What do we mean by cognitive load? Towards more accurate definition of the term for better identification by driver monitoring systems

Accurate definitions and identification of cognitive load

Courtney M. Goodridge*

Institute for Transport Studies, University of Leeds, 36-40 University Rd, Leeds LS2 9JT, UK, C.M.Goodridge@leeds.ac.uk

Rafael Gonçalves

Institute for Transport Studies, University of Leeds, 36-40 University Rd, Leeds LS2 9JT, UK, R.Goncalves@leeds.ac.uk

İbrahim Öztürk

Institute for Transport Studies, University of Leeds, 36-40 University Rd, Leeds LS2 9JT, UK, I.Ozturk@leeds.ac.uk

The 2023 European New Car Assessment Programme (Euro NCAP) [9] protocol states that Original Equipment Manufacturers (OEMs) should include Driver Monitoring Systems (DMS) and appropriate technical assessment dossiers for evaluation by driving authorities. This includes demonstrating how the system can identify elements of driver state; driver distractions, fatigue, and unresponsiveness. Whilst visual distractions have been detailed extensively, cognitive distraction has received less attention within these protocols. Part of the reason for this could be the lack of understanding or general consensus on cognitive distraction within the context of driver state. For example, how do we assess driver state, how do we develop ground truths, how much distraction should be considered too much, and what is and is not considered cognitive? To answer these questions, workshop participants will focus on the methods and metrics used to assess cognitive load and the impact this has on driver state and performance; whether during manual driving, monitoring an automated vehicle, or during takeovers after periods of automation.

Keywords: Driver state monitoring; Driver distraction; Cognitive load; Performance estimation

1 INTRODUCTION

1.1 Experimental manipulation of cognitive load

Euro NCAP defines distraction as anything that takes the driver's focus away from the primary task of driving/controlling the vehicle [9]. Within the literature, a common distinction is made between 3 components of distraction. Visual and manual components refer to modality-specific interference during perceptual and motor processes [37] respectively, (e.g., the competing visual demand for monitoring the road and reading text on an interface; or the simultaneous need for the hands to be on the steering wheel and peeling a banana) [8]. Cognitive distraction, however, typically refers to the general withdrawal of attention away from the driving task [8]. This can include tasks that take drivers' "mind off the road" [36] alongside tasks that load the working memory resources of drivers [23]. Whilst most naturalistic tasks may involve a combination of all 3 components, there are many tasks used in the laboratory that attempt to load the 3 components independently.

In driver behaviour studies, the terms cognitive load and cognitive distraction are often used interchangeably. The former is defined as the demands imposed on the driver by non-visual tasks [8], with the latter referring to a more general diversion of attention away from the driving task [30]. Researchers have used a range of tasks to load or distract participants during both manual and automated driving experiments. These include "artificial" or surrogate tasks, with easy to quantify performance, that are considered to impose the same demand on drivers as hands-free mobile phone conversations. Examples include the N-back task [24], the Sustained Attention Response Task (SART) [14], the Paced Auditory Serial Addition Task [5], and the Twenty-Questions Task [26, 32], with some studies also considering the effect of more naturalistic hands-free phone conversations [29, 35]. A consistent finding when drivers are cognitively loaded is increased gaze concentration toward the road centre [13, 22, 29, 31]. With regard to lateral control, cognitive load has been found to increase steering activity during manual driving [1, 7, 15, 19].

The assessment of cognitive load is particularly relevant for the ever-growing field of Human Factors for vehicle automation. When drivers are driving in an L2+ automated system, it is expected for them to be out of the loop [25]; thus, drivers are more likely to engage on non-driving related tasks (NDRTs) [3]. As such, workload will likely increase thus compromising their ability to takeover. For takeovers after periods of automation, cognitive load has had mixed results. Whilst

* Correspondence concerning this paper should be addressed to Dr Courtney M. Goodridge, Institute for Transport Studies, University of Leeds, 36-40 University Rd, Leeds LS2 9JT, UK, C.M.Goodridge@leeds.ac.uk

some studies highlight slower takeovers times [12, 28], others have found that cognitive load results in faster takeover times due to higher perceived difficulty of the overall task [4]. Whilst simulator study results generally conclude that cognitive load has negative effects on overall driving performance, these are somewhat in contrast to those found in the real world, with some even suggesting that engagement in a handsfree conversation can improve driver safety [2, 38].

This first section of the workshop aims to foster discussion on this topic area from expert researchers in the field in more detail. We want to outline rationales for the use of particular tasks for imposing cognitive load, and the results of their studies in this context. We then aim to focus on the methodological considerations regarding how cognitive load is manipulated experimentally. What are the effects of these tasks on driving performance metrics and physiological measures, and can we identify common indicators relevant to the identification of cognitive distraction in the future. Furthermore, we will discuss which facets of cognition the aforementioned tasks aim to load; how ecologically valid are these tasks with respect to naturalistic non-driving related tasks; what implications does this have on how we assess cognitively loaded drivers using DMS in the real world.

1.2 Assessment of cognitive load

A range of metrics have been used to assess the effect of cognitive load on driving performance and driver physiological metrics [8, 27]. Engström et al. [8] proposed four methods which can be used to identify the effect of cognitively loading tasks on driving performance. These include object/event detection, such as response to the Detection Response Task, lateral vehicle control such as standard deviation of lane position, longitudinal vehicle control such as speed and headway, and decision making such as lane selection and gap acceptance. Ultimately, this review concluded that there are selective and task-dependent effects of cognitive load on driving.

Eye tracking metrics such as fixation duration, dispersion of gaze, and dwell time can also provide information about the cognitive state of the driver (e.g., [21]). Cognitive load can also be assessed using physiological measures (e.g., [11, 34]) such as heart rate, skin conductance, and brain activity. Self-report techniques, such as the NASA Task Load Index, have been used to measure an individual's own assessment of the cognitive load imposed by a task (e.g., [33]). Researchers have also used performance-based measures, such as reaction time to a leading vehicle, to measure the effect of cognitive load, while the Detection-Response Task [17] is one standardized method used to assess the effects of cognitive load on attention.

Currently, there is a lack of consensus among researchers in terms of the tasks used to impose cognitive load and how the effect of these tasks on driver state may differ from that imposed, for example, by driver fatigue. In the section detailed above, we will focus on cognitive load assessment, metrics, and methodological issues.

1.3 Assessment and ground truths of driver state

Cognitive load is one facet under the general topic of driver state that driving research is aiming to better understand. There have been many attempts in the literature to predict the outcome of a drivers' response to a critical situation, based on models that infer the state of the driver. For instance, in the field of automation, Zeeb et al. [39] were able to predict the likelihood of crashes during transitions of control from vehicle automation based on drivers' gaze. Similar work was also done by Louw and Merat [22], which found differences on the probability of crashes of the drivers, based on manipulations of drivers' levels of situation awareness, by projecting a fog, partially or totally occluding their field of view. Latter studies from [6] were able to use cameras and machine learning models to estimate the readiness state of the driver based on visual indicators. With that, the authors were able to draw conclusions about the safety implications of drivers' posture, fatigue, and gaze strategies, in a case of an emergency transition of control. However, the metrics for takeover prediction are not standardized, or consistent across the literature [16].

As for manual driving literature, studies from [19] were able to find detrimental effects of cognitive distraction on drivers' capabilities to maintain lateral control of the vehicle in the lane. When considering eye movements and visual distractions, [18] created a model that dynamically accounts for drivers' off-road glances, to estimate their visual distraction, based on the limitations on humans' short-term memory. In further research, similar techniques were used in prediction models to estimate the probability for drivers to respond to a near-crash scenario [20]. Also, Gomaa et al. [10] presented a framework using machine learning techniques to estimate drivers' workload, and their respective impairments on drivers' capabilities. However, most of the models proposed in the literature are not consistent or directly applicable due to a lack of ground truth for their assessment.

The main issue for the lack of consistency for driver state estimation models is that driver state is an internal representation of an amalgamation of physical and cognitive metrics that are causally correlated with driver's condition. For this reason, driver state cannot be systematically controlled, losing its experimental validity. With that in mind, this section of the workshop will discuss the state of the art in driver state estimation, and how we can use objective measurements to estimate safety outcomes of a transition of control.

2. WORKSHOP GOALS AND EXPECTED OUTCOMES

In this workshop, we will address theoretical and methodological issues related to the future of driver state monitoring systems and the research that informs them. The organisers of the workshop intend to disseminate the results of this workshop to a wider audience. Expert guests have been invited to collaborate, and we are waiting for responses. No previous experience and preparation are required to attend the workshop. All interested participants from academia, industry, or the public are welcome. The workshop will be interactive, and participants will be encouraged to contribute to the discussion. During the workshop we expect a maximum of 20 participants and will use a projector, whiteboard (alternatively flip charts), sticky notes, pens, A4 paper, blu-tack, and highlighters to enhance the visual interactive sections.

The provisional workshop program is as follows. The workshop will be three hours and divided into three parts, lasting 45 minutes each, with 5 minutes intervals between them. The sections will have a 35-minute slot dedicated for the proposed activities (and their subsequent discussions), and a 10-minute debrief session. The workshop will also have a 10-minute ice-breaking introduction, and a 20-minute wrap-up session. Each author will lead one of the sections with the corresponding discussions and the following activities. The list below summarizes the tasks planned, and the referent time allocated to them.

Introduction (10 minutes):

1. Introductory presentation from the members of the panel, and their respective backgrounds.
2. Separation of the audience in groups of up to 4 people, for the following activities throughout the workshop.
3. Introduction and greeting between the members of each group.

Section 1.1 (45 minutes):

1. Task: Define the facets of cognition that differing cognitive distraction tasks attempt to load (I.e., working memory, episodic memory, emotion) and place each task under these headings.
2. What are the effects of these differing cognitive distraction tasks on takeover performance, and how can the effects be compared?
3. Task: Place each cognitive distraction task on a scale regarding how ecological valid they are (ranging from highly artificial to highly realistic) or how controlled they are (ranging from highly controlled to highly uncontrolled).
4. Task x Situation interactions – the same cognitive load tasks might affect people differently in different driving situations.

Break (5 minutes)

Section 1.2 (45 minutes):

1. Assessment of the cognitive load.
2. Identification and comparison of the metrics.
3. Classification of the metrics in terms of different methodological aspects (i.e. reliability, validity, experimental control).
4. Evaluation of the data requirement for the assessment of cognitive load and the need for normative data in order to draw robust conclusions.

Break (5 minutes)

Section 1.3 (45 minutes):

1. How do DMS manufactures measure driver state?
2. How do they assessment their measurements?
3. What ground truths can be used and where are these obtained from?
4. Task: If you are a manufacturer and you need to create a DMS, how do you measure it, how do you control, and how do you assess your measurements.

Break (5 minutes)

Wrap-up (20 minutes):

1. Closing thoughts and debrief of the discussion.
2. Contact sharing and networking space.

At the end of the workshop, we aim to have a rigorous scientific discussion with researchers from academia and industry to better understand the current state of the art regarding driver state and cognitive load from a methodological perspective. We would like to extend our understanding on the methods and metrics used to assess and the methods used to induce cognitive load and assess the driver state.

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