Modelling the effect of cognitive load on driver reactions to a braking lead vehicle: A computational account of the cognitive control hypothesis

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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 intended to account for the key underlying mechanisms. The present paper offers a more explicit account of these mechanisms in terms of a computational simulation model. More specifically, it is shown how this model offers a straightforward mechanistic explanation for why the effect of cognitive load on brake response time reported in experimental lead vehicle braking studies appears to depend strongly on scenario kinematics, in terms of the initial time headway. Moreover, it is shown that this relatively simple model can be fitted to empirical data obtained from a meta-analysis of 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 affects responses to non-practiced, artificial, response tasks such as the Detection Response Task (DRT; [3-8] or speeded and/or instructed responses to the 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 the ability to use a predictive cue (a warning road sign) to guide drivers' 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, and Engström et al. [1] 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] propose 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 less predictable and inherently more difficult. By contrast, tasks that are consistently mapped may initially require cognitive control (such as when learning to ski) but becomes increasingly automatic and effortless with extensive 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.

This idea is generally supported by the experimental literature on cognitive load in driving. As reviewed above, CL has reliably been found to impair DRT response times as well as responses to the brake light onset of a lead vehicle. 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 this task is clearly 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 thus be negatively affected by CL.

By contrast, brake response to strong looming (the optical expansion of the lead vehicle), which typically occurs with some delay after the brake light onset, can be considered to be largely automatic, since this 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 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, as well as recent analyses of driver response in real crashes near-crashes [27].

The same general pattern of results 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].

We have prevously [1, 2, 32] proposed a conceptual model of cognitive control and the development of automaticity, intended to provide a mechanistic account of the above 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 task 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.

While our previous accounts [1, 2, 32] outlined this model on a conceptual level, the general aim of the present paper is to illustrate the proposed mechanism more explicitly in terms of a computational simulation model (similar computational implementations of the GAT model have previously been developed for laboratory tasks such as the Stroop task [34, 35].

More specifically, the present simulation addresses a phenomenon reported in a meta-analysis of studies investigating the effect of CL in lead vehicle braking scenarios [38]. This analysis was motivated by the observation that existing lead vehicle (LV) studies (as opposed to DRT studies) have reported strongly variable response delays attributed to cognitive load, ranging from 50 - 1500 ms. The analysis in [38] 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. A regression analysis on the response delays attributed to CL in these studies against the respective initial time headways indicated an R^2 value of 0.79, indicating that 79% of the variance in the response time difference between cognitively loaded and non-loaded drivers could in fact be attributed to the initial time headway.

This phenomenon 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 the non-automatized task of braking as fast as possible in response to the brake light onset. However, cognitively loaded participants 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 timing of sufficiently strong looming cues depends on the scenario kinematics, particularly the initial headway, which thus explains why the effect of cognitive load on brake RT increases with increased headway.

The specific objective of the present paper is to demonstrate how this proposed mechanism can be made explicit in terms of a neurobiologically plausible computational model. We also investigated the extent by which a relatively simple model (with only a few free parameters) could be fit to the data from the meta analysis in [38].

2. Method

2.1 Driver reaction model

The present model was based on the evidence accumulation framework developed by Markkula [39] and also incorporated key principles from the GAT model [33-36]. In the model, the driver's braking response in a lead vehicle braking scenario 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, representing the degree to which the response is automatized. In this case, looming responses are 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), thus yielding 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. The model is conceptually illustrated in Figure 1.

Looming was here represented as the rate of change of the angle θ, subtended by the lead vehicle at the retina (the optical expansion rate, θ'). An alternative looming signal is $\tau^{-1} = \theta' / \theta$ which, under certain conditions, represents the inverse time to collision [40] (the behaviour of these two looming variables are rather similar and the extent to which they yield different model predictions will be explored in further modelling work). The brake light input was represented by an input s, 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) before being input to the response unit, which was implemented as a simple accumulator of the form

(1)

$$\frac{dA(t)}{dt} = k(w_l l(t) + w_b b + c - g), \tag{1}$$

where the accumulator activation was limited to be $A(t) \geq 0$, l(t) represents the looming perception, here simply given by θ'(t) and b represents the brake light perception (here identical to the constant stimulus s) 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). The cognitive task is represented in Figure 1 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 $A_0 = 1$. The two weights w_l and w_b scale looming input and brake light input respectively, representing the key assumption that automatized tasks (braking in response to looming) are governed by strong pathways while non-automatized tasks (here braking in response to the brake light) are associated with weak pathways. g is a gating parameter which prevents small inputs from accumulating to threshold. In the present model, it was set such that looming, but not the brake light alone, could trigger a braking response. Thus, cognitive control bias c is needed to generate a braking response to the brake light in the absence of looming (mathematically, $w_b b + c - g > 0$, but $w_b b - g < 0$). Finally, k is a scaling factor that determines the rate of accumulation. Elsewhere [41], we have suggested that k may be thought of as representing effects of arousal on neural evidence accumulation rate, as previously suggested by [42, 43]. However, in the present model, k was simply set to 1 to reduce the number of free parameters. Since we were only interested in qualitative effects, noise was not included in the simulation.

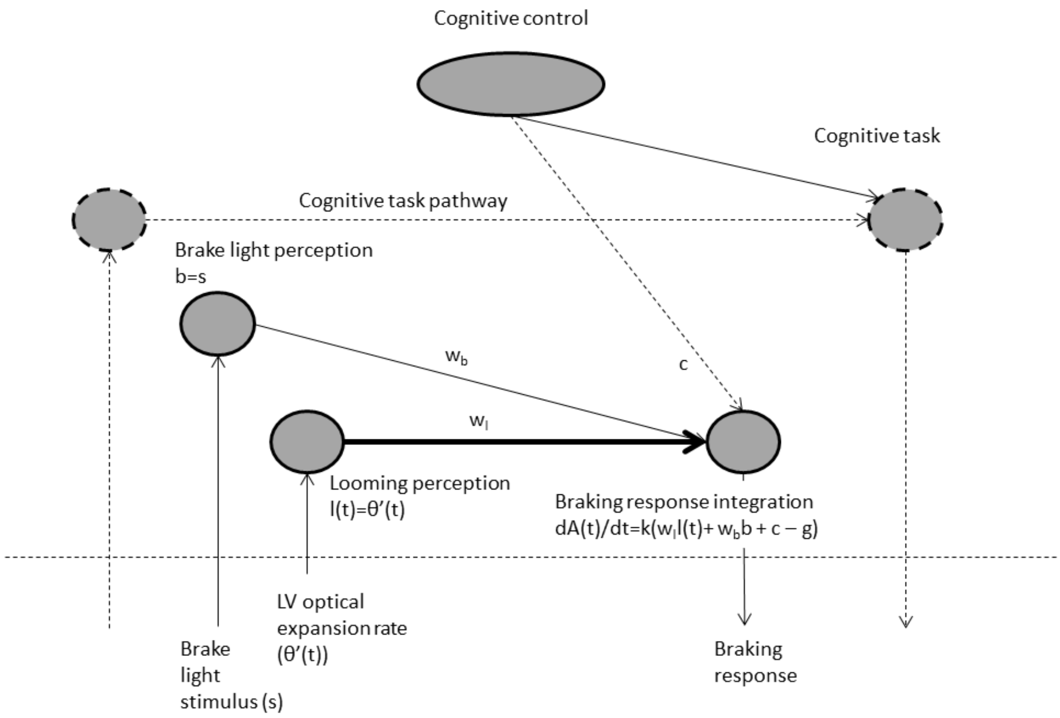

Fig. 1. Conceptual illustration of the simulation model

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 θ' by means of the following equations

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

$$\boldsymbol{\theta}' = -\boldsymbol{W_{LV}}\boldsymbol{v_{rel}}/(\boldsymbol{d}^2 + \frac{\boldsymbol{W_{LV}}^2}{\mathbf{4}}) \,. \tag{3}$$

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. 2 is obtained from the geometry of the situation, and Eq. 2 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 0.5g (roughly representing the typical estimated values in the studies included in [38]).

2.3 Parameter fitting

The present simulations varied two factors: the initial time headway (1, 1.5, 2, 2.5 and 3 s) and cognitive load (on or off), with the aim to investigate if the model could account quantitatively for the findings of [38], where, as described above, the effect of CL on brake response time depended heavily on initial time headway. The parameters w_l, w_b, c and g were manually tuned, given the constraints described above, to fit the response time versus. initial time headway regression lines reported in [38], for non-loaded and cognitively loaded drivers respectively. (Mathematically, some of the parameters in Eq. 1 are of course redundant; for example, the constants c and g could be combined into a single variable. However, the link between the mathematical and the conceptual representation in Figure 1 would then be lost).

It should be emphasized that since the kinematics (initial speed, LV deceleration etc.) differed between the different studies included in the meta-analysis [38], it was not meaningful to optimize the model parameters to fit these data; the sole purpose here was to demonstrate that the general effect of CL and initial THW on brake response time could be quantitatively replicated. The parameter settings used in the simulation are given in Table 1.

Table 1 Parameter values

Parameter	**Value**
initial time headway	{1, 1.5, 2, 2.5, 3}
SV initial speed	85 kph
LV initial speed	85 kph
LV deceleration rate	0.5g
LV width	1.8 m
w_l	188
w_b	0.38
c	{0.53 (baseline), 0 (CL)}
g	0.53
b	1
A_0	1
k	1

3. Results

Figure 2 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 1). The top panel shows the looming (angular rate, θ') signal produced by this scenario and the two lower panels show the corresponding accumulator activation signal for a non-loaded driver and a cognitively loaded driver respectively. As can be seen, for the non-loaded driver, the accumulator reaches the response threshold relatively early, resulting in a brake response time of about 1.4 s. This is because the accumulator is mainly 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 2.1 s. Thus, 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, this dependency should be smaller, but still present since the accumulator is still partly driven by looming.

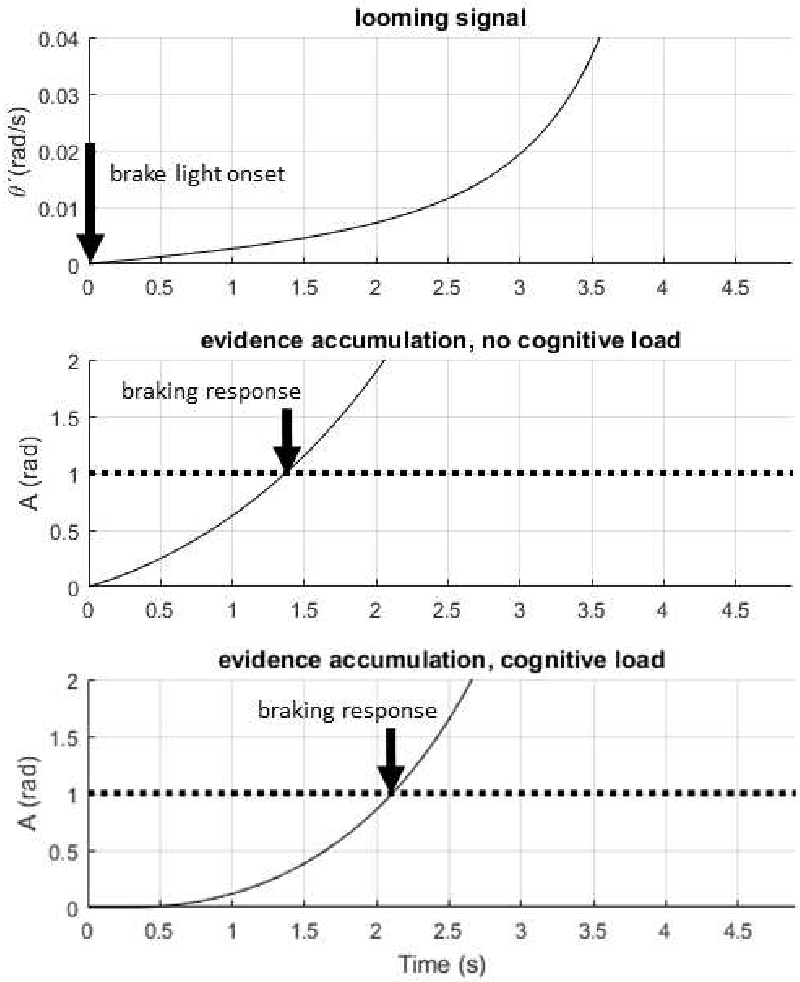

Fig. 2. *The upper graphs represent the looming signal (angular rate, θ') generated by a lead vehicle braking scenario with an* initial time headway of 2.5 s, a lead vehicle deceleration of 0.5 g and equal initial speeds of 85 kph. The two bottom graphs shows the accumulator activation that integrates to the response threshold (bold dashed line), driven by brake light and looming input, for a non-loaded and cognitively loaded driver respectively.

Figure 3 shows the result of varying the initial time headway at {1, 1.5, 2, 2.5, 3} seconds for a cognitively loaded and a non-loaded driver. Plotted in the figure are also the linear regression lines obtained from the meta-analysis in [38]. As can be seen, the simulation model qualitatively replicates the key finding in [38] 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 rely primarily on looming.

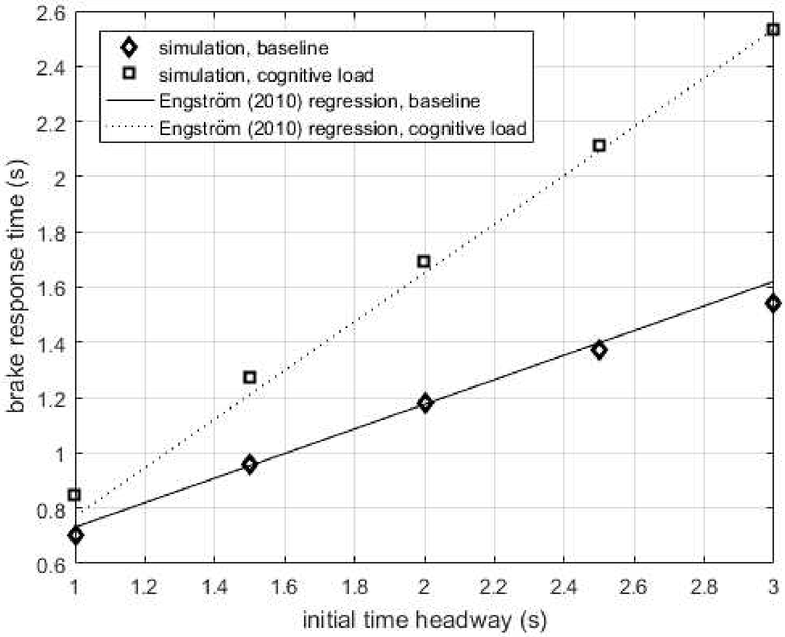

Fig. 3. Simulation results compared to the regression lines obtained from empirical data in [38] on brake response time as a function of initial time headway for cognitive loaded and non-loaded (baseline) drivers

4. Discussion

The general goal of the present paper 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 more mechanistically explicit simulation model. The resulting simulations presented above offer a precise account of why the effect of cognitive load on responses to a braking lead vehicle should depend heavily on the initial time headway, as indicated by the meta-analysis in [38]. According to the model, the key mechanism leading to this effect is the kinematics dependence of brake reaction times in lead vehicle braking scenarios where drivers primarily respond to looming cues and not the brake light onset. In the present case, this occurs since the ability to respond to brake lights is impaired by cognitive load. However, a strong kinematics dependency of braking responses has also been demonstrated in real rear-end crashes and near crashes [27]. Thus, in a LV braking scenario with long initial time headway and/or low lead vehicle deceleration rate, it will take longer for looming cues to accumulate to threshold, resulting in longer RTs and vice versa. The present model suggests that braking as fast as possible in response to expected brake light onsets is an experimental study is an artificial, novel task relying on cognitive control and thus impaired by cognitive load. Hence, the response times of cognitively loaded drivers will depend strongly on the kinematics (in this case initial time headway) while the responses of non-loaded drivers, ready to respond to the brake light, will be much less kinematics-dependent. This has the consequence that not only the response times for loaded drivers but also the effect of CL on response time will depend strongly on initial time headway (as well as other kinematic parameters such as the LV deceleration rate).

As discussed in previous publications [1, 2, 38], this has important implications for how to interpret results from existing experimental studies of effects of cognitive load. In particular, the experimenter can in principle control the effect of CL by the scenario design (and the present model could be used to roughly predict in advance what the effect would be). The key implication of this is the effects of CL on response times reported in existing experimental studies cannot be meaningfully generalized to real world scenarios [see 1, 2 and 38 for more extensive discussions of this point].

It should be emphasized that the purpose of this study was just to illustrate how the present simulation model could be fitted to the aggregated RT data from our previous meta-analysis, thus demonstrating a concrete mechanism able to reproduce the observed data at that general level. However, more work is clearly needed to explore to what extent the present type of simulation model is also able to predict response times for combinations of cognitive load levels and kinematics in a single experiment.

To facilitate understanding of the proposed mechanism, the present model was intentionally relatively simple. There are several ways in which the model can be extended to increase realism. 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 a so-called hidden units located between the input and response units. This, hence, better represents of the idea that top-down cognitive control increases activity in competing neural pathways. Moreover, adding noise to the evidence accumulation process could enable predictions about the distribution of response times in different scenarios.

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 [41].

5. References

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