Article:

Engström, J, Markkula, G orcid.org/0000-0003-0244-1582, Xue, Q et al. (1 more author) (2018) Simulating the effect of cognitive load on braking responses in lead vehicle braking scenarios. IET Intelligent Transport Systems, 12 (6). pp. 427-433. ISSN 1751-956X

https://doi.org/10.1049/iet-its.2017.0233

Simulating the effect of cognitive load on braking responses in lead vehicle braking scenarios

Johan Engström[1*], Gustav Markkula[2], Qingwan Xue[2,3], Natasha Merat[2]

[1]Virginia Tech Transportation Institute, 3500 Transportation Research Plaza
Blacksburg, VA, USA
[2]Institute for Transport Studies, University of Leeds, LS2 9JT, Leeds, UK
[3]MOE Key Laboratory for Urban Transportation Complex Systems Theory and Technology, School of Traffic and Transportation, Beijing Jiaotong University, 100044, Beijing, PR China

[*]jengstrom@vtti.vt.edu

Abstract: The recently proposed cognitive control hypothesis suggests that the performance of cognitively loading but non-visual tasks such as cell phone conversation selectively impairs driving tasks that rely on top-down cognitive control while leaving automatized driving tasks unaffected. This idea is strongly supported by the existing experimental literature and we have previously outlined a conceptual model to account for the key underlying mechanisms. The present paper presents a mechanistically explicit account of the cognitive control hypothesis in terms of a computational simulation model. More specifically, it is shown how this model offers a straightforward explanation for why the effect of cognitive load on brake response time reported in experimental lead vehicle braking studies depends strongly on scenario kinematics, more specifically the initial time headway. It is demonstrated that this relatively simple model can be fitted to empirical data obtained from an existing meta-analysis on existing lead vehicle braking studies.

1. Introduction

It is commonly assumed that the performance of non-visual but cognitively loading tasks (such as cell phone conversation) while driving delays responses to critical events. However, as reviewed in [1, 2] this effect appears to depend strongly on the type of response task used in the experiment. More specifically, cognitive load (CL) reliably impairs response performance on non-practiced, artificial, response tasks such as the Detection Response Task (DRT; [3-8]) or speeded and/or instructed responses to a lead vehicle's brake light onset [9-19]. However, CL appears to leave response performance more or less unaffected for more natural tasks, such as reacting to rapidly closing, visually looming (optically expanding) objects. For example, Muttart et al. [20] conducted a lead vehicle braking simulator study with the brake lights of the braking lead vehicle turned off and as long as the braking event was not cued by an upstream event (and the response thus solely driven by looming), no effects of CL were found on braking performance. Similarly, Baumann et al. [21] conducted a driving simulator study investigating the effect of CL on drivers' ability to use a predictive cue (a warning road sign) to guide their responses to an obstacle hidden behind a curve, and found that CL delayed response performance in the cued condition but not when the cue was absent (in which case participants had to respond solely to the looming obstacle). Mantzke and Keinath [22] found that CL increased response times for the DRT, but not to suddenly appearing pedestrians. Similarly. Finally, Engström [1, Paper III] investigated braking and steering reactions to an oncoming vehicle which suddenly turned across the drivers' path, and found no response delays due to CL for the first, truly surprising, scenario. To the knowledge of the present authors, no existing study (using ecologically realistic stimuli) has demonstrated a negative effect of CL on braking responses to unexpected looming.

Engström et al. [2] proposed that these results may be explained by the cognitive control hypothesis stating that: cognitive load selectively impairs driving sub-tasks that rely on cognitive control but leaves automatic performance unaffected. Cognitive control here refers to higher-level "executive" resources needed to deal with novel tasks and/or tasks with inconsistent stimulus-response mappings [23]. An inconsistent mapping means that a specific stimulus is not consistently associated with a specific response, thus making the task unpredictable and inherently difficult, and dependent on cognitive control for successful performance. Tasks that are consistently mapped may initially require cognitive control (such as when learning to ski) but become increasingly automatic and effortless with practice. Therefore, on the assumption that cognitive control is a limited resource, the concurrent performance of a secondary cognitive tasks also relying on cognitive control would be expected to impair driving performance, but only those aspects of driving that rely on cognitive control[1].

This idea is generally supported by the experimental literature on CL in driving. As reviewed above (and in further detail in [2]), CL has reliably been found to delay DRT responses [3-8] as well as responses to the brake light onset of a lead vehicle [9-19]. While the DRT is consistently mapped, it is an artificial task that is novel to most study participants and hence relies on cognitive control to be performed. By contrast, braking in response to brake light onsets is a naturally occurring, and thus well-practiced, task. However, in everyday driving, braking in response to brake lights is inconsistently mapped since drivers do not always have to brake when seeing a brake light onset. In addition, in several of the studies reviewed above, participants were explicitly instructed to brake as soon as the lead vehicle started braking [9], or when they detected the lead vehicle's brake light onset [10, 15, 19]. This clearly constitutes an unnatural task that, due to its novelty, is expected to rely on cognitive control and should thus be negatively affected by CL.

By contrast, braking responses to strong looming cues (representing the optical expansion of the lead vehicle in the driver's retina) can be assumed to be largely automatic, since this involves a strongly consistent stimulus-response contingency. That is, drivers typically have to press the brake pedal when they experience an object looming towards them at a high rate since they will otherwise collide. This argument is further supported by studies showing that looming automatically captures attention in a bottom-up fashion [24] and elicits automatic avoidance responses in human [25] and monkey [26] infants. Moreover, our recent analysis of real rear-end crashes and near-crashes indicated that the timing of drivers' braking responses could be largely explained in terms of visual looming cues (reflecting situation kinematics) while the timing relation between drivers' reactions and lead vehicle brake light onsets was more variable [27].

The same general pattern of results, where CL selectively impairs non-automatized aspects of driving, has also been demonstrated for other aspects of driving performance such as lane keeping [28], speed selection [29, 30] and gap acceptance at intersections [31] (again see [2] for a detailed review).

[1] This line of reasoning may, at first, appear circular: Cognitive control is needed to perform non-automatized tasks while automaticity is conceptualized in terms of task performance without the need for cognitive control. However, the circularity is broken by the independent hypothesis that automaticity develops though repeated exposure to consistent stimulus-response mappings. Thus, the degree of automaticity of a task (and hence dependence on cognitive control) may be predicted (at least in principle) based on task characteristics and amount of exposure.

We have previously [1, 2, 32] proposed a conceptual model of cognitive control and the development of automaticity, intended to provide a mechanistic account of the above pattern of results. The model is based on the Guided Activation Theory (GAT), originating in cognitive neuroscience [33-36]. GAT suggests that automaticity is determined by the strength of neural pathways in the brain, which is gradually established through exposure to consistently mapped tasks. In this model, the key function of cognitive control is to boost activity in weaker pathways (governing non-automatized, non-practiced and/or inconsistently mapped tasks), and potentially override activity in stronger pathways governing more automatized tasks, when needed to achieve current goals. On the assumption that the cognitive control bias can only be (or, alternatively, is preferably-; see [35, 37]) allocated to one task at a time, CL imposed by a secondary (non-driving) task will selectively impair aspects of driving relying on cognitive control (such as the DRT or speeded/instructed responses to brake lights), as suggested by the cognitive control hypothesis.

In a previous paper [38], we developed a simulation model with the purpose to illustrate the mechanism proposed in the conceptual model described above more explicitly. The model addressed a specific phenomenon reported in a meta-analysis of studies investigating the effect of CL in lead vehicle braking scenarios [39]. This analysis was motivated by the observation that existing lead vehicle (LV) studies (as opposed to DRT studies) have reported highly variable average response times (ranging from 550 – 3500 ms) as well as variable response delays attributed to cognitive load (ranging from 50 – 1500 ms). The meta-analysis in [39], further described in the following section, found that this variability could be largely explained by the initial time headway (i.e., the time gap between the vehicles at the moment the lead vehicle starts braking) used in the respective studies. Studies with larger initial time headways found larger effects of cognitive load and vice versa.

The results from our simulation model reported in [38] showed that a driver reaction model based on the principles outlined in [2] (implementing the principles of the cognitive control hypothesis) could be fitted to the empirical data from the meta-analysis in [39] thus offering a mechanistic explanation for this phenomenon. This initial model was intentionally simple and mainly intended as a proof of concept. The present paper extends the previous paper [38] in three principal ways. First, a more detailed description of the empirical data from the meta-analysis in [38] is included (see the next section). Second, while the parameters of the previous model were manually tuned, the present model was fit to the empirical data by means of maximum likelihood estimation. Third, while the initial model was deterministic, the present simulation included noise which enables predictions of response time distributions.

2. Empirical data

As mentioned above, Engstrom [39] conducted a meta-analysis of a set of existing studies investigating the effect of CL on drivers’ response times in lead vehicle braking scenarios. The studies included in the study are described in Table 1.

Table 1. Overview of studies included in the meta-analysis (adopted from [39]). BRT=Brake Response Time; ART=Accelerator Response Time

Study	Type of study	Scenario	Cognitive task	Response metric	Additional experimental conditions
Alm and Nilsson [9]	Simulator	Lead vehicle braked intermittently during car following with deceleration rate 4 m/s^2. Initial distance headway controlled at 75 m. Speed was self-paced.	Working Memory Span Test	BRT	Young/Old drivers
Brookhuis et al. [11]	Field	Lead vehicle braked intermittently during car following (deceleration rate not reported). Speed instructed to 95 kph and distance headway to 40 m (averages not reported).	Forced pace memory test via mobile phone	BRT	-
Lee et al. [13]	Simulator	Lead vehicle braked intermittently during car following with deceleration rate 2.1 m/s^2. Initial time headway controlled at 1.8 s.	Speech control of email system	ART	Simple/complex driving environment
Salvucci and Beltowska [15]	Simulator	Lead vehicle braked at 3, 6, 9 or 12 s during a 20 second driving epoch (the braking initiation point was randomised between trials). Speed and headway was controlled. Speed increased from zero to 120 kph during the 20s interval. Initial distance headway was always 20 m.	Silent rehearsal of lists of digits	BRT	5 or 9 items for rehearsal
Strayer and Drews [17]	Simulator	Lead vehicle braked intermittently during car following. Deceleration rate not reported. Speed and headway self-paced.	Phone conversation on topics chosen from a list by the subject	BRT	Young/old drivers
Strayer et al. [16]	Simulator	Lead vehicle braked intermittently during car following. Deceleration rate not reported. Speed and headway self-paced.	Phone conversation on topics chosen from a list by the subject.	BRT	Low/high traffic density

As described in Table 1, some of the studies included additional experimental conditions in addition to the manipulation of cognitive load. Moreover, [11] did not report RT values for CL and baseline (BL), only the response delay due to CL. This resulted in, a total of 10 conditions where RT under CL was compared to BL RT (see [39] for details). Based on the information available in the respective papers, the initial time headway (i.e., the time headway when the lead vehicle started to brake) was estimated for each study condition. Since the reporting of kinematic conditions was somewhat incomplete in several papers, some assumptions and approximations were necessary (again, see [39] for details). Figure 1 reproduces the plot in [39] of the average brake response time reported in the different study conditions as a function of (estimated) initial time headway for cognitive loaded and non-loaded drivers respectively. Included in the plot are also estimated regression lines for the CL and BL conditions respectively. The resulting regression equations relating initial time headway (THW) to response time (RT) for the CL and BL conditions were:

$$RT_{BL}=445\times THW+286 \quad (1)$$

$$RT_{CL}=882\times THW-112 \quad (2)$$

The R^2 values for the CL and BL model were 0.88 and 0.89 respectively indicating that the main part of the RT variance was explained by THW in both cases.

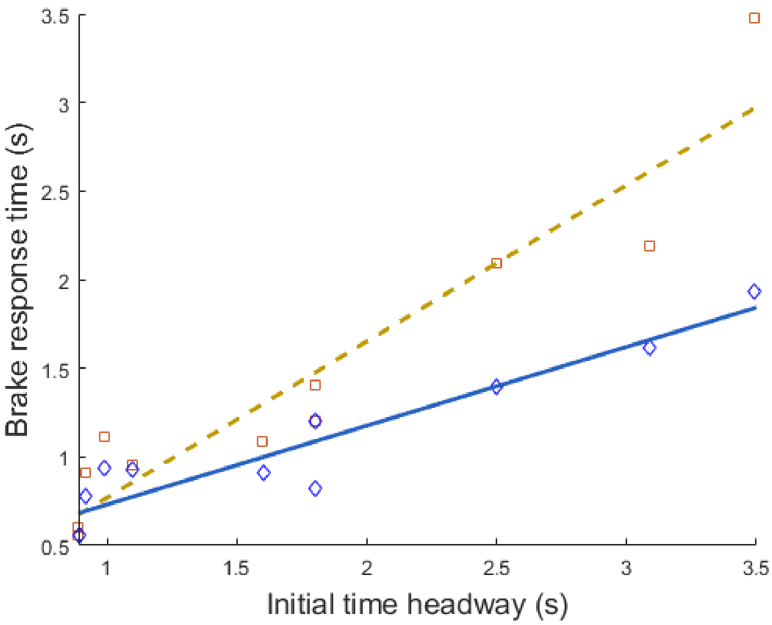

Fig. 1. Average RTs for the different studies and study conditions listed in Table 1 for the cognitive load (CL) and baseline (BL) conditions respectively. Blue diamonds represent baseline and yellow squares represent cognitive load. The blue solid and yellow dashed lines represents the linear regression models for the BL and CL conditions respectively, defined in Eq 1-2. The figure was reproduced based on [39].

Furthermore, the analysis showed that the effect of CL on response time (i.e., the difference in RT between the CL and BL conditions) was not fixed but depended strongly on the initial time headway reported in the respective papers. As can be seen from Figure 1, this is because the dependency of RT on THW is stronger in the CL condition, as indicated by the steeper slope. A regression analysis on the effect (i.e., the response delay) attributed to CL in these studies indicated an R^2 value of 0.79, indicating that 79% of the variance in the response time difference between CL and BL conditions could in fact be attributed to the initial time headway.

3. Modelling

The observed dependency of BRT effects of CL on scenario kinematics found in [39] and reviewed in the previous section dovetails nicely with the cognitive control hypothesis outlined above: In the absence of cognitive load from a secondary task, cognitive control can be allocated to support the non-automatized task of braking as fast as possible in response to the brake light onset. However, cognitively loaded participants, with depleted cognitive control resources, will be impaired in their ability to respond to the brake light and thus have to rely on automatized responses to looming cues, once they appear. The point in time when sufficiently strong looming cues appear in a specific lead vehicle braking scenario depends on the scenario kinematics, in particular the initial headway.

This offers an explaination for why the effect of cognitive load on brake RT increases with increased headway. This section describes the simulation model developed to provide a mechanistic account of this phenomenon.

2.1 Driver reaction model

The present model is based on the evidence accumulation framework developed by Markkula [40, 41] and also incorporated key principles from the GAT model mentioned above [33-36]. Similar computational implementations of the GAT model have previously been developed for laboratory tasks such as the Stroop task [34, 35]. In the model, the driver's braking response to a braking lead vehicle is driven by two sources of sensory evidence: (1) the brake light and (2) visual looming. These two sources of evidence are integrated over time to a response threshold at which the braking action is initiated. Crucially, the sensory evidence is weighted by the strength of the respective neural pathways governing responses to brake lights and visual looming respectively. In line with the GAT model, this weighting represents the degree to which the response is automatized. In the lead vehicle braking case, responses to looming are assumed to be governed by a strong pathway established through repeated exposure to consistent looming-braking mappings. By contrast, responses to the brake light onsets are governed by a weaker pathway, due to the inconsistent mapping between brake lights and braking in everyday driving, as discussed above. Thus the brake light input only yields a weak input to the accumulator unable to trigger a braking response by itself. In order to trigger a braking response in the absence of looming, the brake light onset thus needs to be boosted by cognitive control. This model is conceptually illustrated in Figure 1.

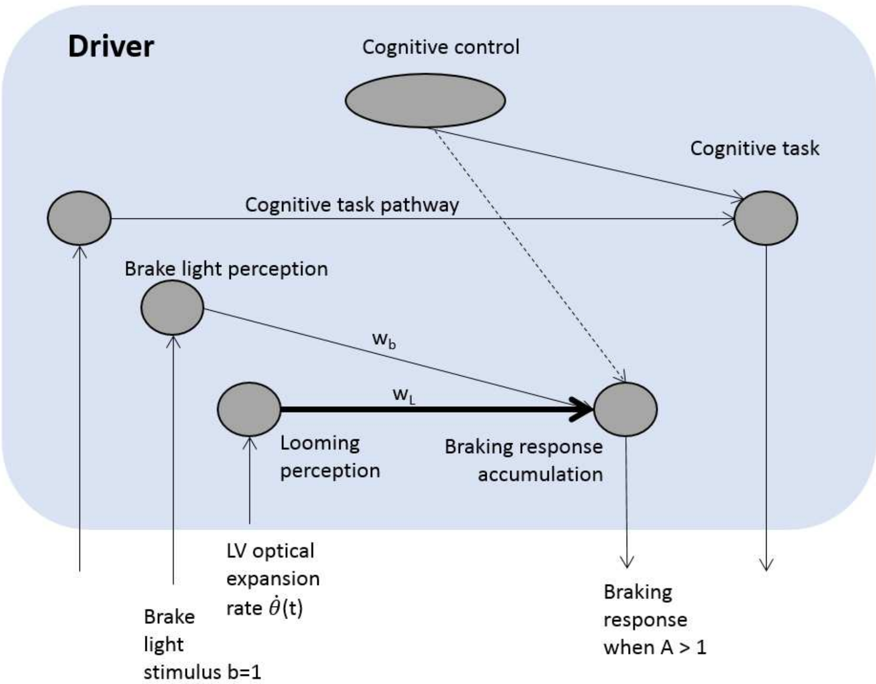

Figure 2 Conceptual illustration of the simulation model (see text for explananation)

Visual looming was here quantified as the rate of change of the angle, θ, subtended by the lead vehicle at the retina (i.e., the optical expansion rate $\dot{\theta}$, or visual looming). The brake light input was represented by a stimulus input b, constantly set to 1 from the moment of lead vehicle brake onset. These two inputs were scaled by two connection weights w_L and w_b respectively (representing the strength of each pathway and, hence, the degree of automation) before being input to the response unit, which was implemented as a simple accumulator of the form[2]

$$\frac{dA(t)}{dt} = w_L L(t) + w_b b + c + \varepsilon(t) \qquad (3)$$

where the accumulator activation was limited to be $A(t) \geq 0$, L(t) represents the looming perception, here given by $\dot{\theta}$(t). The constant c represents top-down bias from cognitive control which is only available in conditions without cognitive load (i.e., when cognitive control is not allocated to a secondary cognitive task). $\varepsilon(t)$ represents Gaussian noise with $\varepsilon(t) \sim N(0, \sigma)$.

The cognitive task is represented in Figure 2 but was only included in the simulation in terms of its effect on cognitive control (i.e., disabling the allocation of cognitive control to the braking task, thus c = 0). A braking response is generated when the value of the activation A(t) exceeds the threshold A_0, set to $A_0 = 1$.

2.2 Lead vehicle braking scenario simulation

The kinematics of the lead vehicle braking scenarios were implemented so that the initial values of subject vehicle (SV) initial speed, the LV initial speed, LV deceleration rate and initial time headway could be controlled. The scenario kinematics were then translated into the optical variables θ and $\dot{\theta}$ by means of the following equations

$$\boldsymbol{\theta = 2 \cdot arctan(\frac{W_{LV}}{2d})} \qquad (4)$$

$$\boldsymbol{\dot{\theta} = -W_{LV} v_{rel} / (d^2 + \frac{W_{LV}{}^2}{4})} \,. \qquad (5)$$

W_{LV} is the width of the lead vehicle, d is the bumper-to-bumper distance between the two vehicles and v_{rel} is the relative velocity. Eq. 4 is obtained from the geometry of the situation, and Eq. 5 by differentiation with respect to time. The initial speeds of the SV and LV were both set to 85 kph and the LV deceleration rate to 4.9 m/s^2 (0.5g). In the empirical studies, the actual initial speed varied somewhat between studies and the lead vehicle deceleration rate was often not reported (see [39] and Table 1). However, since we were mainly interested in the effects of initial time headway, we kept speed and lead vehicle deceleration rate constant in the simulation at 85 kph and 0.5g respectively (this speed represented the mid-range of speeds in the included studies and the 0.5g deceleration value was assumed as a deceleration rate representative of a typical critical lead vehicle braking scenario).

2.3 Parameter fitting

Eq. 3 was used for model fitting with L(t) represented by $\dot{\theta}$(t). Performing a complete fitting of this stochastic model to the meta-analytic data in Figure 1 would be highly non-trivial, even assuming that enough information about response time variabilities could be reconstructed from figures in the original papers. Therefore, the approach taken here is more approximate in nature, and aims not to produce a conclusive and exact fit of Eq. 3 to human data, but rather to show that Eq. 3 can qualitatively reproduce the general patterns observed in [39] and reproduced in

[2] The original model in [38] included some additional parameters but these were here removed to obtain fewer free parameters. With the exception of the noise term, the present model is mathematically equivalent to that in [38]).

Figure 1. Therefore, as a structured approach to get a reasonable estimate of suitable parameters for the model, Eq. 3 was fitted to the average BRTs from the meta-analysis, as follows: Each observed average BRT was classified, based on the THW, into one of six simplified scenarios, differing only in terms of THW, shown in Table 2. For each such scenario, a looming trace $L(t)$ was generated, which was used to stimulate the driver reaction model. Note, again, that this $L(t)$ will not be an exact replication of the looming time histories experienced in the original studies, both because the simplified scenarios do not match the original studies in terms of speeds and deceleration rates, and due to between-participant variability.

Table 2 Scenario parameters in the simulation

Parameter	Values
Initial time headway	{1, 1.5, 2, 2.5, 3, 3.5} s
SV initial speed	85 kph
LV initial speed	85 kph
LV deceleration rate	0.5 g
LV width	1.8 m

Parameter fitting was conducted by searching a uniformly spaced grid for the model parameters listed in Table 3. Note that c_c was always set to zero. The best parameters for both of the two models were generated by maximum likelihood estimation, based on [42]: For each tested model parameter configuration, 200 simulations of the model with noise was run for each of the six simplified scenarios, thus generating a numerical probability distribution of BRT for each scenario. The likelihood of the model parameter configuration was calculated as the product of the probabilities of all of the observed average BRT values according to these probability distributions. Again note that this is an approximate approach, since the observed BRTs are averages rather than individual observations; but it is still deemed sufficient for the present more qualitatively oriented purposes. The resulting maximum-likelihood parameter values are shown in Table 3.

Table 3 Fitted model parameter values

Parameter	Values
w_l	174
w_b	-0.1
c_b (Baseline)	0.41
c_c (CL)	0
σ	0.3

4. Results

Figure 3 shows examples of simulation output for a scenario with an initial THW of 2.5 s (and other kinematic parameters set as defined in Table 2). The top panel shows the looming (angular rate, $\dot{\theta}$) signal produced by this scenario and the two lower panels show the resulting accumulator activation signal for a non-loaded driver and a cognitively loaded driver respectively. The black lines in the activation plots represent accumulation in a deterministic simulation with zero noise, while the grey lines represent some examples from simulations with noise, yielding some variability in RTs. As can be seen, for the non-loaded driver, the accumulator reaches the response threshold relatively early, resulting in brake response times around 1.4-1.8 s. This relatively fast response is possible because the accumulator is largely driven by the brake light signal with the help of top-down cognitive control bias. However, for the cognitively loaded driver, unable to deploy cognitive control, the response is driven mainly by looming, and thus comes significantly later, at around 1.6-2.2s. It follows that, for cognitively loaded drivers, the response time will be strongly dependent on the initial headway since this is a key factor determining the shape of the looming curve (see Eq. 3). For non-loaded drivers, able to respond to the brake light signal, this kinematic dependency should be smaller, but still present since the accumulator is still partly driven by looming.

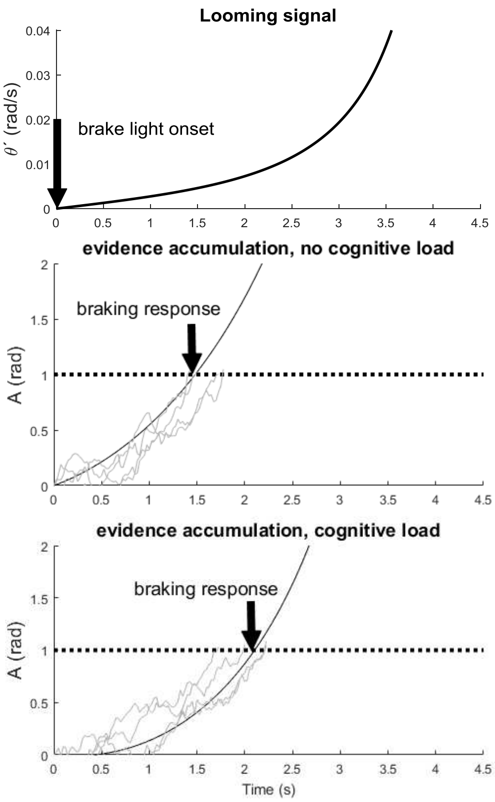

Fig. 3. The upper graph represents the looming signal (angular rate, $\dot{\theta}$) generated by a lead vehicle braking scenario with an initial time headway of 2.5 s, a lead vehicle deceleration of 0.5 g and equal initial speeds of 85 kph. The two bottom graphs show the accumulator activation that integrates to the response threshold (bold dashed line), driven by brake light and looming input, for a non-loaded and cognitively loaded driver respectively. In the two bottom graphs, the black lines represent evidence accumulation with zero noise while the grey lines represent accumulation with noise added.

Figure 4 shows the RTs generated by the simulation for different initial time headways with and without cognitive load. The shaded areas represent the standard deviation of the model's response times. Figure 4 also includes the average values and regression lines from the empirical data [39] plotted in Figure 1.

As can be seen, the simulation model qualitatively replicates the key finding in [39] and Figure 1, where the effect of CL on response time increases with initial time headway, due to a greater dependency on initial time headway (reflected by the steeper slope) for cognitively loaded drivers for which responses are assumed to rely primarily on looming. A further novel prediction yielded by the present stochastic model is that the RT variability should increase with increased initial time headway.

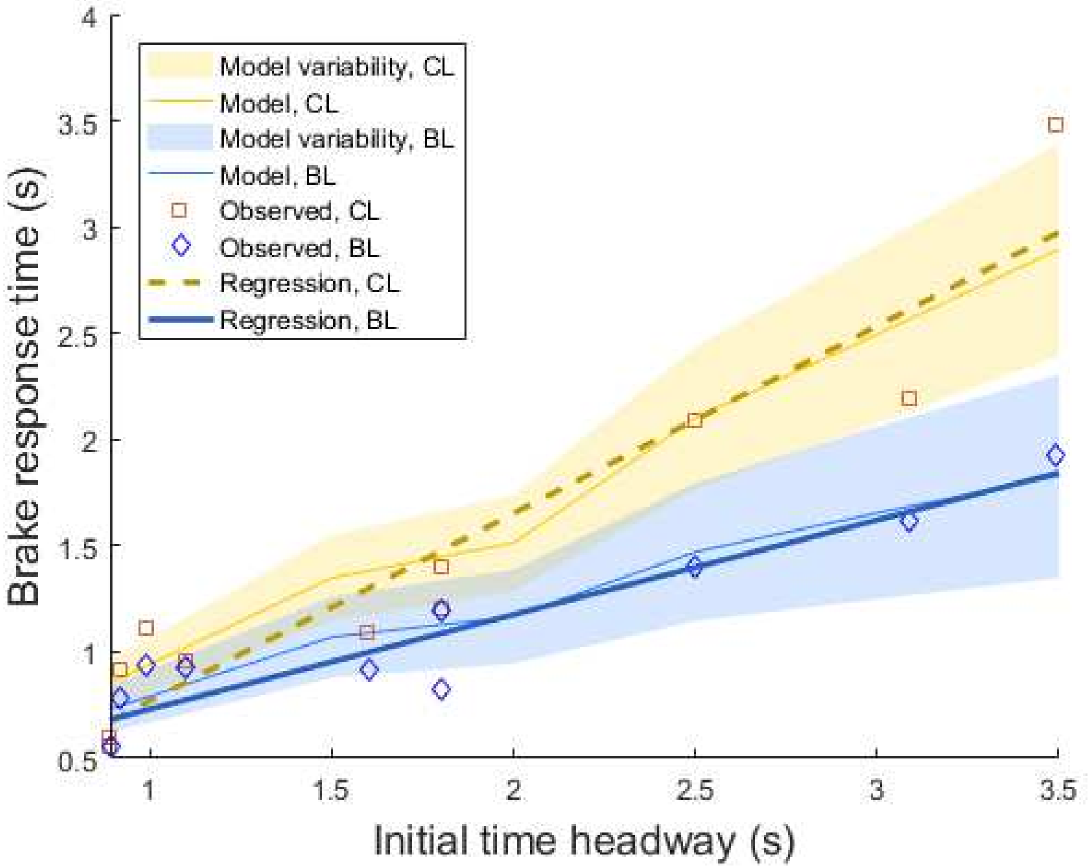

Fig. 4 Simulation results vs. observations obtained from empirical data in Figure 1 and [38]

5. Discussion

The general goal of the present research was to demonstrate how our conceptual model of effects on cognitive load on driving outlined in previous work [1, 2, 32] could be implemented in a mechanistically explicit simulation model. Our initial deterministic, manually tuned, simulation model presented in [38] was here expanded to a stochastic model fitted to the empirical data by means of maximum likelihood estimation. The resulting simulations presented above offer a precise account of why the effect of cognitive load on responses to a braking lead vehicle depends heavily on the initial time headway, as indicated by the meta-analysis in [39]. According to the model, the key mechanism leading to this effect is that cognitively loaded drivers, depleted of cognitive control resources, have to rely on automatic responses to looming, and the time until looming cues appear depends strongly on initial time headway. By contrast, non-loaded drivers are able to deploy cognitive control to boost responses directly to the brake light onset. Hence, their responses will be less dependent on the scenario kinematics (here initial time headway). However, as indicated by the empirical data and replicated by the simulation, the response times of non-loaded drivers are still to some extent dependent on the scenario kinematics, albeit to a lesser degree than for the cognitively loaded drivers. According to the model, this is because the evidence accumulation is still driven partly by the looming cues.

A further prediction from the present stochastic model is that the RT variability should increase with increased initial time headway. The mechanism underlying this effect is that, for longer initial time headways, the looming cues driving the accumulation will grow slower. As a consequence, the accumulation will be slower, thus allowing for more random drift before reaching the response threshold. Unfortunately, the reporting of RT variability in the studies included in the meta-analysis was incomplete, so this prediction could not be tested against the present data (this was also the reason why the model was only fitted to average RT and not RT variability). It would clearly be very interesting to test this prediction in further empirical work.

As also discussed in previous publications [1, 2, 39], the kinematics-dependency of cognitive load effects has important implications for the interpretation of results from existing studies on the effect of CL on braking performance in lead vehicle scenarios. According to the present model, the effect of CL on RT observed in experimental lead vehicle braking studies occurs since drivers in these experiments are tasked to respond as fast as possible to anticipated brake light onsets. Doing so constitutes a novel, non-practised, task relying on cognitive control and hence impaired by cognitive load. As explained by the model presented here, cognitively loaded drivers thus have to rely on automatized responses to looming cues, the timing of which depend on scenario criticality.

However, many (if not most) real-world critical lead vehicle braking scenarios are typically unexpected even to a non-loaded driver. Hence, non-loaded drivers would not be able to pre-allocate cognitive control in anticipation of the response like they could in an experiment with instructions to brake upon the brake light onset after repeated scenarios. The present model implies that, in such unexpected real-world critical events, RTs for non-loaded drivers will be driven more by looming than brake light onsets, and thus depend more strongly on scenario kinematics than responses obtained in an experiment with anticipated events. That is, the blue line in Fig.1 and Fig. 4 (representing non-loaded drivers) would be steeper and thus more parallel to the yellow line (representing cognitively loaded drivers).

The suggestion that drivers' response times in real-world lead vehicle conflicts are mainly determined by scenario kinematics is also strongly supported by the detailed analysis of naturalistic crashes and near crashes in [27]. Thus, the effect of CL on RT would generally be expected to be both smaller and less kinematics-dependent in the real world than in experimental studies (although RTs for non-loaded drivers would be expected to be more kinematics dependent compared to experimental studies).

In fact, the present model further implies that an experimenter can control the effect of CL on RT in a lead vehicle braking scenario a priori simply by adjusting the scenario kinematics (e.g., the initial time headway). The present simulation model (or even the regression model in Eq. 1-2) could be used to predict what the effect of CL on RT would be in a given scenario.

The important general conclusion from what has been said above is that, if the present model is correct, the effects of CL on response times reported in most existing experimental studies cannot be directly generalized to the real world This suggest that a great deal of caution is warranted when interpreting the results from experimental studies on CL (in particular lead vehicle braking studies), and when using these results to guide human machine interaction design or driver distraction policy making [see 1, 2 and 39 for more extensive discussions of this point].

A further specific implication is that RT effects that have been attributed to age may at least partly be caused by the longer headways typically adopted by older drivers. Of the studies included the meta-analysis, both Alm and Nilsson [9] and Strayer and Drews [17] compared younger and older drivers and both studies found that the older drivers adopted longer headways and reacted more slowly to the braking lead vehicle. The present model suggests that the slower reactions may be mediated by the longer headways adopted by the older drivers rather than solely attributed to cognitive factors associated with ageing.

A model closely related to ours have been developed by Ratcliff and Strayer [43], who fitted a single-boundary diffusion model to (among other response variables) driver's braking responses in lead vehicle braking scenarios. The modelling was based on data from two driving simulator studies. The first (Experiment 1) was conducted to support the modelling in [43] while the second data set (Experiment 2) was originally reported by Cooper and Strayer in [44].

A key difference to the present model is that Ratcliff and Strayer's model assumes that the driver reacts to a discrete stimulus that occurs at the lead vehicle brake onset (e.g., the brake light onset). Hence by contrast to the present model, their model does not take into account reactions driven by looming cues and the inherent kinematic dependency of such reactions. Thus, their model predicts kinematic-independent average RTs with some stochastic variation (where the shape of the RT distribution is governed by the model parameters). This general prediction is clearly at odds with both the empirical data presented here [Figure 1, and originally in 39] and the analysis of driver reactions in real naturalistic rear-end crashes and near crashes reported in [27] which both demonstrate a strong kinematic dependency of RTs in lead vehicle braking situations (a dependency which, as shown here, increases with cognitive load).

Interestingly, Ratcliff and Strayer report rather different average RTs for their two data sets, 798 ms vs. 1060 ms for Experiment 1 and 2 respectively (for the BL driving conditions (only Experiment 2 involved a CL condition) but this difference is never discussed in the paper. Based on the present model, a possible explanation for this difference in average RT would be that the scenario kinematics differed between the studies, in particular with respect to the initial time headway. A complete description of the lead vehicle braking scenarios is not provided in Ratcliff and Strayer [43] but the kinematics for Experiment 2 are given in Cooper and Strayer [44], who report a pre-set time headway of 2.00 s. For Experiment 1, it is stated in Ratcliff and Strayer [43] (p. 580) that the following distance when the lead vehicle started braking was "about 100 feet". Combined with the speedometer reading of 60 mph in the vehicle following scenario depicted in their Figure 1 translates to an initial time headway of 1.30 s. Based on the linear regression model in Eq. 1 above [from 39], initial time headway values of 1.30 and 2.0 leads to predicted brake RTs of 864 ms and 1176 ms respectively, which is quite in line with the reported average values of 798 ms vs. 1060 ms in Ratcliff and Strayer's [43] Experiment 1 and 2.

It should be emphasized that the key purpose of the present modelling effort was not to optimize RT predictions for the meta-analytic data. It is not hard to fit more or less advanced statistical models to RT data and even the simple linear regression models estimated in [39; see Eq. 1 and 2] appears to do a rather good job in this respect. Rather, the purpose of the modelling was purely explanatory, with the specific goal to answer the question 'could a model implementing the mechanisms underlying the cognitive control hypothesis be fitted to existing empirical results, thus providing a mechanistic explanation for these results?' As shown above, the answer is clearly yes. Note that, for example, the model proposed by Ratcliff and Strayer [43] and the similar model by Tillmann et al.

[45] would not fit the meta-analysis in [39], since they don't account for the RT kinematics dependency in lead vehicle braking scenarios (although these models can be fitted to each study separately, as long as the kinematics is constant, which is typically what has been done).

More work is clearly needed to explore to what extent the present type of simulation model is also able to predict response times for different combinations of cognitive load levels and scenario kinematics in a single experiment.

Even with the present extensions from the hand-tuned, deterministic, model presented in [38], the present driver reaction model (defined by Eq. 3) is still relatively simple, which is clearly an advantage from an explanatory perspective. There are, however, several ways in which the model can be further extended. For example, in the present model, cognitive control biases the common response unit directly, while in the original GAT simulation models [34, 35] the top-down bias typically boosts the activity of "hidden" units located between the input and response units. Such an architecture better represents the key GAT idea that top-down cognitive control increases activity in competing neural pathways. The present type of simulation model may also be applied to other aspects of driving performance. For example, we have recently developed a similar model that provides an explicit account for effects on cognitive load and drowsiness on lane keeping variability [46].

6. References

[1] Engström, J.: 'Understanding attention selection in driving: From limited capacity to adaptive behaviour'. PhD Thesis, Chalmers University, Sweden, 2011

[2] Engström, J., Markkula, G., Victor, T., Merat, N.: 'Effects of cognitive load on driving performance: The cognitive control hypothesis'. Human Factors. 2017. 59(5), pp. 734-764.

[3] Bruyas, M.P., Dumont, L.: 'Sensitivity of Detection Response Task (DRT) to the driving demand and task difficulty'. In Proceedings of the Seventh International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design, Lake George, NY, 2013, pp. 64–70.

[4] Harbluk, J. L., Burns, P. C., Hernandez, S., et al.: Detection response tasks: Using remote, headmounted and Tactile signals to assess cognitive demand while driving. In Proceedings of the Seventh International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design, Lake George, NY, 2013, pp. 78–84.

[5] Engström, J., Larsson, P., Larsson, C.: 'Comparison of static and driving simulator venues for the tactile detection response task'. In Proceedings of the Seventh International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design, Lake George, NY, 2013.

[6] ISO: 'Road Vehicles -Transport information and control systems -Detection Response Task (DRT) for assessing attentional effects of cognitive load in driving. International Standard, ISO 17488', 2015.

[7] Merat, N., Jamson, A. H.: 'The effect of stimulus modality on signal detection: Implications for assessing the safety of in-vehicle technology'. Human Factors, 2008, 50, (1), pp. 145–158.

[8] Patten, C., Kircher, A., Östlund, J., Nilsson, L. 'Using mobile telephones: cognitive workload and attention resource allocation'. Accident Analysis and Prevention, 2003, 36, (3), pp. 341-350.

[9] Alm, H., and Nilsson, L.: 'The effects of a mobile telephone task on driver behaviour in a car following situation'. Accident Analysis and Prevention, 1995, 27, pp. 707–715.

[10] Bergen, B., Medeiros-Ward, N., Wheeler, K. et al.: 'The crosstalk hypothesis: Language interferes with driving because of modality-specific mental simulation'. Journal of Experimental psychology: General, 2014, 142, pp. 119-130.

[11] Brookhuis, K. A., de Vries, G., Waard, D.: 'The effects of mobile telephoning on driving performance', Accident Analysis and Prevention, 1991, 23, (4), pp. 309-316.

[12] Engström, J., Ljung Aust, M., Viström, M.: 'Effects of working memory load and repeated scenario exposure on emergency braking performance', Human Factors, 2010, 52, (5), pp. 551-559.

[13] Lee, J. D., Caven, B., Haake, S., Brown, T. L.: 'Speech-based interaction with in-vehicle computers: The effect of speech-based e-mail on drivers' attention to the roadway', Human Factors, 2001, 43, pp. 631–640.

[14] Levy, J., Pashler, H., Boer, E.: ‘Central interference in driving - Is there any stopping the psychological refractory period?’, Psychological Science, 2006, 17, (3), pp. 228-235.
[15] Salvucci, D. D. and Beltowska, J.: ‘Effects of memory rehearsal on driver performance: Experiment and theoretical account’, Human Factors, 2008, 50, pp. 834-844.
[16] Strayer, D. L., Drews, F. A., Johnston, W. A.: ‘Cell phone induced failures of visual attention during simulated driving’, Journal of Experimental Psychology: Applied, 2003, 9, pp. 23–52.
[17] Strayer, D. L., Drews, F. A.: ‘Profiles in driver distraction: Effects of cell phone conversations on younger and older drivers’. Human Factors, 2004, 46, pp. 640–649.
[18] Strayer, D. L., Drews, F. A., Crouch, D. J.: ‘A comparison of the cell phone driver and the drunk driver’, Human Factors, 2006, 48, (2), pp. 381–391.
[19] Sonnleitner, A., Treder, M. S., Simon, M. et al.: ‘EEG alpha spindles and prolonged brake reaction times during auditory distraction in an on-road driving study’, Accident; analysis and prevention, 2014, 62, pp. 110–118.
[20] Muttart, J. W., Fisher, D. L., Knodler, M., Pollatsek, A.: ‘Driving without a clue: Evaluation of driver simulator performance during hands-free cell phone operation in a work zone’. Transportation Research Record: Journal of the Transportation Research Board, 2007, 2018, pp. 9–14.
[21] Baumann, M. R. K., Petzoldt, T., Hogema, J., Krems, J. F.: ‘The effect of cognitive tasks on predicting events in traffic’, In C. Brusque (Ed.) Proceedings of the European Conference on Human Centred Design for Intelligent Transport Systems, Lyon, France, 2008, pp. 3–11.
[22] Mantzke, O., Keinath, A.: ‘Relating the detection response task to critical events-consequences of high cognitive workload to brake reaction times’. Procedia Manufacturing, 2015, 3, pp. 2381–2386.
[23] Shiffrin, R. M., Schneider, W: Controlled and automatic human information processing: II. Perceptual learning, automatic attending, and a general theory. Psychological Review, 1977, 84, 127–190.
[24] Franconeri, S. L., Simons, D. J. ‘Moving and looming stimuli capture attention’. Perception and Psychophysics, 2003, 65, (7), pp. 999–1010.
[25] Náñez, J.: ‘Perception of impending collision in 3-to 6-week-old human infants’. Infant Behavior and Development, 1988, 11, (4), pp. 447–463.
[26] Schiff, W., Caviness, J. A., Gibson, J. J.: ‘Persistent fear responses in rhesus monkeys to the optical stimulus of “ looming”. Science, 1962, 136, (3520), pp 982–983.
[27] Markkula, G., Engström, J., Lodin, J., et al.: ’A farewell to brake reaction times? Kinematics-dependent brake response in naturalistic rear-end emergencies’, Accident Analysis & Prevention, 2016, 95, pp. 209–226.
[28] Medeiros-Ward, N., Cooper, J. M., Strayer, D. L.: ‘Hierarchical control and driving’, Journal of Experimental Psychology: General, 2014, 143, (3), pp. 953-958.
[29] Lewis-Evans, B., de Waard, D., Brookhuis, K .A.: ‘Speed maintenance under cognitive load – Implications for theories of driver behaviour’. Accident Analysis and Prevention, 2011, 43, pp. 1497–1507
[30] Recarte, M. A., Nuñes, L. M.: ‘Mental load and loss of control over speed in real driving. Towards a theory of attentional speed control’. Transportation Research, 2002, 5, pp. 111–122.
[31] Cooper, P. J., Zheng, Y., Richard, C. et al.: ‘The impact of hands-free message reception/response on driving task performance’. Accident Analysis and Prevention, 2003, 35,pp. 23–35.
[32] Engström, J., Victor, T., Markkula.: ‘Attention selection and multitasking in everyday driving: A conceptual model’. In M.A Regan, T.W. Victor and J.D. Lee (Eds.) Driver Distraction and Inattention: Advances in Research and Countermeasures. Ashgate, 2013.
[33] Botvinick, M. M., Cohen, J. D.: ‘The Computational and neural basis of cognitive control: Charted territory and new frontiers’, Cognitive Science, 2014, 38, pp. 1249–1285.
[34] Cohen, J.D., Dunbar, K., McClelland, J.L.: ‘On the control of automatic processes: A parallel distributed processing account of the Stroop effect’, Psychological Review, 1990, 97, pp. 332-361.
[35] Feng, S. F., Schwemmer, M., Gershman, S. J., Cohen, J. D.: ‘Multitasking vs. multiplexing: Toward a normative account of limitations in the simultaneous execution of control-demanding behaviors’, Cognitive, Affective and Behavioral Neuroscience, 2014, 14, pp. 129–146.
[36] Miller, E. K., Cohen, J. D.: ‘An integrative theory of prefrontal cortex function’. Annual Reviews of Neuroscience, 2001, 24, pp. 167-202.
[37] Schumacher, E. H., Seymour, T. L., Glass, J. M. et al.: ‘Virtually perfect time sharing in dual-task performance: Uncorking the central cognitive bottleneck’, Psychological Science, 2001, 12, pp. 101-108.
[38] Engström, J., Markkula, G., & Merat, N. ‘Modeling the effect of cognitive load on driver reactions to a braking lead vehicle: A computational account of the cognitive control hypothesis’. Paper presented at the 5th International Conference of Driver Distraction and Inattention, Paris, France, 2017.
[39] Engström, J.: ‘Scenario criticality determines the effects of working memory load on brake response time’, In J. Krems, T. Petzoldt, & M. Henning (Eds.), Proceedings of the European Conference on Human

Centred Design for Intelligent Transport Systems, Lyon, France, 2010, pp. 25–36.
[40] Markkula, G. ‘Modeling driver control behavior in both routine and near-accident driving’, In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 2014, 58, (1), pp. 879-883.
[41] Markkula, G., Boer, E., Romano, R., Merat, N. Sustained sensorimotor control as intermittent decisions about prediction errors: Computational model and application to ground vehicle steering. Submitted manuscript.
[42] Ratcliff, R., Tuerlinckx, F. ‘Estimating parameters of the diffusion model: Approaches to dealing with contaminant reaction times and parameter variability’. 2002. Psychon Bull Rev, 9(3): 438–481.
[43] Ratcliff, R., Strayer, D. L. ‘Modeling simple driving tasks with a one-boundary diffusion model. Psychonomic Bulletin & Review’, 2014, 21(3), 577–589.
[44] Cooper, J.M., Strayer, D. L. ‘Effects of simulator practiced and real-world experience on cell-phone related driver distraction’. 2008, Human Factors, 50, 893–902.
[45] Tillman, G., Strayer, D. L., Eidels, A., & Heathcote, A. ‘Modeling Cognitive Load Effects of Conversation Between a Passenger and Driver. 2017. Attention, Perception, & Psychophysics. Open Science Framework.
[46] Markkula, Engström. ‘Simulating effects of arousal on lane keeping: Are drowsiness and cognitive load opposite ends of a single spectrum? Paper presented at the10th International Conference on Managing Fatigue, San Diego, CA., 2017.