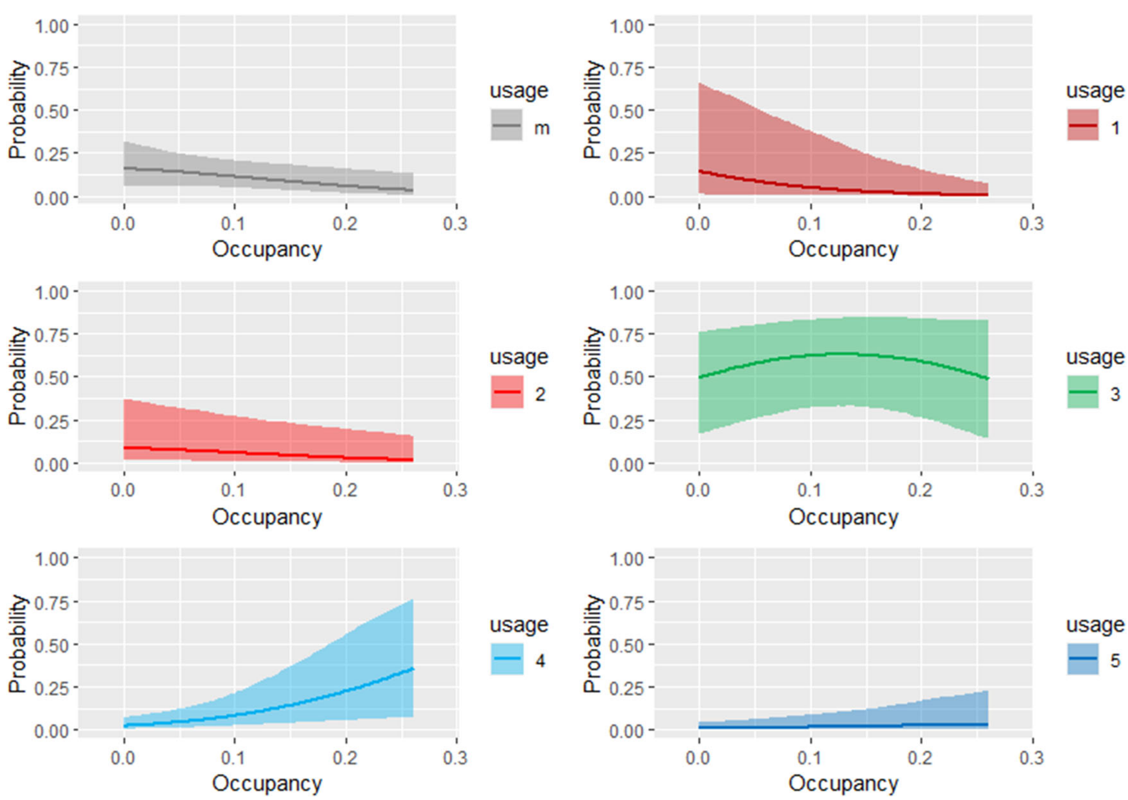

Figure 8. The conditional effect of occupancy on the use of CACC when other variables are fixed (speed = 90km/h, truck position = 2, road grade = 0). The solid lines indicate the mean probability and the colored areas represent the 95% credible interval. “m” represents manual mode and the numbers 1 ∼ 5 represent Gaps 1 ∼ 5.

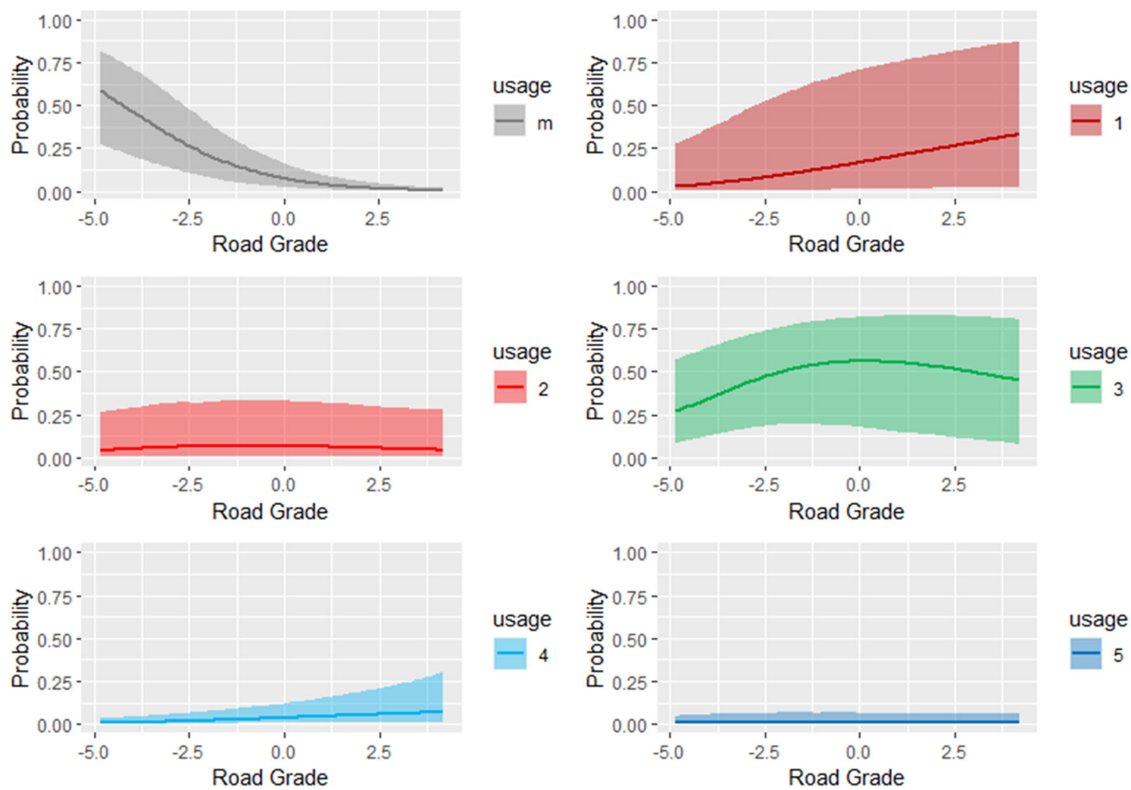

Figure 9. The conditional effect of road grade on the use of CACC when other variables are fixed (occupancy = 0, truck position = 2). The solid lines indicate the mean probability and the colored areas represent the 95% credible interval. "m" represents manual mode and the numbers 1 ~ 5 represent Gaps 1 ~ 5.

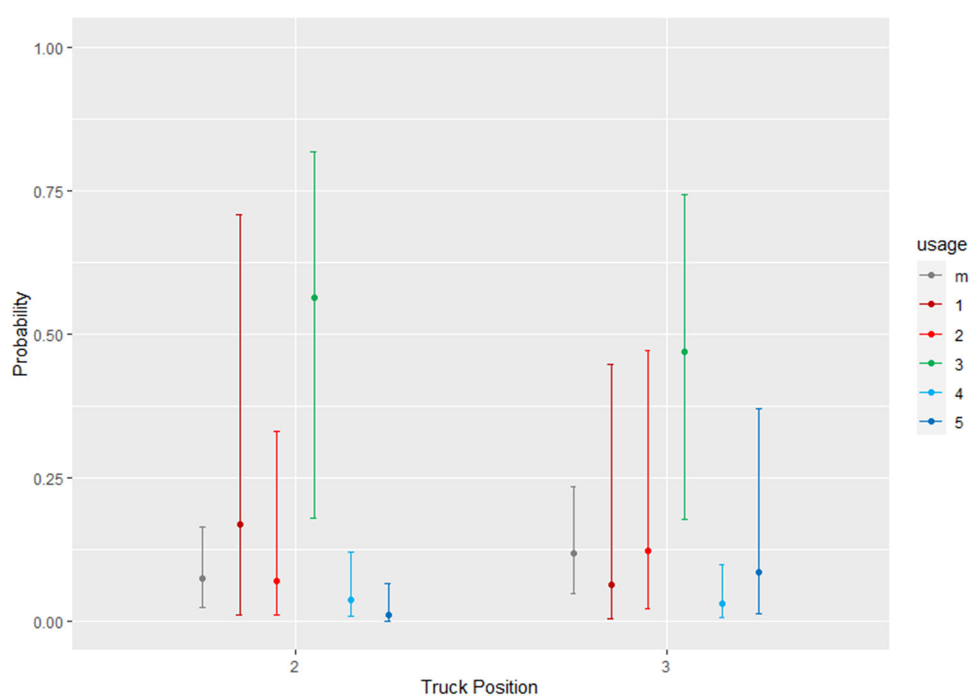

Figure 10. The conditional effect of truck position on the use of CACC when other variables are fixed (speed = 90 km/h, occupancy = 0, road grade = 0). The dots indicate the mean probability and the bars represent the 95% credible interval. "m" represents manual mode and the numbers 1 ~ 5 represent Gaps 1 ~ 5.

et al., 2020; Yang et al., 2018). To further understand driver-CACC interaction, we investigated drivers' actual use of CACC for truck platooning on suburban and rural freeways in Northern California and its relationship with their preference for time gaps. Moreover, we used a Bayesian approach to analyze the effects of truck speed, traffic density, road grade, and truck position on the use of CACC.

The nine truck drivers used Gap 3 the most, which is consistent with their highest preference for this time gap: Gap 3 was neither too small to provide sufficient front-road view, nor too large to encourage unwanted cut-ins (Yang et al., 2018). Also, their usage of time gaps correlated with their preference – they spent less time on their less favored time gaps (see Figure 6). Although Gap 4 was not commonly used, it was still preferred by most drivers, perhaps because its size was similar to Gap 3 but did not increase the view blockage (Yang et al., 2018). Additionally, there is an outlier in Figure 6 – a senior participant reported the lowest preference for Gap 1, which he used the most. This implies that the final decision on preference may be influenced by safety concerns, such as following social norms to maintain sufficient headway for collision avoidance, especially from experienced truck drivers (e.g., Zhang & Kaber, 2013).

However, Castritius, Dietz, et al. (2020) found that truck drivers preferred the small gap of 15 m (equivalent with time gap 0.6 s in 90 km/h) in truck platooning on German public highways, showing diversity in time gap preferences across countries. The study by Castritius, Dietz, et al. (2020) differs from our study in several ways, including additional automated steering control, fewer gap options (15 m vs. 21 m), later hours of the day (6 ∼ 11 PM), different highway conditions (e.g., traffic intensity, road regulations), and younger truck drivers (mean age = 39.3 years). Future research should identify the factors contributing to different preferences and uses of CACC among truck drivers from different countries to support an international standard of time gaps selection for automated truck platooning.

The engagement of CACC is affected by truck speed. According to the BRM, the truck driver is most likely to take control of the truck when its speed (0 ∼ 60 km/h) is much lower than the speed limit (90 km/h), normally at the start or the end of a trip, or in dense traffic on highways. But higher traffic density (occupancy) does not always lead to lower truck speed. By definition, it could be caused by a large number of vehicles passing the detector, even at high speed (Jia et al., 2001). Hence, high traffic density alone, without reducing truck speed, is not necessary to affect the probability of disengaging CACC (see the first plot in Figure 8). When the truck platoon slows down in heavy traffic, the cut-in vehicles increase, or the vehicle-following clearance gap may be reduced to an uncomfortable level, both discouraging CACC engagement (Yang et al., 2018).

If the truck speed is maintained at 90 km/h, the BRM predicted that truck drivers are most likely to choose Gaps 3 and 4, the ones they preferred, as occupancy increases. The time gaps may not prevent cut-ins as well as smaller time gaps, but they provide better visibility for truck drivers to respond to the surrounding traffic. It is worth noting that the accuracy of occupancy in each epoch depends on the quality (e.g., not all detectors use double loops) and density of detectors (e.g., fewer detectors on the highway I-5) of PeMS. The possible noise in the measure of occupancy could affect BRM's estimation of the relationship between occupancy and CACC usage. Outward-facing cameras and sensors may be considered in future research to estimate the instant traffic surrounding the truck platoon, complimenting PeMS.

Large negative grades tended to cause CACC disengagements. Truck drivers were more likely to switch to manual driving mode on downgrades because the braking systems controlled by the prototype CACC could not generate enough deceleration to compensate for the acceleration on downgrades (e.g., the steep Altamont Pass; Yang et al., 2018). When driving on flat or uphill roads, truck drivers often switched back to CACC mode, especially at Gaps 1 or 3, showing less concern with the insufficient acceleration (Yang et al., 2018) to maintain speed on the upgrades.

Although the majority of the participants neither noticed any difference between the second and third truck nor preferred a specific truck position (Yang et al., 2018), the BRM estimated that truck drivers reduce the use of Gaps 1 and 3 and use Gap 5 more often in the third truck. This is more likely to be associated with the control differences between the two following trucks - the third truck had poorer braking performance than the second truck (Yang et al., 2018). We cannot find noticeable evidence about time gap selection differences specifically due to truck position, implying flexibility in forming ad-hoc CACC strings “on the fly”.

Limitations and future research directions

Although statistical differences were found in the analysis of CACC usage, the small sample size may not represent the diversity of the full truck driver population. Also, our three-hour test drive on local highways did not provide enough opportunities for exposure to other driving-related factors, such as time of day, trip lengths, road curvature, and weather condition. Further research is needed to collect more diverse driver data in a wider range of scenarios to statistically explore the relationships between these factors and the use of CACC. Moreover, participants in this study followed the experimenters' instructions to perform lane changes, thus further research is still needed to investigate the naturalistic lane change decision making and performance in CACC-enabled truck platooning. Additionally, the implemented CACC was still an advanced research prototype rather than a commercial product, so it had several limitations that may have affected the usage of CACC in these tests, such as occasional unreliability and jerkiness in the speed control, and wireless communication errors (Yang et al., 2018).

Conclusion

In this case study, we analyzed the use of CACC for truck platooning on suburban and rural freeways in Northern California and the factors affecting it to provide insight into the design and implementation of CACC for the trucking industry. Truck drivers' preferences among CACC time gaps were found to influence their selection of these time gaps – the most preferred Gap 3 (1.2 s) earned the highest usage while the less preferred time gaps (e.g., Gap 2 = 0.9 s) were not used much. According to the BRM, truck drivers are more likely to disengage CACC in low speed traffic (usually due to high traffic density on highways) or on downgrades (due to insufficient braking control). They are more likely to use CACC, especially at Gap 3, when the speed is around the speed limit or driving on flat or uphill roads. Truck position, by itself, does not affect the use of CACC. These findings suggest that driver-preferred time gaps (e.g., Gap 3 = 1.2 s), freeway traffic conditions close to free-flow speed, and smooth and responsive brake controls are key factors to encourage CACC engagement and gain its potential benefits for the trucking industry and traffic systems.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Shiyan Yang http://orcid.org/0000-0002-2402-8126
Xiao-Yun Lu http://orcid.org/0000-0001-6491-3990

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