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The Impact of Cognitive Distraction on Driver Perception Response Time Under Different Levels of Situational Urgency

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ABSTRACT Identifying drivers' perception response time (PRT) is of utmost importance for the development of rear-end collision alarm systems. However, the effects of cognitive distraction on PRT under different levels of situational urgency are unclear. Therefore, the purpose of this study was to quantify and compare the effects of cognitive distraction for both high and low situational urgency. Participants (N = 45) were presented with a simulated car-follow scenario. The effects on both perception time and movement time were analyzed separately under headways of 1.5s and 2.5s using the Bayes factor approach, and a mixed-effects model was constructed to calculate the magnitude and significance of effects of cognitive distraction and situational urgency on PRT. The results revealed (1) the effect on perception time was smaller in the high situational urgency condition, and a high probability of distraction-related delay on perception time was found in both high ($BF_{10} = 15.588$) and low ($BF_{10} = 23.203$) situational urgency conditions; (2) the effect on movement time was larger in the high situational urgency condition, and the delay of movement time was more likely to occur in the high ($BF_{10} = 19.642$) situational urgency condition than in the low ($BF_{10} = 0.493$) situational urgency condition; (3) cognitive distraction increased driver's PRT by 1.556s, the average of drivers' PRT decreased by 0.241s for every 1s reduction in initial time headway. The results are beneficial for designing the lead time and the frequency of warning or intervention in rear-end collision alarm systems.

INDEX TERMS Distraction, perception response time, rear-end collision, situational urgency.

I. INTRODUCTION

Rear-end crashes are one of the frequently-occurring types of crashes that result in substantial property damage, as well as a large number of injuries and fatalities, every year. Statistical data for related accidents illustrate that rear-end crashes account for about 20% and 30% of all traffic accidents in China and the USA, respectively [1], [2]. As in-vehicle systems or portable electronic devices are becoming more frequently used, cognitively distracted driving is an important contributing factor in rear-end accidents [3]–[5]. Thus, some vehicles have begun promoting the use of a rear-end collision alarm system. Rear-end collision alarm systems can monitor the moving state of the car ahead using radar or visual sensors, and provide a warning when there is danger.

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To develop effective rear-end collision alarm systems, it is extremely important to set a reasonable lead time of warning or intervention of possible collisions. A reasonable lead time of warning or intervention can not only avoid unnecessary interference with the driver, but can also help provide adequate sight distance to allow drivers to perceive potential obstacles [6]–[9]. As the basis for setting the warning time of rear-end collision alarm systems, perception response time (PRT) is commonly defined as the amount of time taken to perceive and respond to a hazard, and is very closely related to the stages of human information processing [10]. For these reasons, a better understanding of drivers' PRT to imminent crash situations is required.

In a lead vehicle brake event, PRT is identified as the time between the activation of the lead vehicle's brake lamp and the initial application of pressure to the brake pedal [11]. Studies have found that drivers' braking response to a lead vehicle is driven by two sources of sensory evidence: visual looming and brake light [12]–[14]. Response to visual looming, referred to as the optical expansion of the lead vehicle, can be considered to be largely automatic. It involves a strongly consistent stimulus-response contingency; drivers generally have to press the brake pedal when they experience an object looming towards them at a high rate, as they would otherwise collide. When responding to visual looming, a bottom-up mechanism is triggered that does not involve the cognitive control system. Usually, changes in relative velocity and distance between lead vehicle and subject vehicle can cause visual looming. For example, Aust et al. found that a shorter time headway produced faster responses [15]. NHTSA also tested the effects of situational urgency on braking response time in possible rear-end collisions, and found that drivers released the accelerator and braked to the maximum more quickly as the initial time headway decreased and lead vehicle deceleration increased [2]. Xue *et al.* found that an accumulator model including the lead vehicle speed, deceleration rate, and headway distance fitted the distribution of brake response times better than did pure threshold models, suggesting that these three factors as looming cues together affect brake response time [16]. However, response to the brake light of a lead vehicle was found to be dependent on cognitive control resources and triggered via top-down mechanisms. Cognitive control was found to be related to the supervisory attentional system by applying cognitive control; drivers are able to coordinate ideas and actions to adapt to task goals and changing environmental demands [17], [18]. In general, when drivers are cognitively distracted, their perception response time increases due to inadequate cognitive control resources. For example, Bellinger et al. and Strayer et al. found a significant effect of cellular telephone conversations on PRT in lead vehicle braking scenarios [11], [19].

Cognitive load merely increases PRT in driving tasks that rely on cognitive control, but automatic performance is unaffected [12]. Accordingly, in the absence of cognitive distraction, cognitive control can be allocated to braking in response to the brake light onset. In addition, drivers conducting secondary cognitive tasks rely on automatized responses to looming cues of the lead vehicle due to the impaired ability to respond to the brake light. However, it is unclear how drivers use these two visual cues in different driving situations. In terms of qualitative research, Engström et al. conducted a meta-analysis study and found that the distraction-induced worsening of the overall brake response time was dependent on the initial time headway [20]. However, when considering the actual requirements of the design of rear-end collision alarm systems, it is desirable to quantify the effects of cognitive distraction on perception response time, and to determine the trend of the intensity of evidence in supporting these effects with the accumulation of data under different driving situations.

Noticeably, this can be conveniently accomplished within the framework of Bayesian inference [21]. The Bayes factor approach can be used to quantify the probability of data under the null hypothesis or the alternative hypothesis; for instance, the Bayes factor (BF_{01}) indicates the ratio of the probability of the data under the null hypothesis relative to the probability of the data under the alternative hypothesis. It has become increasingly apparent that the Bayesian approach to data analysis has considerable advantages [22]. However, to the authors' knowledge, it has been little used for analyzing data on driving performance. Furthermore, although perception time and movement time, as two subcomponents of PRT, are influenced by different variables and determined by different processes [23], very few studies have compared the effects of cognitive distraction on perception time and movement time between different levels of situational urgency.

Therefore, further research regarding the effects of cognitive distraction on braking performances should consider different levels of situational urgency. Driving simulator experiments were reported to be easier and more efficient to study drivers' perception response time due to the controlled environment in previous studies [4], [11], [16]. In the present study, a simulated car-follow experiment was conducted to examine the effects of cognitive distraction on perception time and movement time under high and low situational urgency conditions. The initial time headway was used as an indicator of situational urgency in line with previous studies [24], and a delayed digit recall task was used to induce cognitively secondary load due to its high efficiency and sensitivity in different studies [25], [26]. The Bayes factor approach was adopted to quantify the effect of cognitive distraction on perception time and movement time for high and low situational urgency conditions. In previous studies, PRT was affected by various human factors such as expectation, age, gender, and others [27]. Thus, in the current study, a mixed-effects (ME) model was introduced to calculate the magnitude and significance of effects of cognitive distraction and situational urgency on PRT, this approach can extract individual effects from total variations of PRT and explain the remaining variations with manifest variables and their interactions.

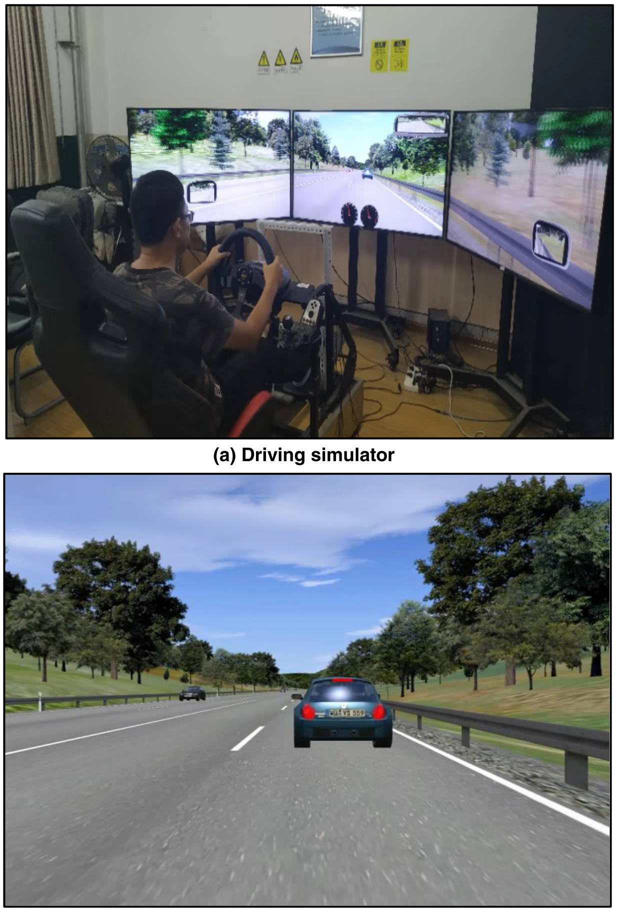
II. METHOD

A. APPARATUS

A fix-based SILAB 5.1 driving simulator was used as the tool for data collection in this study (see Fig. 1). It included a force-feedback steering wheel, a column gear selector, an instrumental dashboard, brake and accelerator pedals. The visual driving scene was presented on three computer screens at a resolution of 1280×800 pixels. The computer system of the simulator recorded the speed and coordinates of the vehicle at 60 Hz.

B. PARTICIPANTS

Forty-five participants were recruited through online advertising and with monetary rewards, and no significant age differences were found between male and female participants ($F(1,43) = 1.437$, $p = 0.238$). All subjects had valid driver's



(a) Driving simulator

(b) Event of lead vehicle brake

FIGURE 1. Apparatus and experiment scenario.

TABLE 1. Demographic information.

Demographic	Population sample
Gender	25 males, 20 females
Age (years)	Range 22-40, Mean = 26.95, SD = 4.66
Driving experiences (years)	Range 2-12, Mean = 4.05, SD = 2.44
Average driving days per week	Range 1-7, Mean = 5.10, SD = 2.10

licenses, and all had normal or corrected-to-normal vision. None suffered from simulator sickness. The ethical protocol of the present study was approved by the Institutional Review Board at Chang'an University. The demographic information is presented in Table 1.

C. EXPERIMENTAL DESIGN AND PROCEDURE

A within-subject experiment was designed. After completing a demographic information questionnaire, a car-follow scenario was presented, and each participant was required to perform a 5-min training drive to become familiarized with the driving simulator. Participants were asked to follow the lead vehicle at a distance of 30-60 meters and respond to the braking behavior of the lead vehicle in the training scenario.

In the testing phase, a car-follow scenario with a fixed speed of the lead vehicle (100 km/h) in a long, straight, undivided, two-lane highway was presented. There was one baseline task and one distraction task conducted in a counter-balanced order. That was, about one half of the participants drove without secondarily cognitive load first, the other half drove with secondarily cognitive load first. The initial time headways were set to 1.5 s and 2.5 s. In both tasks, drivers were asked to drive at a following distance of 30-60 meters and respond to the braking behavior of the lead vehicle. Moreover, in the distraction task, drivers were asked to drive while simultaneously performing secondary cognitive tasks. Cognitively secondary task was induced by one delayed digit recall task (1-back task). Participants were required to listen to a list of single-digit numbers and respond verbally with the digit presented in the previous position. The numbers were presented in a random order with a spacing of 2.25 seconds according to the study by Addario *et al.* [23]. For each driving task, there were two full stops of the lead vehicle with its brake lights on, and various time intervals between the lead vehicle brake onset were adopted to limit the predictability of brake events. The participants were orally informed to drive within the specified following distance during driving. Participants' perception response times were recorded by the simulator.

D. DEPENDENT VARIABLES

Perception response time was used as a dependent variable and divided into two stages (perception time and movement time) in the study (see Fig. 2), as previously applied by Bellinger *et al.* [11].

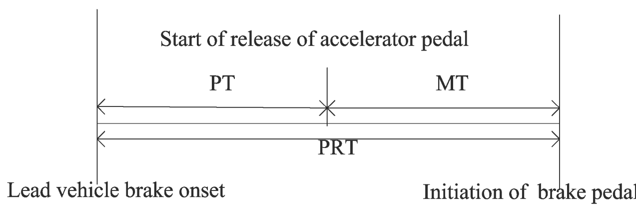


FIGURE 2. Illustration of dependent variables.

(1)Perception time (PT) represents the duration between the lead vehicle brake onset and the moment when the subject vehicle first started to release the accelerator pedal.

(2)Movement time (MT) represents the duration between the initiation of the throttle pedal release and the initiation of the brake pedal.

E. TESTING THE EFFECTS OF COGNITIVE DISTRACTION IN EACH CONDITION

A total of 180 car-following scenarios were recorded in the test, 3 of which were eliminated due to the release of the accelerator pedal before the lead vehicle began to brake, or due to exceeding the preset range of the time headway (2.5 s) at the lead vehicle brake onset. The remaining 177 scenarios were used in the analysis via JASP software. Furthermore, the initial time headway varied at specific intervals and was categorized into two levels: high situational urgency (0-1.5 s) and low situational urgency (1.5-2.5 s) [2]. The Bayes factor approach was conducted to analyze the effect of cognitive load on perception time and movement time in each situational urgency condition, and sequential analyses under the assumption of equal variance were applied to illustrate the evidential trajectory in favor of H1 over H0. The Bayes factors BF_{10} can be computed as follows:

$$\mathrm{BF}_{10} = \frac{p(data|H_1)}{p(data|H_0)} \tag{1}$$

In this study, the null hypothesis (H0) is that there is no difference of perception time or movement time between the baseline and distraction task, while the alternative hypothesis (H1) is that there is a difference of perception time or movement time between tasks. The Bayes factor BF_{10} is employed to express the comparison of the alternative hypothesis (H1) to the null hypothesis (H0). For instance, a BF_{10} value of 5 indicates that the data were 5 times more likely under H1 than under H0.

F. MODELS FOR PERCEPTION RESPONSE TIME CONSIDERING INDIVIDUAL DIFFERENCES

In the experiment, each participant experienced four deceleration scenarios, with different cognitive load and time headway. Therefore, a ME model, considering individual differences, was constructed as follows [28], [29]:

$$y_{ij} = \alpha_0 + \zeta_{1i} + \varepsilon_{ij} \tag{2}$$

where y_{ij} represents the ith PRT of the jth driver, a_0 is the overall intercept, ζ_{1i} represents random intercepts for driver i and follows a normal distribution $(0, \sigma_\zeta^2)$, ε_{ij} represents a residual error term and follows a normal distribution $(0, \sigma_\varepsilon^2)$. It follows from the assumption that the variance of PRT given the covariates can be described as follows:

$$Var\left(y_{ij}\right) = \sigma_\zeta^2 + \sigma_\varepsilon^2 \tag{3}$$

When considering cognitive distraction and situational urgency as fixed effects instead of random effects, as shown in Eq.(4)

$$y_{ij} = \alpha_0 + \zeta_{1i} + \alpha_1 \mathrm{x}_{1ij} + \alpha_2 \mathrm{x}_{2ij} + \varepsilon_{ij} \tag{4}$$

where x_1 and x_2 represent cognitive load and situational urgency respectively, a_1 *and* a_2 is the slopes of the two predictors. Eq.(4) can be extended to include individual difference and rewritten as follows:

$$y_{ij} = \alpha_0 + \zeta_{1i} + \alpha_1 \mathrm{x}_{1ij} + \alpha_2 \mathrm{x}_{2ij} + \zeta_{2i} \mathrm{x}_{1ij} + \varepsilon_{ij} \tag{5}$$

where ζ_{2i} represents random slopes for driver i.

To better compare the effects on PRT in terms of different modeling formulation, a reference model which does not include any predictors and random intercepts are constructed. Then ME models were constructed to include cognitive load and situational urgency, and random intercepts and slopes at individual level. In addition, Akaike's information criteria (AIC) accounts for the number of parameters in the model [30], and Schwarz's Bayesian criterion (BIC) considers number of parameters and sample size [31]. AIC and BIC were calculated to compare the goodness-of-fit of the models and identify a final model (see Eq.(6) and Eq.(7)). Generally, a model is selected if it decreases AIC or BIC by 10 or more [32].

$$AIC = -2\ln(L) + 2k \tag{6}$$
$$BIC = -2\ln(L) + \ln(n) * k \tag{7}$$

III. RESULTS

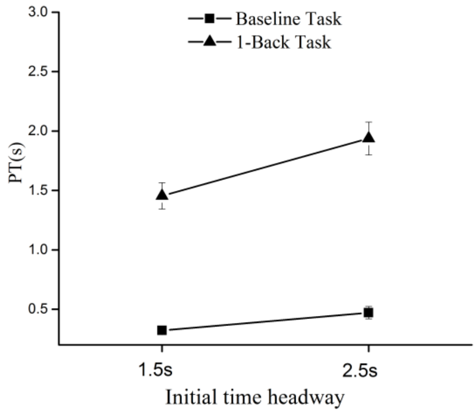
A. PERCEPTION TIME

Figure 3a presents the average perception time per task in both high and low situational urgency conditions. Participants in high situational urgency conditions spent less time on perceiving hazards than those in low situational urgency conditions. For high situational urgency, the perception time increased with the cognitive load; the average perception time in the 1-back task (Mean = 1.454, Std = 0.710) was higher than that in the baseline task (Mean = 0.322, Std = 0.228). Similarly, the average perception time in the 1-back task (Mean = 1.937, Std = 0.834) was higher than that in baseline task (Mean = 0.471, Std = 0.398) in the low situational urgency condition (see Table 2).

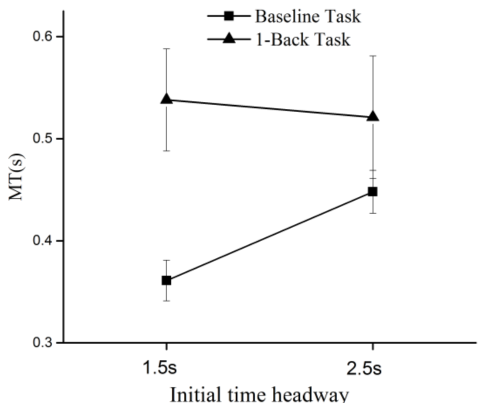
TABLE 2. Statistical summary of dependent variables (s).

Variable	Condition	Task	Mean	Std	Min	Max
PT	High	Baseline	0.322	0.228	0.017	0.900
		1-back	1.454	0.710	0.083	2.933
	Low	Baseline	0.471	0.398	0.017	2.350
		1-back	1.937	0.834	0.267	3.650
MT	High	Baseline	0.361	0.127	0.217	0.817
		1-back	0.538	0.323	0.250	1.617
	Low	Baseline	0.448	0.159	0.233	1.217
		1-back	0.521	0.361	0.200	1.750
PRT	High	Baseline	0.710	0.314	0.300	1.717
		1-back	1.970	0.665	0.450	3.317
	Low	Baseline	0.920	0.389	0.550	2.617
		1-back	2.46	0.906	1.000	4.850

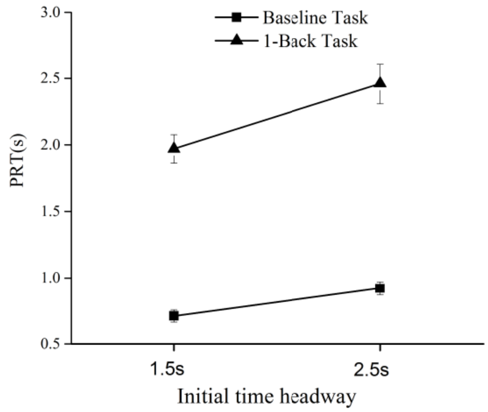
Figures 4a and 4b present the distribution of effect sizes on perception time in both conditions. The posterior distributions assigned the most mass to negative effect sizes. Thus, consistent with the observed data, the posterior distributions for the effect sizes indicated that participants perceived hazard more slowly in the 1-back task than in the baseline task. The effect size was smaller for the baseline versus 1-back task comparison in the high situational urgency condition



(a) The average perception time

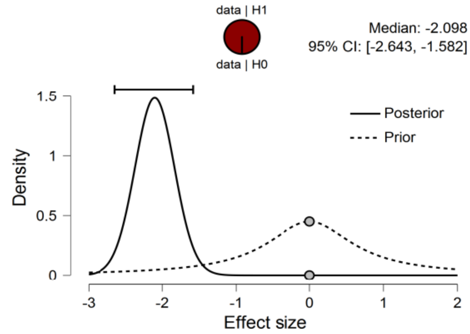


(b) The average movement time

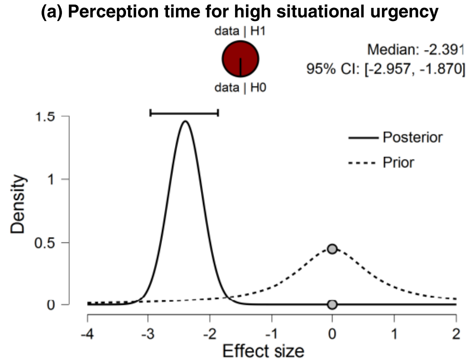


(c) The average perception response time

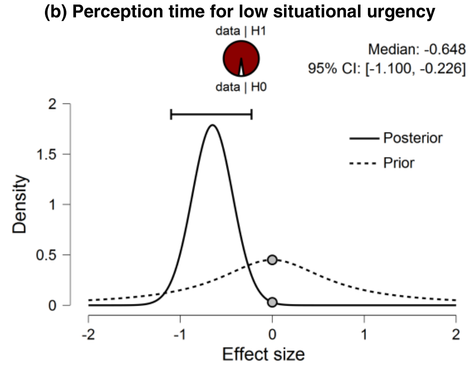
FIGURE 3. Dependent variables per task in both high and low situational urgency conditions. The error bars indicate the standard error.



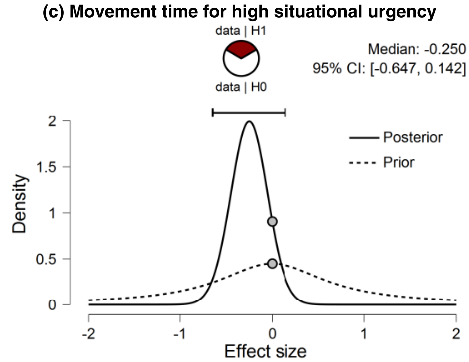
(a) Perception time for high situational urgency



(b) Perception time for low situational urgency



(c) Movement time for high situational urgency



(d) Movement time for low situational urgency

FIGURE 4. The distribution of the estimated effect sizes in both high and low situational urgency conditions. Prior (dotted line) represents prior distribution of the estimated effect size, while posterior (solid line) represents posterior distribution of the estimated effect size. The pie charts show the probability of the data in favor of the alternative hypothesis (H1) relative to the null hypothesis (H0).

(|Median| = 2.098) than in the low situational urgency condition (|Median| = 2.391).

Figures 5a and 5b present the results of the sequential analyses of the Bayes factor for the comparison of perception time using unpaired Bayesian t-tests under the assumption of equal variance. For the high situational urgency condition, the evidence in favor of H1 gradually increased as the data was accumulated. The Bayes factor indicated that the data of the difference between the baseline and the 1-back task was about 15 times more likely under H1 than under H0 (BF_{10} = 15.588). Likewise, for the low situational urgency condition, the Bayes factor indicated that the data of the difference between the baseline and 1-back task was about 23 times more likely under H1 than under H0 ($BF_{10} = 23.203$). In sum, the Bayes factor indicated strong evidence in favor of H1 for the baseline versus 1-back task comparisons in both conditions, whereas in terms of magnitude, cognitive load affected perception time more strongly in the low situational urgency condition than in the high situational urgency condition.

B. MOVEMENT TIME

Figure 3b presents the average movement time per task in both high and low situational urgency conditions. The results revealed that the movement time increased with the cognitive load. To be specific, the average movement time in the 1-back task (Mean = 0.538, Std = 0.323) was higher than that in the baseline task (Mean = 0.361, Std = 0.127) in the high situational urgency condition, and the average movement time in the 1-back task (M = 0.521, Std = 0.361) was higher than that in the baseline task (Mean = 0.448, Std = 0.159) in the low situational urgency condition (see Table 2).

Figures 4c and 4d present the distribution of each of the effect sizes on movement time. The posterior distributions assigned most mass to negative effect sizes, and the posterior distributions for the effect sizes indicated that participants executed the brake pedal more slowly in the 1-back task than in the baseline task for both situational urgency conditions. The effect size was larger for the baseline versus 1-back task comparison in the high situational urgency condition (|Median| = 0.648) than in the low situational urgency condition (|Median| = 0.250), though the estimated parameters were relatively small.

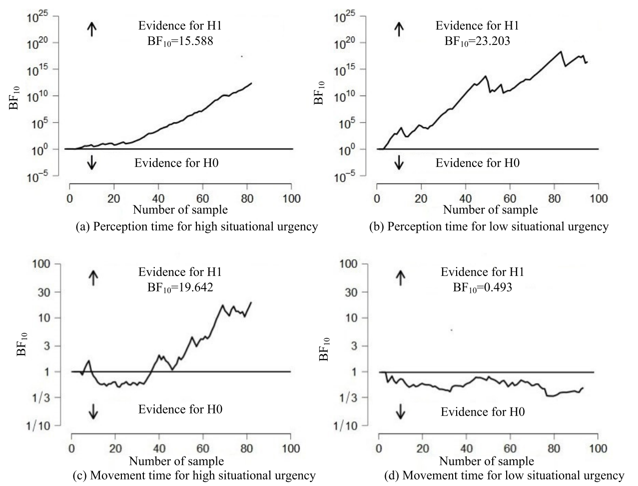


FIGURE 5. Bayes factors for the comparison of perception time and movement time between tasks in both high and low situational urgency conditions. The sequential analysis plots show the Bayes factor as a function of the number of samples per condition; Bayes factors less than one indicate evidence for H0, whereas Bayes factors greater than one indicate evidence for H1.

Figures 5c and 5d present the results of the sequential analyses of the Bayes factor for the comparison of movement time using unpaired Bayesian t-tests under the assumption of equal variance. For the high situational urgency condition, the Bayes factor indicated that the data of the difference between the baseline and the 1-back task was about 19 times more likely under H1 than under H0 ($BF_{10} = 19.642$). However, for the low situational urgency condition, the Bayes factor indicated that the data was about 2 times more likely under H0 than under H1 ($BF_{10} = 0.493$). That is, the Bayes factor indicates strong evidence in favor of H1 for the baseline versus 1-back task comparisons under the high situational urgency condition, but only moderate evidence in favor of H0 for the baseline versus 1-back task comparisons under the low situational urgency condition.

C. PERCEPTION RESPONSE TIME

Figure 3c presents the average perception response time per task in both high and low situational urgency conditions. The results revealed that perception response time increased with the cognitive load. To be specific, the average perception response time in the 1-back task (Mean = 1.970, Std = 0.665) was higher than that in the baseline task (Mean = 0.710, Std = 0.314) in the high situational urgency condition, and the average perception response time in the 1-back task (M = 2.46, Std = 0.906) was higher than that in the baseline task (Mean = 0.920, Std = 0.389) in the low situational urgency condition (see Table 2).

TABLE 3. Comparison of fit statistics of the models.

Model	Log likelihood	AIC	BIC	p
Null model	-235.780	475.559	481.912	<0.001
Model 1	-160.317	328.635	341.339	<0.001
Model 2	-158.795	327.589	343.470	<0.001
Model 3	-150.050	312.100	331.156	<0.001

As shown in Table 3, a total of four models were constructed. Null model was without any predictors and random intercepts, as benchmark models for model comparisons, model 1 considered cognitive task and situational urgency as fixed effects, model 2 was with random intercepts at driver level, but without random slopes, model 3 was with random intercepts and slopes of cognitive task. All four models yielded stable and consistent results in terms of the sign and magnitude of the independent variables, and had a significance level of $p<0.001$. As suggested above, larger than 10 AIC or BIC differences across models implied very strong evidence that the model fitted the data better than other model did. In this study, AIC and BIC of model 3 were 312.100 and 331.156 respectively, AIC and BIC differences between model 3 and other models were larger 10 or more, it suggested that the proposed model was valid and it outperformed other three models, and the inclusion of individual difference was found to significantly improve model goodness-of-fit.

TABLE 4. Parameter estimates of final model.

ME model		Estimate	S. E.	95% IC
Fixed effects	Intercept	0.412	0.131	[0.155, 0.669]
	Task	1.556	0.144	[1.274, 1.837]
	Condition	0.241	0.071	[0.103, 0.380]
Random effects	sd(Task)	0.513	0.119	[0.326, 0.810]
	sd(cons)	$1.58e^{-12}$	$1.37e^{-8}$	NA
	sd(Residual)	0.519	0.030	[0.464, 0.581]

Parameter estimates of the final model were summarized in Table 4. Both cognitive distraction and situational urgency affected driver's PRT significantly. Driving with cognitively secondary task (1-back) increased driver's PRT by 1.556s while controlling for initial time headway. In other wards, the average of drivers' PRT was 1.968s when drivers were in a state of cognitive distraction (1.968s = 0.412s + 1.556s). Additionally, the average of drivers' PRT decreased by 0.241s for every 1s reduction in initial time headway when controlling for cognitive load. It should be noted that random effects were very significant in terms of the slope of task (sd(Task) = 0.513, 95% IC = [0.326, 0.810]), this implied individual factors had a significant effect on drivers' PRT and should not be ignored in the study of cognitive distraction or situational urgency effects.

IV. DISCUSSIONS

The aim of this research was to investigate the cognitive distraction effect on PRT under different levels of situational urgency. In this study, perception response time was categorized into two subcomponents: perception time and movement time. Varying effects of cognitive distraction were found for different levels of situational urgency. In particular, cognitive distraction affected perception time more strongly in the low situational urgency condition than in the high situational urgency condition, whereas cognitive distraction affected movement time more strongly in the high situational urgency condition than in the low situational urgency condition. The evidential trajectory in favor of the effect of cognitive distraction was revealed. Strong evidence in favor of a difference in perception time between the baseline and 1-back task was provided in both high and low situational urgency conditions. The evidence in support of a difference in movement time between tasks in the high situational urgency condition was also strong, but was only moderate in support of a difference in the low situational urgency condition. In addition, the ME model were constructed and the results suggested that the proposed model fitted better than other models when individual differences were introduced as random factors, and it also demonstrated cognitive distraction, situational urgency and individual differences affected drivers' PRT significantly. These results can provide a better understanding of the effects of cognitive distraction on different stages of PRT.

The present study not only revealed that cognitive distraction affected perception time in both situational urgency conditions, findings which were consistent with the results of previous studies [33], [34], but also found that the effect size was smaller in the high situational urgency condition than in the low situational urgency condition. A previous study found no effects of cognitive load on braking performance when the brake light of the lead vehicle turned off, and suggested that cognitive load merely increased the perception response time to the brake light [35]. Combined with the cognitive control hypothesis suggested by Engström *et al.* [12], these results suggest that visual cues from the brake light are less effective in high than in low situational urgency conditions, even though they play a crucial role in triggering the driver's response under both conditions. In other words, in a car-follow scenario with a relatively small headway, drivers' brake responses could be mainly triggered by visual looming. In contrast, in a car-follow scenario with a relatively large headway, drivers' brake responses could be mainly triggered by the brake light of the lead vehicle, and are dependent on cognitive control resources.

In the study by Addario *et al.* [23], the authors found that movement time increased for abrupt hazard onsets (right incursion vehicle hazard) during driving with cognitively secondary load. Similarly, the results of the present study demonstrated that movement time increased with cognitive load for both high and low situational urgency conditions. Additionally, a larger effect was found in the high situational urgency condition compared to the low situational urgency condition, although the magnitude was relatively small. One possible explanation of the results is that, a similar delay on movement time is caused by cognitively secondary load both in the high and in the low situational urgency conditions. However, movement time is shorter in the high situational urgency condition than in the low situational urgency condition when driving without secondarily cognitive load, thus, a larger difference of movement time is observed in the high situational urgency condition. This is contrary to the result regarding perception time, which suggests that, although they are sequentially executed in braking, perception time and movement time may be determined by different information processing. This finding is of crucial importance because it suggests that an earlier intervention on the brake pedal conducted by rear-end collision alarm systems is necessary to help the driver shorten the braking distance in an emergency car-follow scenario, even if the individual does notice the braking of the car ahead.

As described above, the average of drivers' PRT decreased by 0.241s for every 1s reduction in initial time headway when controlling for cognitive load, whereas driving without cognitively secondary task decreased driver's PRT by 1.556s while controlling for initial time headway. Therefore, when the initial time headway is relatively small in car-follow scenarios, cognitively secondary task has a greater effect on PRT than situational urgency. This suggests that cognitive distraction is a predominant factor influencing PRT and drivers should be educated to be more vigilant and maintain a greater attention in emergency car-follow scenarios. It also suggests that both initial time headway and cognitively secondary load should be considered in setting the warning time of rear-end collision alarm systems. Furthermore, the Bayes factor indicated a great probability of distraction-related delay on perception time in both high and low situational urgency conditions ($BF_{10} = 15.588$ and $BF_{10} = 23.203$, respectively), and it was further found that distraction-related delay of movement time was more likely to occur in high than in low situational urgency conditions ($BF_{10} = 19.642$ and $BF_{10} = 0.493$, respectively). These results can be useful in setting the warning frequency of rear-end collision alarm systems when the driver is cognitively in a state of distraction. For example, the frequency of warning or intervention should be higher in emergencies than in non-emergencies.

In summary, the findings of the present study provide further support that cognitive distraction can affect drivers' perception response time during the braking process. However, there are several limitations of the present study that should be noted. First, the sample participants are relatively younger and have less driving experience, which prevents the generalization of findings to other driver groups. Second, using simulation tasks and environments that provide precisely controlled cognitive demands to generally represent real-world driving can be problematic; the degree to which the simulator presents drivers with actual roadway demands should be determined in subsequent studies. Third, previous studies have shown that both the initial time headway and the deceleration rate of the lead vehicle affect drivers' brake response times [2], [16]. It is therefore conceivable that the combination of the initial time headway and deceleration rate could exacerbate the influences of situational urgency on perception response time. Thus, the effects of cognitive distraction on perception response time can be explored in future research by combining the initial time headway with the deceleration rate as indicators of situational urgency.

V. CONCLUSION

In this paper, the effects of cognitive distraction on brake response to a lead vehicle were investigated under different levels of situational urgency in a simulated driving scenario. A within-subjects experiment was designed by considering two levels of cognitive load as independent variables. Two subcomponents of perception response time, namely perception time and movement time, were assessed. The results revealed that cognitive distraction affected perception time more strongly in the low situational urgency condition, whereas the effect on movement time was greater in the high situational urgency condition. Distraction-related delay on perception time was found to be more likely to occur in both high and low situational urgency conditions, and the probability of distraction-related delay on movement time was larger in the high situational urgency condition than in the low situational urgency condition. Furthermore, cognitive distraction had a greater effect on PRT than situational urgency in car-follow scenarios with a small time headway. These results can be used to design advanced driving assistant systems or evaluate the safety of in-vehicle information and communication technologies.

REFERENCES

[1] X. Wang, M. Zhu, M. Chen, and P. Tremont, "Drivers' rear end collision avoidance behaviors under different levels of situational urgency," *Transp. Res. C, Emerg. Technol.*, vol. 71, pp. 419–433, Oct. 2016.

[2] *By First Harmful Event, Type of Collision and Crash Severity*, NHTSA, Washington, DC, USA, 2014.

[3] NHTSA, Washington, DC, USA. (2017). *Distracted Driving in Fatal Crashes*. Accessed: 2019. [Online]. Available: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812700

[4] M. Haque and S. Washington, "Effects of mobile phone distraction on drivers' reaction times," *J. Australas. College Road Saf.*, vol. 24, no. 3, pp. 20–29, Nov. 2013.

[5] Y. Liang and J. D. Lee, "Combining cognitive and visual distraction: Less than the sum of its parts," *Accident Anal. Prevention*, vol. 42, no. 3, pp. 881–890, May 2010.

[6] A. Tang and A. Yip, "Collision avoidance timing analysis of DSRC-based vehicles," *Accident Anal. Prevention*, vol. 42, no. 1, pp. 182–195, Jan. 2010.

[7] K. W. Ising, J. A. Droll, S. G. Kroeker, P. M. D'Addario, and J.-F. Goulet, "Driver-related delay in emergency braking response to a laterally incurring hazard," *Proc. Hum. Factors Ergonom. Soc. Annu. Meeting*, vol. 56, no. 1, pp. 705–709, Dec. 2012.

[8] C. Wang, Z. Li, R. Fu, Y. Guo, and W. Yuan, "What is the difference in driver's lateral control ability during naturalistic distracted driving and normal driving? A case study on a real highway," *Accident Anal. Prevention*, vol. 125, pp. 98–105, Apr. 2019.

[9] R. Fu, Y. Zhou, W. Yuan, and T. Han, "Effects of cognitive distraction on speed control in curve negotiation," *Traffic Injury Prevention*, vol. 20, no. 4, pp. 431–435, May 2019.

[10] A. Smiley, T. Smahel, D. C. Donderi, J. K. Caird, S. Chisholm, J. Lockhart, and E. Teteris. (Jan. 2007). *The Effects of Cellphone and CD Use On Novice and Experienced Driver Performance*. [Online]. Available: http://www.ibc.ca/en/Car_Insurance/documents/road_safety/DriverDistraction_full_study_jan2007.pdf

[11] D. B. Bellinger, B. M. Budde, M. Machida, G. B. Richardson, and W. P. Berg, "The effect of cellular telephone conversation and music listening on response time in braking," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 12, no. 6, pp. 441–451, Nov. 2009.

[12] J. Engström, G. Markkula, T. Victor, and N. Merat, "Effects of cognitive load on driving performance: The cognitive control hypothesis," *Hum. Factors, J. Hum. Factors Ergonom. Soc.*, vol. 59, no. 5, pp. 734–764, Feb. 2017.

[13] N. K. Greenwell. *Effectiveness of Led Stop Lamps for Reducing Rear-End Crashes: Analyses of State Crash Data*. Accessed: Mar. 27, 2013. [Online]. Available: http://www-nrd.nhtsa.dot.gov/Pubs/811712.pdf

[14] J. M. Watson and D. L. Strayer, "Supertaskers: Profiles in extraordinary multitasking ability," *Psychonomic Bull. Rev.*, vol. 17, no. 4, pp. 479–485, Aug. 2010.

[15] M. L. Aust, J. Engström, and M. Vistrom, "Effects of forward collision warning and repeated event exposure on emergency braking," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 18, pp. 34–46, May 2013.

[16] Q. Xue, G. Markkula, X. Yan, and N. Merat, "Using perceptual cues for brake response to a lead vehicle: Comparing threshold and accumulator models of visual looming," *Accident Anal. Prevention*, vol. 118, pp. 114–124, Sep. 2018.

[17] E. A. Crone and R. E. Dahl, "Understanding adolescence as a period of social-affective engagement and goal flexibility," *Nature Rev. Neurosci.*, vol. 13, no. 9, pp. 636–650, Sep. 2012.

[18] N. Lavie, "Attention, distraction, and cognitive control under load," *Current Directions Psychol. Sci.*, vol. 19, no. 3, pp. 143–148, Jun. 2010.

[19] D. L. Strayer, F. A. Drews, and W. A. Johnston, "Cell phone-induced failures of visual attention during simulated driving," *J. Exp. Psychol., Appl.*, vol. 9, no. 1, pp. 23–32, Apr. 2003.

[20] J. Engström, "Scenario criticality determines the effects of working memory load on brake response time," in *Proc. Eur. Conf. Hum. Centred Design Intell. Transp. Syst.*, Apr. 2010, pp. 25–36.

[21] D. Matzke, S. Nieuwenhuis, H. van Rijn, H. A. Slagter, M. W. van der Molen, and E.-J. Wagenmakers, "The effect of horizontal eye movements on free recall: A preregistered adversarial collaboration," *J. Exp. Psychol., Gen.*, vol. 144, no. 1, pp. 1–15 Mar. 2015.

[22] J. Gill, *Bayesian Methods: A Social and Behavioral Sciences Approach*, 3rd ed. Boca Raton, FL, USA: CRC Press, 2015.
[23] P. Addario and B. Donmez, "The effect of cognitive distraction on perception-response time to unexpected abrupt and gradually onset roadway hazards," *Accident Anal. Prevention*, vol. 127, pp. 177–185, Jun. 2019.
[24] E. J. Nilsson, M. L. Aust, J. Engström, B. Svanberg, and P. Lindén, "Effects of cognitive load on response time in an unexpected lead vehicle braking scenario and the detection response task (DRT)," *Transp. Res. F, Psychol. Behav.*, vol. 59, pp. 463–474, Nov. 2018.
[25] N. Medeiros-Ward, J. M. Cooper, and D. L. Strayer, "Hierarchical control and driving," *J. Exp. Psychol., Gen.*, vol. 143, no. 3, pp. 953–958, Jun. 2013.
[26] B. Mehler, B. Reimer, and J. F. Coughlin, "Sensitivity of physiological measures for detecting systematic variations in cognitive demand from a working memory task: An on-road study across three age groups," *Hum. Factors, J. Hum. Factors Ergonom. Soc.*, vol. 54, no. 3, pp. 396–412, Apr. 2012.
[27] M. Green, "'How long does it take to stop?' methodological analysis of driver perception-brake times," *Transp. Hum. Factors*, vol. 2, no. 3, pp. 195–216, Jun. 2000.
[28] K. Wu and Y. Lin, "Exploring the effects of critical driving situations on driver perception time (PT) using SHRP2 naturalistic driving study data," *Accident Anal. Prevention*, vol. 128, pp. 94–102, Jul. 2019.
[29] B. H. Baltagi, *Econometric Analysis of Panel Data*. Hoboken, NJ, USA: Wiley, 2013.
[30] H. Akaike, "A new look at the statistical model identification," *IEEE Trans. Autom. Control*, vol. AC-19, no. 6, pp. 716–723, Mar. 1974.
[31] G. Schwarz, "Estimating the dimension of a model," *Ann. Statist.*, vol. 6, no. 2, pp. 461–464, 1978.
[32] H. Bozdogan, "Model selection and Akaike's information criterion (AIC): The general theory and its analytical extensions," *Psychometrika*, vol. 52, no. 3, pp. 345–370, Sep. 1987.
[33] P. Choudhary and N. R. Velaga, "Modelling driver distraction effects due to mobile phone use on reaction time," *Transp. Res. C, Emerg. Technol.*, vol. 77, pp. 351–365, Apr. 2017.
[34] J. Gao and G. A. Davis, "Using naturalistic driving study data to investigate the impact of driver distraction on driver's brake reaction time in freeway rear-end events in car-following situation," *J. Saf. Res.*, vol. 63, pp. 195–204, Dec. 2017.
[35] J. W. Muttart, D. L. Fisher, M. Knodler, A. Pollatsek, "Driving without a clue: Evaluation of driver simulator performance during hands-free cell phone operation in a work zone," *Transp. Res. Rec.*, vol. 2018, no. 1, pp. 9–14, Jan. 2007.

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