Cognitive Interference during Driving

A Multimethod Neurophysiological Study of Cognitive Load

Moritz Held

This thesis was partially supported by the DFG-grant RI 1511/3-1 awarded to J. Rieger. The cover was designed by Mia Nitsche

Moritz Held, Freiburg, Germany, 2026.

Cognitive Interference during Driving

A Multimethod Neurophysiological Study of Cognitive Load

PhD thesis

to obtain the joint degree of PhD of the
University of Groningen and the University of Oldenburg

on the authority of the
Rector Magnificus of the University of Groningen
Prof. J.M.A. Scherpen
President of the University of Oldenburg
Prof. Dr. Ralph Bruder

and in accordance with
the decision by the College of Deans of the University of Groningen.

This thesis will be defended in public on

Tuesday 21 April 2026 at 14:30 hours

by

Moritz Leonard Che Held

born on 26 December 1994

Supervisors

Prof. N.A. Taatgen
Prof. J.W. Rieger
Prof. J.P. Borst

Assessment Committee

Prof. D. de Waard
Prof. D. Salvucci
Prof. M. Bauman
Prof. S. Boll

Table of Contents

1
Introduction

Humans routinely perform tasks that require the simultaneous coordination of perception, attention, memory, and motor actions, such as navigating busy environments, multitasking in highly safety-critical situations, or operating complex tools. A central challenge in cognitive psychology is to understand how these functions interact under conditions of high demand and how interference between tasks affects behavior. Studying these mechanisms in realistic, dynamic environments is crucial not only for advancing theories of cognition beyond tightly controlled laboratory tasks, but also for positively contributing to safety, efficiency, and well-being in everyday life.

One of the most common, yet simultaneously complex, examples of these tasks is driving. It requires continuous monitoring of the environment, motor coordination, spatial reasoning, and rapid decision-making, often while multitasking or under time pressure. Driving relies greatly on human performance and bears great risk when humans fail (Highway Traffic Safety Administration and Department of Transportation, 2016). Therefore, this thesis covers driving as a show-case scenario for examining how cognitive systems cope with complexity in naturalistic settings and how limitations in these systems may translate into real-world risks.

1.1 Previous Work

Research on cognitive workload and multitasking has a long history. Classic frameworks, such as Kahneman's capacity model of attention (Kahneman, 1973) and Wickens' multiple resource theory (Wickens, 2008) established the notion that, while our cognitive resources are limited, they may be flexibly allocated across tasks depending on arousal or intentions to deal with increasing workload. At the same time, the interference between the tasks may vary depending on whether the tasks draw on shared (e.g., two visual-spatial tasks) or distinct resource pools (e.g., one visual-spatial task and one auditory-verbal task). Further work has shown that interference can also arise from structural bottlenecks in information processing. Studies on dual-task performance demonstrated that even when tasks rely on different modalities, some bottlenecks, such as the problem-state bottleneck, remain and can prevent two operations from being carried out simultaneously (e.g., Pashler, 1994; Borst et al., 2010; Welford, 1952; Levy et al., 2006).

These perspectives have remained far from purely theoretical and have often been relied upon to explain the effects of performance degradation in real-life domains such as driving while multitasking (Broadbent et al., 2023; Unni et al., 2017; Weaver and DeLucia, 2022; Held et al., 2024b). Although considerable evidence exists for the predicted degradation of driving performance when drivers are multitasking, *how* their performance degrades varies (e.g., Li et al., 2018; Hancock et al., 2003; Horberry et al., 2006; Papantoniou et al., 2017; Ito et al., 2001; Alm and Nilsson, 1995; Jenness et al., 2002; Tsimhoni et al., 2004; Strayer et al., 2015; Kass et al., 2007; Salvucci and Beltowska, 2008; Unni et al., 2017). Researchers have attempted to consolidate these findings, suggesting that cognitive load induced by secondary tasks may selectively impair driving subtasks that rely on cognitive control while leaving automatic performance unaffected (Engström et al., 2017). However, to this date, this discussion remains ongoing, in part due to some results suggesting that drivers may even benefit from cognitive load induced by secondary tasks in various circumstances (Nijboer et al., 2016b; Cao and Liu, 2013; Fitch et al., 2014; He and McCarley, 2011). Consequently, understanding the interference of secondary tasks solely based on driving performance remains a challenge in real-world driving.

During driving, the demand for cognitive resources may vary dynamically in both intensity and dimension, as it involves numerous subtasks such as visual scanning, spatial reasoning, and motor control - all while keeping track of surrounding vehicles, the current speed limit, and more. It is unsurprising that behavior is insufficient to elucidate our understanding of how real-life scenarios, such as driving, engage the human brain, which is necessary to understand the impact of elevated cognitive workload. While there exists an arsenal of neurophysiological measuring techniques to expand our understanding of these phenomena experimentally, the complexity of real-world driving inherently resists the constraints of laboratory control (Lohani et al., 2019). Consequently, investigating driving-related concepts using (neuro)physiological measures is infrequently conducted and focuses on portable devices such as eye-tracking or fNIRS (Haghani et al., 2021; Zhang et al., 2023; Lohani et al., 2019), which trade off spatial resolution for mobility.

In addition, even when applying these methods using complex experimental setups, neurophysiological methods focus on indicating where task-relevant information processing is located in the brain by linking experimental conditions to brain activation. However, they are limited when attempting to explain the functional mechanisms that drive task performance (Kriegeskorte and Douglas, 2018, 2019; Scheunemann et al., 2019). As Newell (2012) has already elaborated in his famous comment on the state of experimental psychology in the early 1970s, to fully understand how the human mind works, it is not only insufficient to merely enrich an ill-posed question with neurophysiological data, but it may also lead to conflicting evidence. Thus, he proposed a new way of studying the brain by building and utilizing functional and executable models of the human mind, and thereby became one of the founders of cognitive architectures (Anderson, 2007). Cognitive modeling is now a widely established method for understanding human cognition and has been used successfully to evaluate hypotheses and determine how different tasks depend on available cognitive resources in real-life tasks such as driving (Salvucci, 2006; Salvucci and Beltowska, 2008; Salvucci and Macuga, 2002; Kujala and Salvucci, 2015; Gunzelmann et al., 2011; Scharfe and Russwinkel, 2020; Cina and Rad, 2023; Park et al., 2018; Wiese et al., 2019; Held et al., 2024a,b)

1.2 A Multimethod Approach

Motivated to understand task interference in realistic situations, this thesis endeavors to address the gaps of single methods used in isolation by combining behavioral, physiological, and modeling approaches to investigate task interference in real-life tasks. As a working example, this thesis focuses on driving and cognitive workload induced by multitasking. However, the concepts discussed extend to other domains in which human performance in critical situations is vital, such as aviation or power-grid control.

Specifically, this thesis integrates:

- behavioral analysis to provide the most direct link between task workload and driving performance,
- eye-tracking, as an ecologically valid measure of attention and workload,
- computational cognitive modeling with ACT-R aims to formalize theories of multitasking and simulate performance under varying conditions,
- and functional magnetic resonance imaging (fMRI) to reveal the spatially precise neural mechanisms underlying workload and interference in realistic driving scenarios.

Eye-tracking offers a direct and ecologically valid measure of driver attention and workload. It uses an infrared camera placed in front of participants to track the gaze direction and pupil size of the eye. As such, it can be used to track the objects drivers are fixating at high temporal resolution, which provides useful information about what agents are relevant, how attention is allocated, or stages of human processing (Einhäuser, 2017). Further, the link between pupil size and cognitive load has long been established in cognitive psychology since Kahneman and Beatty (1966) found that pupil size can be used to infer the number of items stored in working memory. However, pupil dilation does not have a unique interpretation, as the pupil is also sensitive to many other effects, such as changes in lighting, arousal, or anxiety (e.g., Einhäuser, 2017; Mathôt et al., 2013b; Simpson and Molloy, 1971). In addition, meaningfully interpreting gaze locations in a dynamic environment may require additional data, as drivers could be performing different cognitive processes while looking at the same location (e.g., Sharma and Chakraborty, 2024).

We complemented the recordings of eye-tracking with computational models of human cognition developed in the ACT-R architecture (Anderson, 2007). ACT-R is a psychological theory as well as a *cognitive architecture* implemented using executable cognitive models that simulate brain activity. These modules simulate the information flow in the brain by interchanging *chunks* of information via *buffers*. ACT-R also imposes empirically validated restrictions and possibilities that define how these models may process information. As an exceedingly simple example, a person can steer and listen at the same time, but they cannot look at two locations at once; thus, that is also not possible when developing a model in ACT-R. Another common example we may face is that fewer cognitive resources are available to retain information about the latest speed sign if we have been in a deep conversation on the phone, causing us to be unable to remember how fast we should be going. Researchers can test hypotheses they may have pertaining to these phenomena and others by modeling the information flow in ACT-R in multiple ways and comparing the model behavior with that of human participants. This way, researchers can understand processes that are otherwise difficult to investigate. For example, Borst et al. (2010) used ACT-R to uncover cognitive bottlenecks at the so-called problem-state. Further, ACT-R cannot only be used to retroactively explain effects observed in psychological experiments, but it can also make predictions about the future by simulating possible upcoming events. This feature of ACT-R makes it especially attractive in the context of driving, as it can be used to evaluate possible user interfaces, vehicle controls, or assistive technologies without endangering human participants (Scharfe and Russwinkel, 2020; Damm et al., 2019).

This thesis also employs fMRI to explore the spatial organization of cognitive functions involved in driving, adding to the temporal precision of eye-tracking and providing neurophysiological data often needed to interpret cognitive models (Borst and Anderson, 2017). fMRI is a non-invasive neuroimaging technique that measures brain activity by detecting changes in blood oxygenation levels, known as the blood-oxygen-level-dependent (BOLD) response. Neural activation leads to increased metabolic demand and a subsequent localized increase in cerebral blood flow, which alters the ratio of oxygenated to deoxygenated hemoglobin. fMRI utilizes strong magnetic fields and radiofrequency pulses to detect subtle differences in the magnetic properties of hemoglobin, which exhibits different magnetic properties depending on the level of oxygenation. Although the temporal resolution of fMRI is limited due to the relatively slow BOLD response, fMRI can map neural activity at a high spatial resolution for both surface level activation and deeper brain structures. However, fMRI is not easily accessible due to its high cost in setup, maintenance, and personnel to operate the machine. In addition, it is very sensitive to motion artifacts, which is why it has often been forgone in driving related research. However, a custom-made setup used in this thesis allowed for a realistic driving simulation using a steering wheel and pedals while minimizing head movement. As such, fMRI acts as an ideal complementary measuring technique to eye-tracking, with the goal of acquiring information about neural structures at a high spatial resolution to interpret overt driving behavior.

Used in isolation, behavioral data reveal performance outcomes but not their underlying causes, physiological measures provide continuous markers of workload but are ambiguous with respect to interpretation and fMRI offers spatial precision but at the cost of poor temporal resolution. To overcome these trade-offs, this thesis adopts a multimethod framework that combines complementary sources of evidence. Our primary focus is on driving as the experimental context because it naturally instantiates the demands of multitasking and workload management in realistic scenarios. Specifically, we investigate two showcase scenarios: 1) maintaining a straight trajectory on highways and 2) executing left turns at intersections. These scenarios were selected as representative tasks to highlight the effect of cognitive workload on routine and automated tasks (straight driving) as well as on more complex driving situations (left-turns).

1.3 Thesis Outline

The body of this thesis is structured into four chapters, each leveraging the strengths of these methods to investigate the effects of cognitive load on driving, both at the behavioral level and the brain level.

In the second chapter, we utilized ACT-R to model the effect of cognitive load on driving performance in two separate, functionally different models: The *central-bottleneck model* vs. the *problem-state-bottleneck* model. Each of the models simulated a human driver performing a working memory task while driving on a straight highway, and their performance was validated against human participants performing the same experiment. However, the models differed at one crucial point: the *central-bottleneck model* simulated that multitasking in this situation would use different resources and thus only encounter a bottleneck at a central resource that manages resource allocation in the brain, akin to Wickens (2008) central executive. The *problem-state-bottleneck model* revealed a different implication. In this model, both the working memory task and the driving task share a specific working memory-related resource, which must be managed to accomplish both tasks. The results of the latter match human performance, implying that driving, even at the most basic level, requires working memory, which results in drivers being able to perform fewer control actions towards the driving task when working memory load increases.

The third chapter builds on the validated *problem-state-bottleneck* model from chapter two, which was able to simulate the effects of cognitive overload. In this chapter, we expanded the model to investigate the effects of potential cognitive underload on driving performance. Accordingly, we simulated the effect of mind-wandering during driving, which often leads to a performance decrement due to inattention or delayed reaction times (de Winter et al., 2014; Yanko and Spalek, 2014; Bencich et al., 2014). First, we showed the performance decrease induced by mind-wandering. Second, we evaluated the potential positive and negative effects of interventions on drivers, as they may assist or distract them if they are perceived as intrusive. Thus, this chapter explores the cost-benefit analysis that must be considered when designing a suitable intervention, as interventions also come with a cognitive cost. Furthermore, it serves as a proof-of-concept for ACT-R to be integrated into live systems to predict upcoming driving performance as a consequence of interventions from automated systems.

In chapter four, we used the model developed in the previous chapters to build a prototype for an automated system that tracks cognitive workload by pupil dilation as a physiological proxy for cognitive workload. The automated system tested in this chapter continually runs in parallel with a human participant participating in a driving study. When the cognitive load, indicated by pupil size, exceeds a critical threshold, the prototype first attempts to take over lateral control of the vehicle (i.e., steering) and only assumes full control of the vehicle when pupil dilation exceeds a second critical threshold. Thus, it operates on the principle of reducing invasiveness, as established in chapter three. While the prototype showcased real-time, continuous workload estimation and adaptive vehicle control, our findings also convinced us that pupil dilation alone does not sufficiently capture the complexity of cognitive workload during driving. Specifically, it lacks the resolution to differentiate how various aspects of cognitive workload manifest across different driving situations and what may be needed to alleviate it at what time. Thus, we turned our focus towards identifying the neural and physiological correlates of cognitive workload, with particular attention to how these are affected in difficult driving situations.

In chapter five, we used fMRI to further investigate the effects of cognitive workload while driving. Brain imaging techniques allow for a deeper understanding of the underlying processes behind cognitive workload and its effect on driving. Using fMRI, we went beyond mere behavioral changes and investigated the neural correlates of safety-critical cognitive states such as situational awareness and decision making. Due to the high spatial resolution of fMRI, we were able to locate deep brain structures related to situation awareness at intersections as well as understand their temporal dynamics across a left-turn situation.

The general discussion in chapter six discusses the main findings of the work in this thesis. In addition, it discusses the implications this work may have for future automated systems that adapt to human drivers.

2
Modeling Bottlenecks during Driving

This chapter has been published as: Held, M., Rieger, J. W., & Borst, J. P. (2024). Multitasking while driving: central bottleneck or problem state interference?. Human factors, 66(5), 1564-1582. The article and the chapter are identical in content. MH, JW and JB planned and conceptualized the research including the design of the models and experiments as well as the analysis of the results. MH developed the models and experiments. MH conducted the experiments and carried out the analysis. MH wrote the initial draft of the manuscript. JW and JB provided critical feedback and helped shape the research, analysis and manuscript.

Abstract

The objective of this work was to investigate if visuospatial attention and working memory load interact at a central control resource or at a task-specific, information-processing resource during driving. In previous multitasking driving experiments, interactions between different cognitive concepts (e.g., attention and working memory) have been found. These interactions have been attributed to a central bottleneck or to the so-called problem-state bottleneck, related to working memory usage. We developed two different cognitive models in the cognitive architecture ACT-R, which implement the central vs. problem-state bottleneck. The models performed a driving task, during which we varied visuospatial attention and working memory load. We evaluated the model by conducting an experiment with human participants and compared the behavioral data to the model's behavior. The problem-state bottleneck model could account for decreased driving performance due to working memory load as well as increased visuospatial attentional demands as compared to the central-bottleneck model, which could not account for effects of increased working memory load. The interaction between working memory and visuospatial attention in our dual tasking experiment can be best characterized by a bottleneck in the working memory. The model results suggest that as working memory load becomes higher, drivers manage to perform fewer control actions which leads to decreasing driving performance. Predictions about the effect of different mental loads can be used to quantify the contribution of each subtask allowing for precise assessments of the current overall mental load, which automated driving systems may adapt to.

2.1 Introduction

Driving is one of the most complex tasks that people do on a daily basis. In order to safely navigate traffic, drivers must monitor in-vehicle controls such as the speedometer or navigation devices while also paying attention to the surroundings and watching out for other road users and pedestrians. Thus, it is unsurprising that an estimated 94% of motor vehicle crashes can be attributed to human error (Highway Traffic Safety Administration and Department of Transportation, 2016). One of the main sources of human error while driving is cognitive overload (e.g., Engström et al., 2017), next to distraction (e.g., Hancock et al., 2003) and fatigue (e.g., Gunzelmann et al., 2011). However, the effect of cognitive workload on driving is not straightforward and depends on many factors such as the specific kind and amount of workload as well as driving difficulty.

2.1.1 Cognitive Workload while Driving

Researchers investigating cognitive workload during driving often focus on visual distractors that impose additional workload on the drivers as it is considered central to driving. Consequently, the literature of the negative effects of extended visual distraction on driving performance is comprehensive (e.g., Hancock et al., 2003; Horberry et al., 2006; Ito et al., 2001; Li et al., 2018; Papantoniou et al., 2017). However, even when secondary tasks impose only minimal visual demands, driving performance has been shown to suffer as well (Alm and Nilsson, 1995; Jenness et al., 2002; Tsimhoni et al., 2004) suggesting that driving draws on multiple cognitive resources, which are affected by cognitive distractions.

Similar to visual distractors drawing the eyes away from the road, which exploit the limitations of human sensing, cognitive distractors take away cognitive resources from the driving task and interfere with the driving task at the level of information processing. For example, Strayer and colleagues (2015) induced high cognitive workload by a variety of different factors such as engaging in a conversation or operating a speech-to-text system to reply to text messages. They found that higher mental demand of the secondary task, as measured by NASA-TLX ratings (Hart and Staveland, 1988), can be linked to longer brake reaction times in a car-following task as well as to worse scanning behavior for hazard locations. Another study found lower situational awareness and a higher number of driving infractions (e.g., missing stop sign) while engaging in a phone conversation while driving (Kass et al., 2007).

Contrary to intuition, slightly increased levels of cognitive workload can also improve driving performance when the driving task is monotonous (Nijboer et al., 2016a). Nijboer and colleagues (2016a) attempted to reconcile these results by proposing that cognitive workload may have a preventative effect when mundane driving situations might otherwise lead to mind-wandering or fatigue, which have been associated with poor driving performance (e.g., Martens and Brouwer, 2013; Gunzelmann et al., 2011). Results showing that this effect disappears when driving difficulty is varied, provide additional support for this explanation (Engström et al., 2017; Medeiros-Ward et al., 2014). While the beneficial effect of additional load in monotonous driving situations can be found using a variety of different secondary tasks such as interactive verbal tasks (Atchley and Chan, 2011), n-back tasks (Medeiros-Ward et al., 2014) or simply repeating a sequence of numbers in reverse order (He et al., 2011) in lab studies, it is not as consistent in naturalistic driving situations (Engström et al., 2017).

The complexity of the interaction is further highlighted by studies of Unni and colleagues (2017) and Scheunemann and colleagues (2019) who attempted to classify the cognitive workload of drivers from fNIRS data in a realistic driving simulator. The authors manipulated both visuospatial demands through different lane width and working memory load induced by a modified n-back task. Guided by Wickens' model of multiple resources (Wickens, 2002), the authors predicted that both tasks required a different set of cognitive resources and expected little interference of one task on the other. Following that line of reasoning, Unni and colleagues (2017) attempted to classify the working memory load independent of visuospatial demands from the recorded fNIRS data using multivariate regression. They found high correlations between the predicted workload and the induced workload. However, when attempting to reversely classify visuospatial demands independent of working memory load levels, Scheunemann and colleagues (2019) only reached low classification accuracies. In a follow-up analysis, the authors showed high classification accuracy when the classification was done for individual working memory load levels (e.g., intermediate working memory load) demonstrating brain-level interactions between the two manipulated cognitive concepts. Theories of multitasking can account for this finding in different ways. The authors posited as one option that the two tasks might not be separated to different cognitive resources and share a common resource specific to the two tasks, which according to Wickens' model of multiple resources (Wickens, 2002) would incur a significant cost of multitasking. Alternatively, the two tasks might interact at a task-unspecific level instead. Both Wickens' model (at the central executive) as well as the often observed effect of the psychological refractory period (PRP) (Welford, 1952; Pashler, 1994) similarly predict a performance loss when multitasking due to a bottleneck at a central resource (Levy et al., 2006).

The goal of this study was to identify the mechanisms underlying the observed interaction between visuospatial demands and working memory load (Scheunemann et al., 2019). While decoding models such as the one used by Scheunemann and colleagues (2019) are useful to indicate where task relevant information processing is located in the brain, these models are limited when trying to explain the functional mechanisms that drive task performance (Kriegeskorte and Douglas, 2018). As an alternative, cognitive models are particularly useful in this regard as they permit insight into *how* people are performing a task. Cognitive modeling is a widely established method to understand human cognition and, moreover, to create explainable computational models, which can be used not only to evaluate hypotheses about task strategies but also to determine how each task depends on available cognitive resources (Kriegeskorte and Douglas, 2018; Newell, 2012).

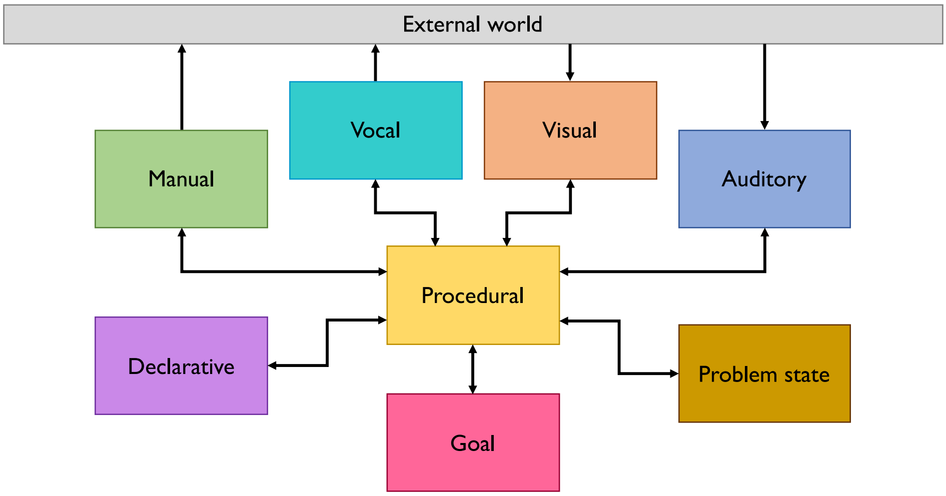
To elucidate the effects of workload on driving, we adapted the seminal driving model by Salvucci (2006) designed in the Adaptive Control of Thought – Rational (ACT-R; Anderson, 2007) cognitive architecture. We contrasted two different bottleneck models, which have both been related to considerable interference in multitasking situations: 1) A central bottleneck model, where interference is due to competition for a central coordination system (Salvucci and Taatgen, 2008; Taatgen et al., 2009; Pashler, 1994) and 2) a problem-state-bottleneck model, where interference is due to contention of a working memory resource (Borst et al., 2010; Nijboer et al., 2016a). To test which of these models can better account for cognitive interactions in driving, we conducted an experiment in which two cognitive concepts often utilized in driving situations were manipulated, working memory and visuospatial attention (Unni et al., 2017; Scheunemann et al., 2019).

2.1.2 Modeling approach

To investigate the interaction described by Scheunemann et al. (2019), we developed two cognitive models in the cognitive architecture ACT-R. ACT-R is a psychological theory of human cognition implemented as a computer simulation (Anderson, 2007). It aims to incorporate the basic cognitive processes that enable the human mind and can model cognitive processes not as a single operation but as part of a coherent system that produces all of human behavior. It allows for the development of cognitive models, which can be understood as an implementation of a hypothesis of how humans solve a particular task. ACT-R has been used to develop one of the most well-known driving models (Salvucci, 2006) and, furthermore, has been used in previous studies to model visual sampling on in-car displays (Kujala and Salvucci, 2015), and to simulate the effects of memory rehearsal (Salvucci and Beltowska, 2008) and phone dialing (Salvucci and Macuga, 2002) on driving performance.

ACT-R simulates human cognition by a set of modules and buffers, which are each specialized to process a specific kind of information. How available information is processed is determined by how the information is passed through the modules of ACT-R, which communicate with each other via their respective buffers and are coordinated by a central production system (Figure 2.1). A production is a specific action formulated as an if-then rule that takes 50 ms to execute. For example, *if* the visual module perceives a speed sign, *then* the speed can be either stored in the problem state or in declarative memory. Thus, cognitive processes are expressed as a series of productions, which each occupy a module for a certain amount of time. Productions are executed by the procedural module, which makes up the procedural knowledge of the model.

Figure 2.1. ACT-R cognitive architecture



Next to the procedural module, other relevant modules for driving are the declarative memory module, the goal module and the problem state. Declarative memory makes up long-term knowledge of ACT-R and contains chunks of information with slot-value pairs. Chunks can be manually defined or learned by the model during the experiment. Each chunk has a certain activation level that is based on the recency (i.e., when the chunk has last been processed) and frequency (i.e., how often the chunk been processed). The activation B_i of a chunk i continuously decays following the equation

$$B_i = ln(\sum_{j=1}^{n} t_j^{-d}),$$

where n denotes the total number of presentations of chunk i, t_j denotes the time since the jth presentation of said chunk and finally d represents a decay parameter usually set to 0.5. To successfully retrieve a chunk, the activation has to be above the retrieval threshold, which is set by the modeler. By clearing the buffer of any module, the chunk currently in that buffer is stored in declarative memory – thereby essentially creating new memories.

The problem state holds the current information that is necessary to carry out the task; it serves as a one-chunk working memory, reflecting the focus of attention in modern working memory theories (Borst et al., 2010; Nijboer et al., 2016a). The goal module contains the control information needed to perform the task. Thus in a real task, the goal module would, for example, hold the goal information that upcoming speed signs need to be attended, the visual module would perceive and attend speed signs, and the encoded speeds would be stored in the problem state. Upon entering the problem state, a retrieval to a previous sign could be issued, for example to check if the new speed sign is the same as the previous. If there is a chunk in declarative memory above the retrieval threshold which matches the description of the retrieval attempt, the chunk would enter the declarative memory buffer upon which it can be accessed by other modules.

ACT-R is limited by the central processing unit, which can only initiate one production at a time. When the conditions for two productions are met at the same time, only one of them can be executed at once, resulting in a processing bottleneck. At the same time, multiple processes may run in parallel when separated to different modules –- for example, a memory retrieval can be made while the model focuses on a speed sign – but each module can only deal with one instruction at a time (Byrne and Anderson, 2001). This limited parallelism has strong implications for multitasking, as it not only leads to a high contention for the central processing unit, but also implies that tasks that are reliant on different modules can be performed more efficiently than others.

On top of the inherent multitasking behavior of ACT-R, Salvucci and Taatgen (2008, 2010) developed the multitasking theory *threaded cognition*, which is integrated into ACT-R. Threaded cognition specifies further how available resources are used in pursuit of multiple task goals. It allows the model to interleave two or more tasks by using a greedy and polite principle which dictates that productions occupy modules as quickly as possible but also release the modules as soon as they are not needed. Production rules will simply be executed based on the availability of modules and buffers independently of their urgency. If two production rules of different task goals can be executed, the production of the least recently attended goal will be selected. Since its inception, threaded cognition has been used successfully in a variety of multitasking settings and has been established as a sophisticated multitasking theory that can account for a range of multitasking behavior (e.g., Borst et al., 2010; Kujala and Salvucci, 2015; Salvucci and Beltowska, 2008) and associated brain activity (e.g., Borst et al., 2010, 2011; Nijboer et al., 2014). Due to its management of multiple resources, threaded cognition is often regarded as a computational implementation of Wickens' model of multiple resources (Wickens, 2002).

Inspired by the work of Salvucci and Beltowska (2008) who implemented a memory task while driving and matched the model to human behavior, we developed two ACT-R models. In the first model, we relied on the inherent multitasking behavior of ACT-R, which is limited by the serial initiation of production rules and thereby modeled a bottleneck at a task unspecific resource (central bottleneck), which is independent of the specific tasks of the model. In the second model, the multitasking behavior was characterized by a dependency on the problem state during multitasking and thereby implemented a bottleneck at a task specific resource (problem-state bottleneck). By comparing the behavior of the two models, we contrasted the two possible hypotheses posited by Scheunemann et al. (2019). Both models performed an experiment designed by Unni et al. (2017). To allow for better validation of the model, we collected new human data with this experimental setup. Furthermore, we used eye-tracking to assess cognitive workload of the human participants.

2.2 Methods

2.2.1 Participants

25 participants (12 male, 13 female) aged between 20-37 years (mean = 26; SD = 4.1) were recruited in the Oldenburg area, which was a similar sample size as in previous studies (e.g., Unni et al., 2017). All participants were in possession of a valid driver's license in Germany at the time of the experiment. They gave informed consent prior to the experiment and received 10€/hour as a reimbursement. This research complied with the American Psychological Association Code of Ethics and this experiment was approved by the Ethics Committee of the Carl von Ossietzky University Oldenburg. The data of three participants had to be excluded due to a technical error with the eye-tracker. Average age of the included participants was 26.2 (SD = 4.3).

2.2.2 Materials

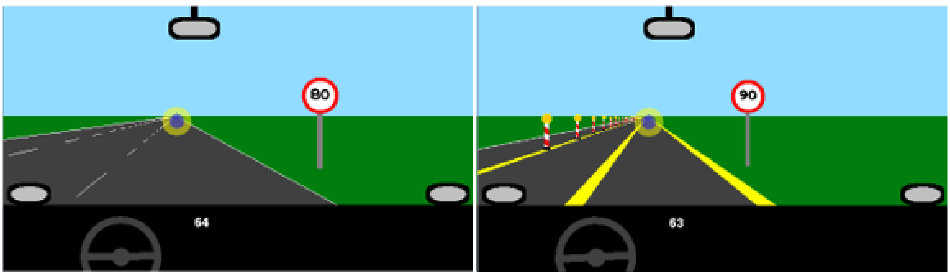
The driving experiment was programmed in Java using the code framework of previous research by Kujala and Salvucci (2015) and made public at: https://www.cs.drexel.edu/ salvucci/cog/act-r/download.php. It was conducted in the behavioral lab of the Applied Neurocognitive Psychology Laboratory at the University of Oldenburg. It was run on a 1920x1080 px monitor in a Microsoft Windows 10 environment in combination with a Logitech G20 wheel, which included a throttle and brake pedal. Experimental data (e.g., car position) were sampled with a rate of 200Hz.

A Portable EyeLink Duo 2 (SR Research Ltd., Ottawa, Canada) eye-tracker was used to track gaze position and pupil dilation with a sampling rate of 500Hz. For this set-up we selected nine-point calibration with mono-ocular tracking (left eye) in remote tracking mode.

2.2.3 Design

The experiment used a within-subject design which varied the factors visuospatial attention and working memory load. Adapted from Unni and colleagues (2017) and Scheunemann and colleagues (2019), visuospatial attention requirements were manipulated by either driving on a highway with three lanes of 3.5m each or through a construction site with lanes of 2.5m each. In the construction site the left-most lane was blocked off by red-white pylons (Figure 2.2). The participants were instructed to stay in the middle of their current lane and drive on the right-most lane that was not occupied by another vehicle. In both conditions the road was completely straight with no bends to either side.

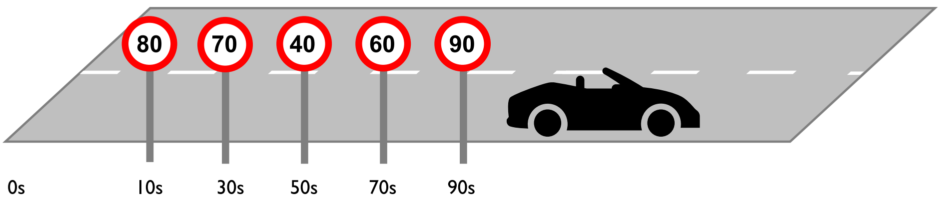
Figure 2.2. Road conditions in the highway condition (left) and the construction condition (right)



Note. The blue circle indicates the visual focus of the model (not visible to participants).

Working memory load was manipulated by a modified n-back task. Participants were instructed to watch out for speed signs which appeared on the right side of the road. The first speed sign appeared 10 seconds in to the block, subsequent signs appeared every 20 seconds thereafter. The signs displayed a speed limit of base 10 between 40 km/h and 120 km/h. Participants were instructed to drive according to the speed limit that was displayed *n* signs ago. To keep to the task-compliant speed, participants had to monitor the surrounding traffic on adjacent lanes and the available mirrors in order to perform overtaking maneuvers which became necessary ca. 2-3 times per block. Five different n-back levels were used, ranging from 0-back during which participants simply followed the latest speed sign (i.e. regular driving) to 4-back during which participants had to keep their speed in accordance with the speed sign that they saw four signs ago (Figure 2.3). To be able to successfully perform this task, n speed signs needed to be passed before the experimental phase could start. This build-up phase of the complete to-be-memorized sequence preceded the experimental phase of each block and was not analyzed.

Figure 2.3. Example of an n-back block at the 90s mark



n-backlevel	0-back	1-back	2-back	3-back	4-back
correct speed	90	60	40	70	80

Note. Bottom row displays the appropriate speed at the car's position depending on the n-back level.

2.2.4 Procedure

Upon arrival, participants were seated and the eye-tracking equipment was calibrated. Afterwards, participants started with a 5-minute training session, during which they performed a 2-back task in the highway condition to get used to the driving environment and vehicle controls. If participants were not comfortable with the controls after the training session or did not understand the instructions of the n-back task, we repeated the training session. Before starting the experiment, we applied a drift correction of the eye-tracker and re-calibrated if necessary.

The main experiment lasted ca. 70 minutes with a break in the middle. Each block of the experiment lasted exactly 160 s of experimental phase in addition to the build-up phase (see above). For the first half of the experiment the n-back levels were each paired once with either visuospatial condition such that visuospatial condition altered between every block and no n-back level would occur twice in a row. This set of ten blocks was then repeated in reverse order for the second half of the experiment resulting in a total number of 20 blocks (following Scheunemann et al. (2019); Unni et al. (2017)).

2.2.5 Analysis

The build-up phase was excluded for all analyses from both human and model data. One block for one participant was additionally excluded due to disregarding the instructions, which was indicated by the participant remaining stationary during the first minutes of the block. Driving segments during which a lane-change maneuver occurred were discarded. These segments were defined by a six second interval around a crossing of the lane markings (Nijboer et al., 2016a). To avoid classifying lane keeping errors as lane-changes, only segments during which participants drove for at least five seconds in the adjacent lane after crossing the lane marking were considered as lane-changes.

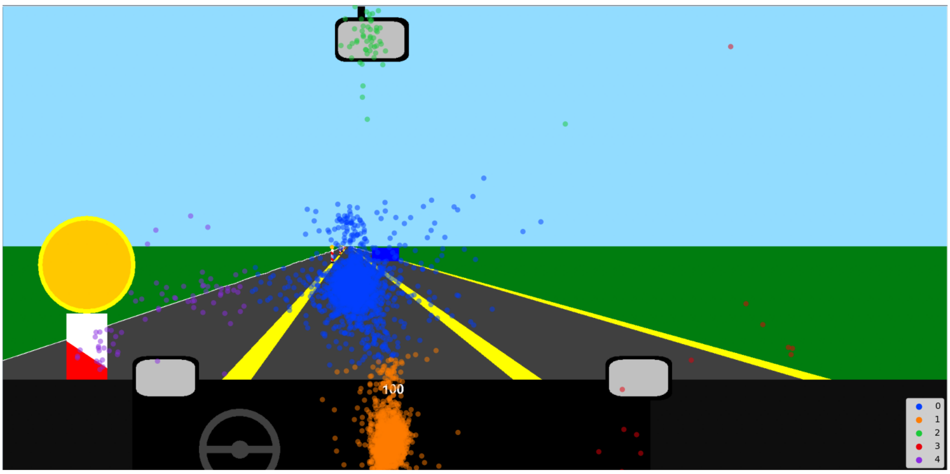
As a measurement for driving performance, we calculated steering reversal rates which have been indicated to increase with increased effort in the driving task (Greenshields, 1963; Hicks and Wierwille, 1979; Macdonald and Hoffmann, 1977; McLean and Hoffmann, 1975; Scheunemann et al., 2019). Steering reversals were defined as a crossing of the steering wheel's center position (i.e., going from left to right or vice versa). Errors in the speed regulation task were difficult and inefficient to evaluate automatically as participants showed vastly different acceleration patterns when encountering a speed sign. Thus, the trials were each manually inspected and rated as incorrect when participants failed to reach and maintain the correct speed with a tolerance of ±5 km/h on average. In addition to steering reversals, we also calculated the average lane deviation. Lane deviation was defined as the mean of the absolute distance to the center of the currently occupied lane.

Before analyzing pupil dilation as an indicator for cognitive workload (Kahneman and Beatty, 1966), the data were pre-processed by removing eye-blinks, which were identified by the integrated blink detection provided by SR Research. Other artifacts (e.g., due to temporary eye tracker failures) were identified as being rapid changes in pupil sizes to values at least four standard deviations away from the mean. They were corrected by removing all samples from 25 samples (50ms) before until 25 samples after the blink and replacing the samples by monotonic cubic spline interpolation following the recommendations of Mathôt and colleagues (2018). Afterwards, we calculated the percentage change to a baseline period, which was determined to be the time window of five seconds after the start of the experiment and five seconds before the occurrence of the first speed sign. The baseline was calculated as the median pupil size of the fixations during the baseline period (Mathôt et al., 2018). Furthermore, we calculated the average percentage change for pupil size of the fixations per unique combination of n-back level and visuospatial condition. Fixations were determined via the integrated software by

SR Research, which categorized a fixation as a temporary spatially stable gaze direction.

For the analysis of gaze position, we clustered the fixations with k-means clustering. We selected the number of the clusters manually due to the vast differences regarding participants' use of mirrors and determined the number for each participant and visuospatial condition. The number of clusters was deemed appropriate when at least $k - 1$ clusters could be assigned a distinct location (e.g., three clusters: speedometer, road, mirror) with one optional cluster accounting for noise (see Figure 2.4 for a demonstration of this method). Labels were assigned manually. Afterwards, we calculated the average number of fixations on the speedometer in between two speed signs for each combination of visuospatial and n-back combination.

Figure 2.4. Clustering of fixations shown on example participant (Participant 5)



Note. Clusters 0, 1, 2, 4 can be assigned to specific locations (upcoming road, speedometer, rear-view mirror, and left lane, respectively). Cluster no. 3 cannot be assigned to a location and accounts for noise.

2.2.6 Model

The model used in this study was a combination of a driving model and an n-back model. The driving model was a modification of the Salvucci driving model (Salvucci, 2006), which is able to drive on an empty highway. However, as the original model does not account for effects of different lane-widths, we adapted the model for this study.

Driving Model

For lateral control, that is maintaining a smooth trajectory in the center of the lane, we implemented a system with a high-control and a low-control loop. The high-control loop closely resembles the model of (Salvucci, 2006), which employs the two-point steering model described by Salvucci and Gray (2004). The model negotiates a new steering angle at every iteration of the loop based on a near point and far point at the lane center, which are 10m and 100m in front of the car, respectively.

The low-control loop follows a different strategy that does not update the steering angle until necessary and thereby models a more passive control mechanism. Here, the model maintains the same steering angle until the car comes close to the edge of a lane. Once that happens, the model switches back to the high-control loop to safely move back to the center.

Both the minimal lateral distance to the lane edge that triggers the high-control loop ($dist$) and the time the model stays in the high-control loop (t_{hc}) to move back to the center of the lane are parameters which affect driving performance. As more time in the high-control loop equates to a tighter control of the steering resulting in more steering corrections, the parameters have been adjusted for a good fit of the model's steering behavior (see Appendix, Table 2.5).

For longitudinal control, the model continuously accelerates and decelerates to maintain a fixed distance to a point moving at the target speed. The control law of the model utilizes to achieve this was based on the control law by Salvucci (2006):

$$\Delta\Phi = k_{\Delta thw} \cdot \Delta thw + k_{thw} \cdot thw\Delta t,$$

where Φ denotes an acceleration value ranging from -1, which translates to maximally pressing down the brake, to 1, which translates to maximally pressing down the throttle and $\Delta\Phi$ denotes the difference between two acceleration values between two iterations of the driving loop. At the value of 0, neither throttle nor brake are pressed down. thw describes the time headway between the car and a fictional point in the distance, which moved according to the speed limit and Δthw the difference between two iterations of the driving loop. In other words, the distance from the car to the distant point is defined as the distance an object travels in the time interval Δt when following the speed limit. Δt describes the time difference between the last update of the model and the current time t.

Additional adaptations of the model include overtaking surrounding cars by changing the near and far point to the adjacent lane (following Salvucci (2006)) while using the side and rear-view mirrors to monitor the cars in the adjacent lanes and driving in the right-most lane whenever possible.

N-back Model

The part of the model performing the modified n-back task works via a sequential recall mechanism. As soon as a speed sign appears, it is encoded with an episodic tag as a single chunk and released to the declarative memory of ACT-R (Table 2.1). Episodic tags (ID in 2.1) are necessary to avoid the merging of speed signs that display the same speed at different moments of the experiment as well as to ensure that the speed signs are encoded in the correct order. Additionally, the chunks contain a slot with the episodic tag of the previous speed sign (previousID in 2.1). Thus, the encoding of the speed signs can be described as a linked list going backwards in time. To successfully recall a sign, the model sequentially goes through the speed signs starting at the most recent speed sign and ending at the nth sign depending on the n-back level of the current task. For each step going backwards, the model initiates a retrieval request for a chunk carrying the episodic tag of the previous sign. This episodic tag is stored in a chunk in the problem state buffer. When the chunk of the previous sign is retrieved from memory, it replaces the chunk in the problem state buffer causing the chunk of the current sign to be released to declarative memory. As rehearsal is a prominent strategy to accomplish the n-back task in humans, the sequence of task-relevant speed signs is rehearsed via the same sequential mechanism, after successful recall (Chooi and Logie, 2020).

Due to the limitations in multitasking in ACT-R models, which reflect human limitations, the number of rehearsals affected driving performance, because the steering updates compete with the initiation of productions of the rehearsal. As a consequence, we adjusted the number of rehearsals ((analogous to Salvucci and Taatgen, 2010, Chapter 4)) for a good model fit of the participants behavior (see Table 2.5 in Appendix).

Table 2.1. Example of a memory chunk

slot	value
isa	nback
ID	80
previousID	60
speed limit	70

It seems unlikely that speed signs were completely forgotten. Therefore, the retrieval threshold rt was set to a low value. Errors are modeled by partial matching, which can be thought of as mixing up two signs (Lebiere, 1999). How easily a chunk can be erroneously retrieved instead of the matching chunk is determined by the similarity between the two chunks. The similarity was chosen to be linearly decreasing with the time difference when two speed signs appeared. For example, two consecutive speed signs are more similar than two speed signs with a one minute time difference in between. Similarity ranged from 0 meaning that two chunks encoded the same speed sign and decreased by -0.1 for each speed sign that occurred in between (Table 2.2). The experiment and the two driving models below are available under: https://github.com/ANCPLabOldenburg/.

Table 2.2. Similarity of speed signs appearing at different times to the exemplary chunk in Table 2.1, which appeared at 80 seconds.

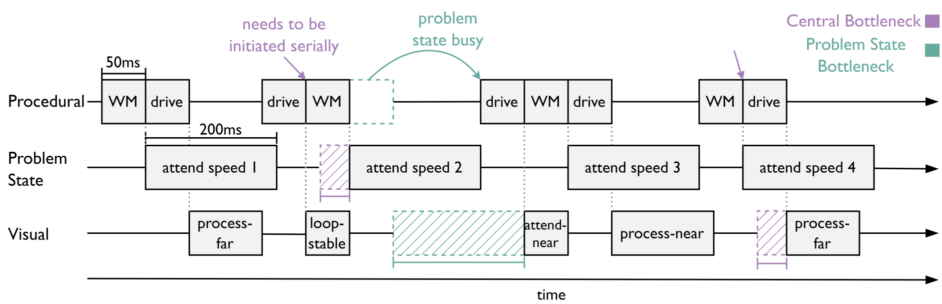
Time	20	40	60	80	100	120	140	160	…
Similarity	-0.3	-0.2	-0.1	0	-0.1	-0.2	-0.3	-0.4	…

Multitasking

Multitasking was modeled by employing two goals (driving and the n-back task), which are continuously interleaved using threaded cognition (Salvucci and Taatgen, 2008). Salvucci and Beltowska (2008) identified a bottleneck at the central processing unit of ACT-R when two tasks are being performed simultaneously, which negatively affected driving performance. In the central-bottleneck model, we did not explicitly model an interaction between the driving part of the model and the n-back part of the model. Instead, following the work of Salvucci and Beltowska (2008), the model is based on the competition for the processing unit of ACT-R. Because only one production rule can be initiated at any one time and its execution takes 50 ms, it can cause delays in either task when multiple production rules have their conditions met at the same time. For example, in Figure 2.5 purple arrows indicate when productions can be initiated for both the driving task and n-back task as all resources are available. As the production rule of the least recently attended goal gets initiated first, this delays the productions of the other task (purple dashed lines in Figure 2.5), which in the case of driving can result in fewer steering updates, when n-back productions are initiated first (Anderson et al., 2005).

In the problem-state-bottleneck model, we used the same driving and n-back mechanisms as in the central-bottleneck model. However, we made the multitasking requirement stronger by introducing a dependency on working memory (i.e. the problem state) into the driving task. In concrete terms, this meant that each iteration of the high or low control loop, which starts with a so-called "attend-near"-production, could only be initiated when the problem state was not busy (green arrow in Figure 2.5 indicates the delay). As a consequence, no new steering actions are initiated while working memory is actively used. As the sequential recall of speed signs for the n-back task requires constant swapping of the contents of the problem state buffer, it will remain active for longer periods during the task (i.e., 200 ms after each recall). This mechanism results in significant delays regarding the initiation of the driving loop as it falls more often together with a swap of the content of the problem state (green dashed lines in Figure 2.5. Note that, as the bottleneck in the central processing unit is an inherent feature of the multitasking behavior of ACT-R, it was also part of the problem-state-bottleneck model. We re-fit the driving parameters (see Table 2.5 in Appendix) to ensure that delayed control operations due to the restrictions in multitasking did not cause the model to lose control of the vehicle.

Figure 2.5. Demonstration of the two different bottlenecks.



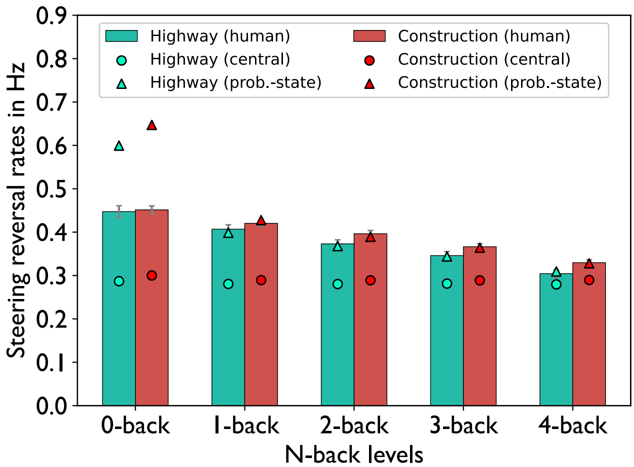
Note. The two goals, WM (working memory) and drive, are initiated by the procedural module.

2.3 Results

2.3.1 Driving Performance

In line with previous studies, for human drivers we hypothesized an effect of working memory load (n-back level) and driving difficulty (narrow vs. wide lane) on driving behavior measured by steering reversal rate (SRR) and lane deviation (de Waard, 1996). Figure 2.6 shows the significant decrease in SRRs in human participants that we observed across all n-back levels ($F(4, 84) = 38.4, p < 0.001, \eta_p^2 = 0.65$) as well as a significant increase in SRRs in the construction condition compared to the highway condition ($F(1, 21) = 16.3, p < 0.001, \eta_p^2 = 0.44$), which was supported by a two-factor repeated measures analysis of variance (ANOVA) with the factors n-back level and lane width. There was no interaction effect ($F(4, 84) = 1.5, p = 0.22, \eta_p^2 = 0.07$).

Figure 2.6. Average steering reversal rates



Note. Error bars indicate the standard errors of the mean.

Table 2.3 shows the 'cost' of the two bottlenecks as the average sum of all production delays in between two speed signs due to the respective bottlenecks. As the n-back level increases, the cost increases for both bottlenecks. However, as the central-bottleneck is solely impacted by the increased competition for the procedural memory, it shows a lower increase and a lower total cost when compared to the problem-state bottleneck. Importantly, the problem-state-bottleneck model is impacted by both bottlenecks whereas the central-bottleneck model is merely restricted by the central bottleneck.

The problem-state-bottleneck model predicted both significant effects regarding n-back level and lane-width, and matched the human data closely. This shows that, with respect to SRR prediction, the problem-state-bottleneck model (triangles in Figure 2.6) can clearly account for both effects. We calculated the root

Table 2.3. Cost of the two bottlenecks

	Problem-state bottleneck		Central bottleneck	
N-back	Construction	Highway	Construction	Highway
0-back	0.006	0.009	0.151	0.160
1-back	0.345	0.272	0.526	0.543
2-back	0.518	0.515	0.664	0.682
3-back	2.205	1.865	0.835	0.841
4-back	4.941	4.406	0.971	0.995

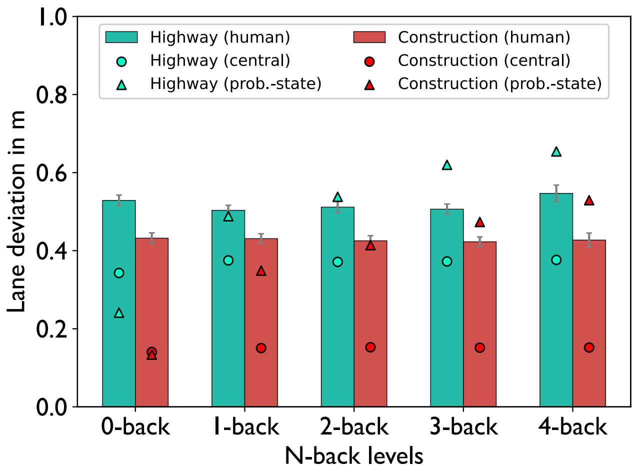
mean square error (RMSE) (Chai and Draxler, 2014) and the determination coefficient R^2 to formally evaluate the models and calculated an $RMSE = 0.08$ and an $R^2 = 0.77$ for the problem-state-bottleneck model (see Table 2.4). However, the central-bottleneck model (circles in Figure 2.6), while steering slightly more often in the construction condition and thereby reflecting the human behavior, 1) underestimated this effect, and – more importantly – 2) was not able to capture the effect of decreasing SRRs across n-back levels ($RMSE = 0.11$, $R^2 = 0.31$).

Table 2.4. Formal model fit metrics

	RMSE	R^2
SRR (central)	0.11	0.31
SRR (problem state)	0.08	0.77
Lane deviation (central)	0.22	0.92
Lane deviation (problem state)	0.15	0.14
Errors (central	0.08	0.95
Errors (problem state)	0.07	0.83

Analysis of lane deviation (Figure 2.7) showed that human participants deviated more from the lane center in the highway condition than in the construction condition ($F(1, 21) = 81.2, p < 0.001, \eta_p^2 = 0.79$). Although there was no main effect of n-back difficulty ($F(4, 84) = 0.19, p = 0.94, \eta_p^2 = 0.01$), the two-factor repeated measures ANOVA revealed a significant interaction effect ($F(1, 21) = 3.3, p = 0.0156, \eta_p^2 = 0.13$), where the difference between highway and construction increased with increasing n-back level. This interaction seems to be mostly carried by a lane deviation increase in the wide road condition at the highest n-back level. The problem-state-bottleneck model (triangles in Figure 2.7) predicts an effect of lane width on lane deviation as the model deviates more from the lane center in the highway condition. While predicting an increase of lane deviation across n-back levels in the construction condition, which is not present in the human data, the problem-state-bottleneck model predicts the effect of lane width closely with regard to human behavior ($RMSE = 0.15$, $R^2 = 0.14$). In contrast, the central-bottleneck model (circles in Figure 2.7) shows no effect of n-back level, but overestimates the effect of lane width on lane deviation while still underestimating the total lane deviation ($RMSE = 0.22$, $R^2 = 0.92$). Although, the model results do not favour the problem-state-bottleneck model as clearly, we argue that it shows a slightly better fit as the effect of lane width reflects human behavior while the central-bottleneck-model does not capture the effects of either condition well.

Figure 2.7. Average lane deviation

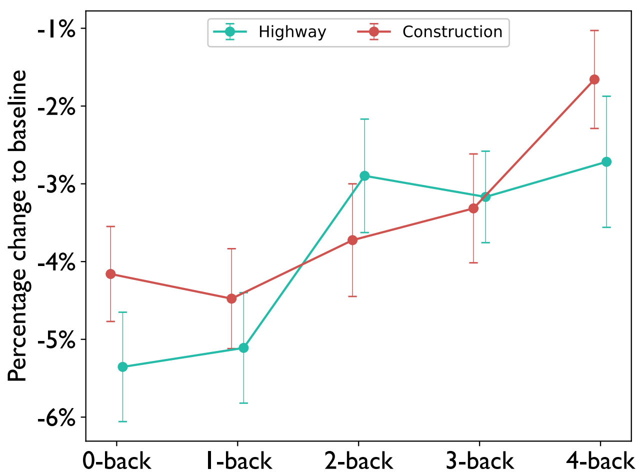


Note. Error bars indicate the standard errors of the mean.

2.3.2 Eye-tracking Results

Before analyzing the performance in the n-back task, we assessed the task demand induced by the different levels of the task to validate the induced working memory load. Previous research has found increased pupil size as the contents in working memory increase suggesting that pupil size can be used as an indicator for working memory load (Kahneman and Beatty, 1966). Accordingly, analysis of the eye-tracking data revealed a significant increase in pupil size with respect to the baseline with increasing n-back difficulty ($F(4,21) = 4.5, p = 0.002, \eta_p^2 = 0.18$) calculated by a 2-way repeated measures ANOVA. There was no interaction effect ($F(4,21) = 0.69, p = 0.6, \eta_p^2 = 0.03$) and no difference could be found between driving conditions ($F(1,21) = 0.83, p = 0.37, \eta_p^2 = 0.04$) (Figure 2.8). Furthermore, we analyzed the observed number of fixations on the speedometer in between two speed signs to assess how often participants monitored their speed to keep to the task-compliant speed. The data show a decrease with increasing n-back level ($F(4,21) = 12.7, p < 0.001, \eta_p^2 = 0.38$) (Figure 2.9). While the participants seemed to show a numerically higher number of fixations on the speedometer in the construction condition compared to the highway condition, the difference was not significant according to a 2-way repeated measures ANOVA ($F(1,21) = 1.3, p = 0.26, \eta_p^2 = 0.06$) and there was no interaction effect ($F(4,84) = 0.71, p = 0.58, \eta_p^2 = 0.03$).

Figure 2.8. Percentage change to baseline of the pupil size across n-back levels

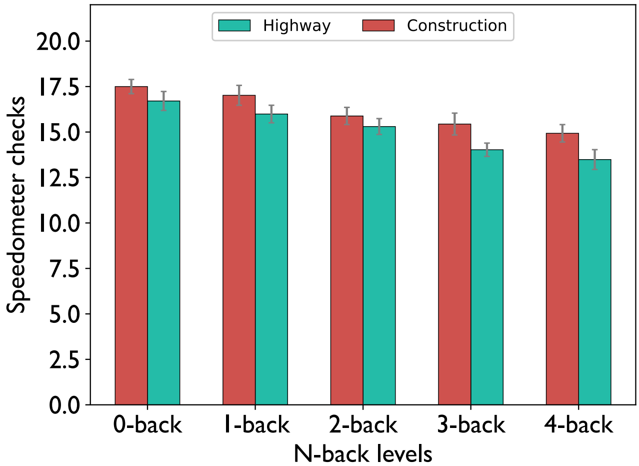


Note. Error bars indicate the standard errors of the mean. The baseline pupil size was larger than the average pupil size leading to negative values on the y-axis.

2.3.3 N-back Performance

As illustrated in Figure 2.10, participants made significantly more errors in the speed regulation task as n-back difficulty increased, which was revealed by a two-factor repeated measures ANOVA ($F(4,84) = 30.35, p < 0.001, \eta_p^2 = 0.59$). However, no significant differences in speed errors between lane widths

Figure 2.9. Number of fixations on the speedometer in between two consecutive speed signs



Note. Error bars indicate the standard errors of the mean.

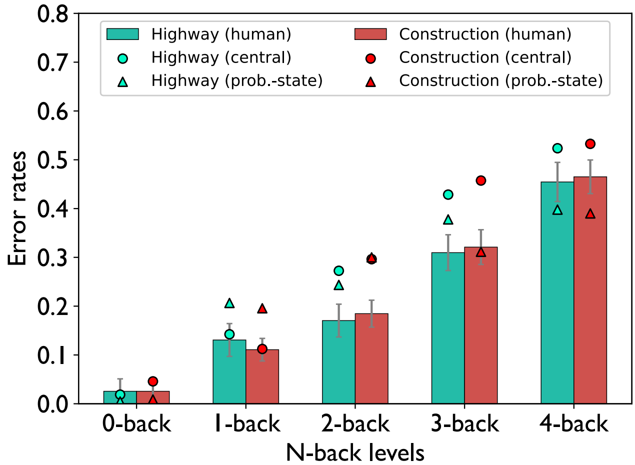
($F(1, 21) = 0.03, p = 0.85, \eta_p^2 < 0.01$) or interaction effects between n-back and lane width were observed ($F(4, 84) = 0.18, p = 0.95, \eta_p^2 < 0.01$).

In addition to the matching effect in the driving performance, both the central-bottleneck model ($RMSE = 0.08$, $R^2 = 0.95$) as well as the problem-state-bottleneck model ($RMSE = 0.07$, $R^2 = 0.83$) mirror the effect of n-back difficulty on the performance in the speed regulation task with respect to human participants: as n-back difficulty increases, the model performed worse in the n-back task. However, the models overestimated this effect for higher n-back difficulties and made more errors than human participants. There is no effect of visuo-spatial demands on n-back performance in the models. As both models exhibit similar behavior regarding n-back performance, they represent human behavior equally well.

2.4 Discussion

In this study, we investigated whether a bottleneck at a task-specific resource or a bottleneck at a task-unspecific resource could better account for interactions between working memory and visuospatial attention during driving. Scheunemann

Figure 2.10. Errors in the speed regulation task (n-back task)



Note. Error bars indicate the standard errors of the mean.

et al. (2019) proposed that the interactions could be due to a common resource at a task-specific level that needed to be accessed by both tasks (e.g., working memory) or due to a common resource, which is independent of the tasks (e.g., the central executive in Wickens' model (Wickens, 2002)). We contrasted the two hypotheses by developing two cognitive models implementing these hypotheses. The central-bottleneck-model is restricted by a bottleneck at a task-unspecific resource. The problem-state-bottleneck model implements a bottleneck at a task-specific resource (i.e., the problem state). We evaluated the behavior of the models by comparing their behavior to data collected in a dual-tasking driving experiment. Our study showed that the effect of working memory on driving performance cannot be adequately categorized by a contention at a task-unspecific resource like the central processing unit, due to the relatively poor fit of the central-bottleneck model to human data with regard to driving performance. Instead, the models suggest an interaction at a common, task-dependent resource like the problem state, representing working memory usage, which is indicated by the problem-state-bottleneck model accounting for human driving behavior across both working memory load and lane width.

Regarding steering behavior, both models showed increased SRRs in the construction condition, which is in line with the behavior of human participants in the current study as well as with previous research that showed that SRRs increase with the task demand as long as the task is within capacity of the mental resources (Macdonald and Hoffmann, 1980; Greenshields, 1963; McLean and Hoffmann, 1975; Scheunemann et al., 2019). However, these findings are highly dependent on the exact nature of the task, as reduced SRRs have also been shown when drivers performed a secondary task, while driving difficulty remained constant (Macdonald and Hoffmann, 1977). Macdonald and Hoffmann (1980) suggested that steering reversals increase with additional effort being put towards the driving task, which increases as the task demand in the driving task rises. However, when a secondary task exceeds the maximum mental capacity, mental resources (e.g., attention) are divided and are then drawn away from the driving task. Consequently, the effort being put into the driving task decreases, which results in a lower number of steering reversals. This effect is nicely demonstrated by the two models. In both models, steering control is modeled by the implementation of two control loops: high control vs. low control. The low control loop does not update the steering position via the near and far point but merely checks whether the car is in an unsafe position in the lane and thereby models driving with low effort. In the construction condition the model remains in the low control state for less time as high control is initiated when the model approaches the lane edges, which are closer to the car if the lane is narrower. This mechanism reflects the hypothesized behavior of human participants that driving in a construction site requires more effort and, thus, more resources.

However, while mirroring human behavior across lane widths, the central-bottleneck-model falls short in predicting human behavior as it cannot account for the decrease in SRRs over increasing n-back levels. In contrast, the problem-state-bottleneck model implies that the problem state is needed even for a well-practiced control task such as driving and, therefore, predicts a decrease in steering operations over n-back levels. From human pupil data, we can conclude that the task demand increases with n-back level because we observed an increase in pupil size indicating higher workload. This is also reflected by human participants committing more errors across n-back levels as more speed signs have to be stored in working memory for longer periods of time. Furthermore, we observed that participants showed a decreasing number of fixations on the speedometer as the n-back difficulty increased. This further indicates that participants have less time available to invest in monitoring the car's speed due to the increasing task demand of the n-back task. Thus, it can be argued that with increasing difficulty in the n-back task, the task draws away more resources from the driving task resulting in less time spent on the driving task in human participants.

The two models can account for this behavior in two ways via the different bottlenecks and their respective costs. In the central-bottleneck model, the competition for initiating production rules increases with increasing n-back level as higher n-back levels initiate more productions to recall speed signs further back in time. However, the cost of the central bottleneck is relatively low overall, leading to a low effect on steering reversal rates. In the problem-state-bottleneck model, driving is dependent on the problem state meaning that more resources between the two tasks are shared. Consequently, fewer processes can be executed in parallel and the n-back task draws away more time from the driving task when the n-back level increases resulting in fewer steering reversals across n-back levels in the problem-state-bottleneck model. This higher cost of the bottleneck is evident when comparing the total delay of steering updates caused by the problem-state bottleneck as n-back levels increase. This explanation is in line with threaded cognition, which claims that both tasks share the mental resources and an increased effort in the working memory task draws away resources from the driving task resulting in less time spent overall on steering control. According to this theory, the addition of a secondary task will result in fewer steering reversals as the central processing unit acts as a bottleneck for any two tasks that are performed simultaneously.

Lane deviation in human participants showed a similar pattern as observed in previous studies, with lane deviation decreasing in narrower lanes (Godley et al., 2004; Dijksterhuis et al., 2011; de Waard et al., 1995). However, no clear pattern emerged across working memory load levels. Previously, lane deviation has shown to *decrease* with increasing working memory load (Brookhuis et al., 1991; He et al., 2014), although Unni et al. (2017) reported no changes across n-back levels using the same experimental design as we did. Both models in our study capture the effect of increased lane deviation in the highway condition. In addition, the problem-state-bottleneck model also predicted an effect of increased lane deviation across n-back levels in the construction condition, which is not present in the human data. The effect between road conditions in the models is due to the increased time in the low-control loop in the highway condition, which does not adjust the steering to move back to the center until a critical distance to the lane edge has been reached. With regards to the effect of working memory load, the increased time spent on the n-back task leads to less time in the high-control loop, which further increases lane-deviation, similarly to steering reversals. Similarly, as the driving productions cannot be initiated while the problem state is occupied, which leads to fewer steering productions, lane deviation is higher in the problem-state-bottleneck model when compared to the central-bottleneck model. This effect primarily affects the construction condition as the contention for resources is stronger in this condition. As the model spends more time in the high-control loop, the effect of the working memory task, which restricts time in the driving loop, becomes stronger.

Interestingly, neither the models nor the steering behavior of the human participants showed an *interaction* between the two manipulated concepts suggesting that the found interactions by Scheunemann et al. (2019) are exclusively present at the brain level, but not at the behavioral level.

Overall, the problem-state-bottleneck model captured human steering behavior across different task conditions and could account for different kinds of induced workload. In the future, well-tuned cognitive models that predict human behavior in different driving situations could support human-machine integration as proxies for humans in automated vehicles. Automated vehicle approaches, like ”adaptive automation” (Hancock et al., 2013), could especially benefit in this regard as they attempt to adjust the level of automation in the vehicle to the operator’s mental load. The authors envision a system that monitors the driver’s cognitive state measured by brain activity or physiological sensors to determine periods of high cognitive workload. In these situations, the envisioned system could intervene to alleviate the driver’s cognitive workload. The objective in this endeavour is for the driver to remain attentive and actively engaged in the driving task but re-adjust the driving responsibilities when the driver’s safe handling of the situation cannot be guaranteed or when the automated system is failing. In an ideal system, the driving task should be optimized such that the driving responsibilities are matched to the general and momentary capabilities of the individual driver. Although such a system does not yet exist, the idea has been evaluated before using brain measurements to classify frustration in human drivers, which showed significant safety gains (Damm et al., 2019). While this research is promising, it is currently unclear how much mental workload is induced by the task demands that are part of everyday driving leading to high uncertainties in the classification of the human state. Consequently, which driving responsibilities should be automated, which should be performed by the human and what the mode of intervention needs to look like remains largely unspecified to this date.

A crucial step towards effective adaptive automation is to be able to accurately assess cognitive workload while driving, in order to know when the system should adapt the driving responsibilities assigned to the human operator. While predicting cognitive workload can potentially be done using physiological measures like heartrate variability or pupillary response (Kahneman and Beatty, 1966) and even neuroscientific methods like electroencephalography (EEG; e.g., Aricò et al., 2016; Scerbo et al., 2003) or functional near infrared spectroscopy (fNRIS;

e.g., Bunce et al., 2011; Unni et al., 2017), these methods are limited because overall workload is driven by multiple external factors which interact at the brain level. Interactions between different factors have the potential to considerably deteriorate the accuracy of the system as was evidenced by Scheunemann et al. (2019) constituting a real challenge in brain-based adaptive automation technologies.

Herein lies the great potential of using explainable computational models as showcased in this work. The model we present here provides not only behavioral predictions during multi-factorial driving, it can also be used to disambiguate how different factors contribute to a degradation of driving performance, for example, by a bottleneck in working memory. As such, it can be used to infer modes of intervention, which alleviate the mental load of the driver by eliminating crucial points of failure in cognitive processing. Furthermore, since cognitive models are inherently explainable in their predictions, they potentially transfer well to hitherto unseen situations, which can be helpful to constrain the output of conventional black-box models used in previous work (Damm et al., 2019). For example, in a stressful highway situation, which might potentially overload the driver, the ACT-R model could be used to identify concrete assistance to the driver such as increased steering automation or highlighting information that might otherwise be stored in working memory.

2.4.1 Limitations

An important point to mention is the overestimation of the steering reversal rates by the problem-state-bottleneck model in the 0-back task (Figure 2.6), which represents normal driving conditions. To understand why this happens, we repeat that in the 0-back, similarly to higher n-back levels, the chunk that encodes the target speed is transferred from the visual buffer to the problem state buffer after a speed sign is encountered. However, we categorized the target speed as control information in the problem-state-bottleneck model meaning that it was eventually stored in the goal buffer. This means that once the information is recalled and stored in the goal buffer, there is no need to retain the information in the problem state and it can be instantly released causing the problem state to be free. With regards to the multitasking behavior of the problem-state-bottleneck model, this means that the bottleneck at the problem state is limited to the recall phase but not the rehearsal phase in the 0-back task, eliminating a large part of the interaction between the two tasks. This shortcoming of the model should be addressed in future models possibly by extending the model to involve a tighter control of the currently followed speed, which would impact the problem state in the ACT-R model. As performing the 0-back task likely requires working memory usage in human participants, evidenced by the non-zero error rate for this task condition, it is reasonable to include such a control-mechanism in a future model. With steering control being dependent on the availability of the problem state, we estimate that this may show decreased driving performance in the model. However, as this was not the primary focus of this work, implementing and validating such a mechanism was out of scope.

2.4.2 Conclusion

In this paper, we provided explainable predictions with regards to the interactions between visuospatial attention and working memory load during driving. These predictions could be used by future automation systems to disambiguate the effect of different external mental loads to evaluate when driver's are in need of assistive technologies. Further studies could attempt to predict brain activation to quantify the contribution of each subtask to overall workload on the brain level. Ultimately, this could lead to reducing mental load as a risk factor for driving and thereby to significant safety improvements in everyday traffic.

Key points

- Interactions between visuospatial attention and working memory load can be accurately modeled by a bottleneck at the problem state resource in ACT-R.
- A central bottleneck, which is independent of the specific tasks does not reflect the impact of working memory load on driving performance.
- Drivers can perform fewer control actions with increased working memory load resulting in decreased steering performance.
- Interactions between visuospatial attention and working memory load do not show at the behavioral level.

2.5 Appendix

Table 2.5. Model parameters

parameter	central	problem state
rt	-100	-100
mp	19	24
ans	0.4	0.5
lf	1.0	0.3
$dist$	0.7	0.75
thc	3	3
$scale$	0.6	0.925
k_{thw}	16	16 * scale
$k_{\Delta thw}$	4	4 * scale
k_{far}	0	0
k_{near}	3	3
Θ_{nmax}	0.07	0.03

Note. The middle column displays the values that have been selected for the central-bottleneck model, whereas the right column displays values that have been fit for the problem state model. The top four values are ACT-R memory parameters and determine the accuracy (rt, mp, ans) and the speed (lf) of items being recalled. The bottom parameters are general driving ($dist$, thc) and steering parameters ($scale$, k_{thw}, $k_{\Delta thw}$, k_{far}, k_{near},Θ_{nmax}) that constrain the lateral and longitudinal control functions.

3

Adapting to the Mind-wandering Driver

This work has been published as: Held, M., Minculescu, A., Rieger, J. W., & Borst, J. P. (2024). Preventing mind-wandering during driving: Predictions on potential interventions using a cognitive model. International Journal of Human-Computer Studies, 181, 103164. The article and the chapter are identical in content. MH, JW, AM, JB planned and conceptualized the research including the design of the models and the analysis of the results. MH developed the models and experiments. MH carried out the analysis. MH wrote the initial draft of the manuscript. JW and JB provided critical feedback and helped shape the research, analysis and manuscript. JB and AM conceived the original idea.

Abstract

In this study, we made predictions on the effects of different interventions by adaptive automation systems designed to prevent mind-wandering while driving. Although cognitive load associated with secondary tasks tends to affect driving negatively, a simple secondary task can improve driving performance when the driving scenario is mundane. Nijboer and colleagues (2016b) have hypothesized that if the driving task is simple, people might start mind-wandering, which interferes with driving. Furthermore, the authors proposed that a simple secondary task, which imposes less workload than mind-wandering, could prevent this from happening and thereby improve driving performance. Automation systems that are informed about and adapt to the cognitive state of the driver could leverage this effect by inducing mild cognitive load during mundane driving scenarios. To test suitable interventions, we combined an existing driver model with an existing model of mind-wandering implemented in the cognitive architecture ACT-R as executable theories of mind-wandering and cognitive processing in driving. Using these different models we show how mind-wandering harms driving performance at the behavioral level and that interventions eliciting mild cognitive load can mitigate this behavioral effect. However, the model indicates that some interventions incur a significant cognitive processing cost that adaptive automation systems must account for.

3.1 Introduction

"Keep playing trivia, it may save your life" - this ominous warning might seem out of place in the context of driving, but is a real-life example of increasing the driver's workload by adding a minor external task to a monotonous driving scenario to prevent driver fatigue, which was responsible for at least 17% of fatal crashes in parts of Australia in 2019 (Transport for NSW, 2019; THC Staff, 2017).

Optimizing the amount of cognitive load of the human operator is the goal of adaptive automation, which aims to increase task performance by changing appropriate aspects of the task to adapt to the current capabilities of the human (Hancock et al., 2013). In the context of driving, the system is envisioned to estimate the current mental state of the driver through sensors and models and, when a critical mental state is detected, redirect the driver towards a more task-appropriate mental state (Byrne and Parasuraman, 1996). To accomplish this, the system could increase or decrease external load to guarantee that drivers are neither becoming fatigued nor mentally overloaded by the driving task. As such, the adaptive automation system aims to avoid excessive workload as well as severe underload (Hancock, 1989).

Reducing excessive workload is desirable as it has been shown to be detrimental to driving performance across different modalities (Horberry et al., 2006; Ito et al., 2001; Strayer et al., 2003; Held et al., 2024b; Alm and Nilsson, 1995; Salvucci and Macuga, 2002). In modern vehicles, the risk of cognitive overload is decreasing by rising levels of automation, which delegate an increasing number of tasks to machines. However, until autonomous vehicles reach high standards of safety, humans are widely expected to remain in the loop using semi-autonomous cars that operate many, but not all, of the driving tasks. Thus, for the near-future, highly automated vehicles that require little human input potentially increase the risk of cognitive underload.

For example, Biondi et al. (2018) monitored drivers in a real-life driving study using state-of-the-art semi-automated vehicles and the participants showed reduced physiological activation and increased reaction times to a peripheral detection task when compared to manual driving. In addition, by fully automating the driving experience in a driving simulator study, Saxby et al. (2013) have induced fatigue resulting in participants showing lower task engagement and increased crash probability. This pattern has emerged in many studies: de Winter et al. (2014) reviewed 32 studies and report that highly automated vehicles lead to a reduction of self-reported workload and situation awareness as well as reduced response times in monotonous automated driving situations.

In semi-autonomous vehicles that maintain an appropriate level of workload, human drivers and cars would form an adaptive "Human-cyber-physical system" (HCPS Schirner et al., 2013; Liu and Wang, 2020). In an adaptive HCPS, the adaptive automation must maintain a model of the human capabilities and allocate resources away from or towards the human driver to continuously ensure that they are optimally engaged in the driving task. For example, in stressful urban environments, the HCPS would recognize the operator's elevated workload level and could assist the driver by highlighting safety-relevant information or suggesting control options. Reversely, in highly monotonous environments, the system could induce low amounts of workload to the driver to keep them engaged in the driving task.

However, inducing additional workload may be a dangerous intervention as it might have detrimental consequences to safety when the system is miscalibrated and induces additional load in environments that are already stressful to the driver. In addition, low cognitive workload does not directly imply that driving performance is decreased and the cognitive mechanisms behind human failure due to low cognitive load in monotonous driving situations are not yet fully understood (Engström et al., 2017). Therefore, it is unsurprising that while many researchers have attempted to assess the cognitive stage of the driver in low workload scenarios (e.g., Baldwin et al., 2017; Bencich et al., 2014; Walker and Trick, 2018; Alsaid et al., 2018; He et al., 2011; Burdett et al., 2019; Zhang and Kumada, 2018; Lin et al., 2016; Pepin et al., 2021; Lin et al., 2021; Zhang and Kumada, 2017; Kutila et al., 2007; Bosch and Mecacci, 2023), few have aspired to leverage this information and increase the cognitive workload to optimize performance (drivers: e.g., Mishler and Chen (2023), pilots: e.g., Schwerd and Schulte (2021). However, any automated system needs to be defined in terms of what changes to the level automation occur at what times (Byrne and Parasuraman, 1996). Therefore, until HCPSs can endeavour to increase the cognitive workload of drivers, the mechanisms behind poor driving performance due to low cognitive load need to be fully understood.

Nijboer and colleagues (2016b) explored the effects of cognitive load in multiple driving scenarios to investigate the effects of excessive mental load, underload and optimal load. The authors contrasted two different driving scenarios (traffic vs. no-traffic). The no-traffic condition was monotonous and boring, posing no challenge to the participants, whereas the traffic scenario required frequent overtaking maneuvers. In addition to the manipulation of traffic density, the authors tested the effects of a secondary task on driving performance. Among others, they contrasted a *no secondary task condition* vs. a *listening condition* during which the car radio was turned on but no task-relevant information was presented. Finally, they implemented a *radio-quiz condition*, during which participants had to verbally answer questions presented on the radio. Similar to previous studies (Engström et al., 2017), the authors found that participants achieved the best driving performance in the listening condition, which imposed minor cognitive load (no-traffic + listening condition). The authors concluded that a minor cognitive task (i.e., listening to a radio) is not distracting enough to substantially decrease driving performance but having no external task in monotonous driving situations decreases driving performance, hypothesized to be due to mind-wandering. Thus, a minor cognitive task might prevent drivers from starting to mind-wander in monotonous driving situations.

However, as we will outline, there is no clear consensus in the literature regarding the effects of mind-wandering while driving and how it might be prevented by secondary tasks. Therefore, we attempted to formalize the existing evidence in the literature regarding low cognitive load, mind-wandering and secondary tasks into core assumptions. Using these assumptions, we built executable models in the cognitive architecture Active Control of Thought - Rational (ACT-R) that enabled us to show the emergent behavior of the models, which are based on these assumptions and simulate the effects of different amounts of cognitive load at different times. In total, using six models, we show how mind-wandering can affect driving as well as potential ways to reduce mind-wandering while driving.

3.1.1 Mind-wandering during driving

Mind-wandering can be characterized as a self-generated train of thought that is unrelated to the current task (Smallwood and Schooler, 2015). As mind-wandering is by definition task independent but still requires mental resources, it is linked to poor performance in a wide variety of tasks, for example, in class-room learning (Smallwood et al., 2007; Szpunar et al., 2013), sustained attention tasks (e.g., McVay and Kane, 2009) and random-number generation (Teasdale et al., 1995). The probability of a person starting to mind-wander and the magnitude of the resulting performance drop typically both shows an inverse relationship with task difficulty (Smallwood et al., 2007; Jin et al., 2020). In other words, as the task becomes harder, humans tend to mind-wander less often but, when doing so, often suffer greater performance losses. Whereas in relatively easy tasks, participants report a greater time spent on mind-wandering but their performance decreases less. However, a consistent performance drop due to mind-wandering can be observed even in low-effort tasks with superficial engagement with the environment (Smallwood et al., 2007).

In the context of driving, mind-wandering is a considerable safety risk because a) driving environments are designed around lowering the mental workload for the drivers, which increases the risk for mind-wandering, and b) even small lapses of attention can result in injury or death. For example, Martens and Brouwer (2013) tested three groups of participants (induced mind-wandering, external distraction and control) to investigate the potential safety hazard caused by mind-wandering in an exploratory driving simulator study. The authors found that induced mind-wandering led to less attentional involvement in the driving task and consequently negative effects on driving performance on a comparable level to external distractions (i.e., secondary tasks). Similarly, a recent study by Pepin et al. (2021) showed that mind-wandering while driving reduces visual components of event-related potentials in electroencephalography (EEG) implying that mind-wandering impacts the visual processing depth negatively. Notably, when a minor task, for example, through audio signals, is induced, mind-wandering can often be reduced (Nijboer et al., 2016b; Yanko and Spalek, 2014; He et al., 2014; Engström et al., 2017). In addition, mind-wandering can also be reduced by a change in driving difficulty as drivers have shown to selectively recover from mind-wandering when the driving situation demands attention, for example, at high-crash rate locations (Burdett et al., 2019), when driving through curves (e.g., Alsaid et al., 2018) or due to sensory triggers in the driving environment (Burdett et al., 2018). Thus, we derive the first two assumptions from the literature: 1) mind-wandering while driving has a negative effect on driving performance because it lowers the (visual) attentional involvement in the driving task, and 2) these effects seem reversible when a minor additional task is induced or when the driving task requires effortful attention.

While less attentional involvement in the main task has generally negative consequences for driving performance, there are inconsistent findings regarding the concrete changes in behavior. For example, research has shown that mind-wandering, induced by road familiarity, can lead to shorter following distances, higher average speeds and increased reaction times to events (Yanko and Spalek, 2013, 2014). Furthermore, Baldwin et al. (2017) report fewer steering reversals and less lane deviation as a result from mind-wandering. While the former is often interpreted as a negative performance metric, reducing lane deviation, that is, driving at the center of the lane, is generally desirable. In contrast, other researchers found either no effects of mind-wandering on lateral control He et al. (2011); Bencich et al. (2014), an increased number of steering reversals or increased lane deviation (Walker and Trick, 2018; He et al., 2014). However, some of the studies involved driving through curves (Baldwin et al., 2017) or were affected by wind gusts (He et al., 2011). Though the researchers attempted to correct for this, regular changes in the driving difficulty could explain the discrepancy in the literature. Acknowledging the vast range of behavior, Alsaid et al. (2018) investigated mind-wandering while driving using a wider range of metrics and taking the road layout into account. The authors found that while driving on straight roads, drivers that mind-wander show a high proportion of steering holds, that is, periods of unchanging steering angles.

Given that both mind-wandering and secondary tasks have negative effects on driving performance, it may be intuitive to categorize mind-wandering as a regular secondary task. While this intuition has shown merit in previous work (Taatgen et al., 2021), it is not undisputed as mind-wandering has shown to activate different neural networks than external tasks (Yanko and Spalek, 2014). Whereas external tasks typically activate the *task-positive network* (Fox et al., 2005; Nijboer et al., 2014; Borst et al., 2011), mind-wandering has been shown to activate the *default-mode network* (Raichle et al., 2001; Mason et al., 2007;

Gruberger et al., 2011). This network is active in relation to self-referential processing (Northoff and Bermpohl, 2004; Gusnard et al., 2001), disengagement from attention-demanding tasks, rest and low amounts of cognitive load (Fox et al., 2005).

In addition, in the context of driving, mind-wandering exhibits a more diverse set of behavioral changes that is often different compared to external secondary tasks. For example, as opposed to the commonly observed *increased* headway when multitasking, mind-wandering drivers often show *decreased* headway and *increased* instead of *decreased* average speed (Yanko and Spalek, 2014; Bencich et al., 2014; Walker and Trick, 2018; He et al., 2014).

Differences between external tasks and mind-wandering are also highlighted in models of mind-wandering. Van Vugt and colleagues (2015) have created a cognitive model of mind-wandering to simulate the effects on task performance. The authors simulated mind-wandering as a process of consecutive retrievals from memory, similar to the concept of a "train of thoughts". During this time of mind-wandering, the model does not perform any actions towards the primary task – unlike in standard multitasking settings (Salvucci and Taatgen, 2010; Wickens, 2002). Furthermore, standard multitasking theories, for example, Wickens' Theory of Multiple Resources (2002), predict similar interference between mind-wandering and driving as between other secondary tasks that do not occupy visual/manual resources such as auditory tasks and driving. These empirical findings lead us to the assumption 3) mind-wandering seems to be functionally and behaviorally different from regular secondary tasks and cannot be adequately simulated by models of multitasking (van Vugt et al., 2015; Yanko and Spalek, 2014; Wickens, 2002; Salvucci and Taatgen, 2010), and 4) mind-wandering appears to induce periods, where no substantial updates are made to the main task (Alsaid et al., 2018; Moye and van Vugt, 2021; van Vugt et al., 2015).

To summarize, the assumptions made from literature that went into the modeling approach were:

1. Mind-wandering while driving has a negative effect on driving performance by lowering the (visual) attentional involvement in the driving task (Martens and Brouwer, 2013; Pepin et al., 2021; Baldwin et al., 2017; Smallwood, 2011; He et al., 2011).

2. The effects of mind-wandering seem reversible when a minor additional task is introduced (Nijboer et al., 2016b; Engström et al., 2017; Yanko and Spalek, 2014; He et al., 2014) or when the driving situation becomes more demanding (Burdett et al., 2018, 2019; Alsaid et al., 2018).

3. Mind-wandering seems to be functionally and behaviorally different from regular secondary tasks and cannot be adequately simulated by models of multitasking (Yanko and Spalek, 2014; van Vugt et al., 2015; Bencich et al., 2014; Walker and Trick, 2018).

4. Mind-wandering appears to induce periods, in which no substantial updates are made to the main task (van Vugt et al., 2015; Moye and van Vugt, 2021; Alsaid et al., 2018).

3.1.2 Current Study

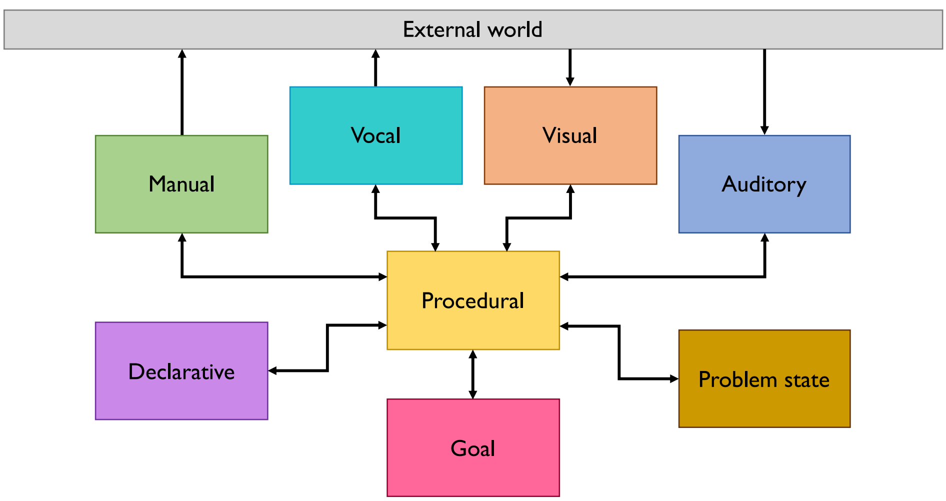
In this study, we simulated the effects of mind-wandering on driving performance and made predictions about four potential adaptive automation interventions (HCPSs) intended to prevent mind-wandering. To this end, we contrast six cognitive models in the cognitive architecture ACT-R (Anderson, 2007) by combining existing models that have been tested in isolation before. We first show the effect of mind-wandering on driving performance by combining Salvucci's seminal driving model (referred to as *focused driving model* hereafter; Salvucci, 2006) with an existing model of mind-wandering (*MW + driving model*; Van Vugt et al., 2015). Secondly, we used the *MW + driving model* to simulate the cost-benefit trade-off that occurs when drivers are presented with cognitive load. The *mild load model* simulates the effects of a system that induces low amounts of cognitive load regardless of the cognitive state of the model, akin to the listening condition by Nijboer et al. (2016b). Similarly, the *intermediate load model* disregards the cognitive state and simulates the effects of an HCPS that induces intermediate cognitive load. Finally, we simulated the effects of two adaptive automation systems, which leverage the information about the current cognitive state of potential HCPSs to induce additional workload when the driver is mind-wandering but lowering cognitive load when the driver is focused. In the *warning model*, there is no auditory input during normal driving but the simulation displays an auditory warning message when the model is engaging in mind-wandering. Finally, the *mild load + warning model* induces mild load throughout the experiment and a warning message when mind-wandering is detected. By simulating and evaluating the different interventions by an HCPS to prevent mind-wandering, we can evaluate the cost-benefit trade off of different interventions.

3.2 Methods

3.2.1 ACT-R

Computational cognitive models allow researchers to test different hypotheses about cognitive processes and evaluate their usefulness by comparing the model's behavior to human behavior. The cognitive architecture ACT-R (Figure 3.1) is a simulated environment, which implements a holistic psychological theory with the same name that attempts to evaluate cognitive processes as part of a coherent system (Anderson, 2007). The architecture consists of different modules and buffers simulating brain regions that specialize in processing specific kinds of information, for example, the auditory module may perceive sounds in the environment. Information can pass through the modules of ACT-R via the modules' respective buffers, which can be filled and emptied by so-called *productions*. Productions are if-then rules that are defined by the modeler. For example, *if* there is a sound in the environment, *then* direct the attention towards that sound. Productions are executed by the procedural module, which takes a central role in ACT-R's organization of modules. The procedural module executes productions serially, creating a central bottleneck in the ACT-R architecture (Anderson et al., 2005; Held et al., 2024b). Next to the procedural module, the most important modules for this study are the declarative module, the auditory module and the goal module.

Figure 3.1. ACT-R cognitive architecture.



The declarative module contains all declarative memories of the model. Facts in memory are represented by chunks that are made up of slot-value pairs, which contain one piece of information. For example, a chunk with the slot-value pairs “capital Paris” and “country France” could encode that Paris (value) is the capital (slot) of the country (slot) France (value). The model can interact with chunks in declarative memory via productions that issue a retrieval request, which places the chunk in the retrieval buffer once it is successfully retrieved. All chunks have an activation level that determines if the retrieval will be successful and at which speed. If the chunk is below a pre-specified retrieval threshold, the chunk is inaccessible (i.e., forgotten).

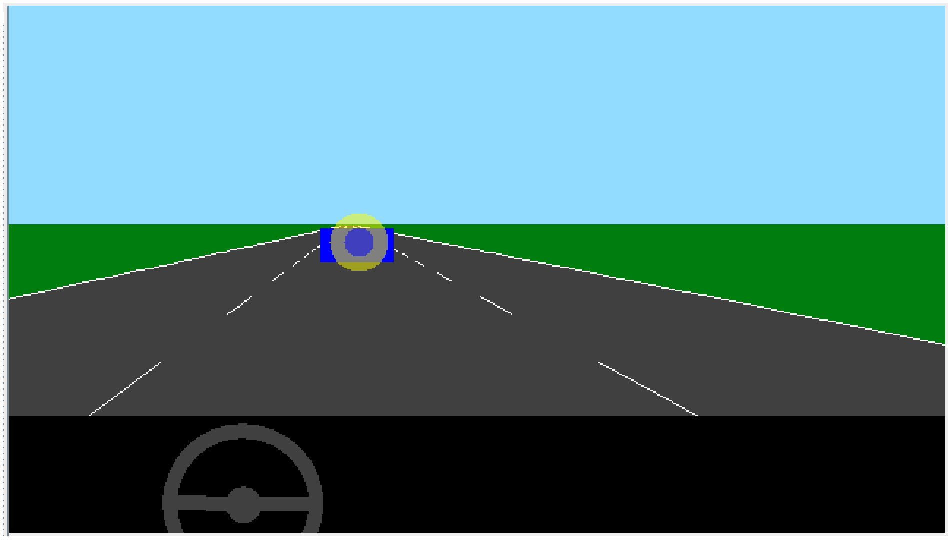
The auditory module has two buffers. When it senses an auditory signal in the environment, the chunk encoding the signal is initially placed in the aural-location buffer. The aural-location buffer contains information about where a sound is coming from but cannot access any information from the audio signal. If the model’s attention is directed towards the sound, the chunk encoding the audio signal is then placed in the aural buffer, which makes the content of the signal accessible.

The goal module holds the currently pursued task goal, for example, driving at the center position of the lane. To pursue more than one goal (i.e., multitask), the content of the goal buffer can either be replaced by a different goal or, as is most commonly done, the model can interleave multiple goals using *threaded cognition* (Salvucci and Taatgen, 2008, 2010). Threaded cognition is a theory of multitasking that has been embedded into the ACT-R architecture to explain multitasking behavior in a variety of different settings (e.g., Borst et al., 2010; Kujala and Salvucci, 2015; Salvucci and Beltowska, 2008; Borst et al., 2010, 2011; Nijboer et al., 2014; Held et al., 2024b). Threaded cognition allows for interleaving multiple tasks based on the availability of resources – ACT-R modules – making use of a greedy and polite principle. The model is greedy, meaning that required modules are occupied as soon as they are available but polite implying that modules are also released as soon as they are not needed. Threaded cognition has been successfully used in various driving situations such as memory rehearsal during driving (Salvucci and Beltowska, 2008; Held et al., 2024b), cellular-phone dialing during driving (Salvucci and Macuga, 2002) or repeated nighttime driving (Khosroshahi et al., 2016).

3.2.2 Simulation Environment

The task in this simulation was to drive on a three-lane highway of standard US Highway lane width (Figure 3.2). The model did not have to perform any lane-changes or overtaking maneuvers but needed to remain at a central position within the central lane. Ahead of the car drove a lead car at a consistent speed of 100 km/h. The lead car did not break or accelerate at any point in the simulation. Depending on the model, audio events were injected into the simulation that the model could attend to. The simulation environment was designed to emulate the monotonous no-traffic scenario of Nijboer et al. (2016b). The experimental framework including the model code can be accessed at: https://github.com/ANCPLabOldenburg/mindwandering-driving.

Figure 3.2. Simulation environment



3.2.3 Driving model

The first model is the *focused driving model* and serves as a baseline for driving performance. It simulates highly concentrated driving with no external distractions (i.e., audio events) nor internal distractions (i.e., mind-wandering). The model executes control operations according to the well-known driving model described by Salvucci (2006). This model maintains lateral as well as longitudinal control by executing a series of five production rules which operate in a loop.

Lateral control is maintained in the model by re-calculating a steering wheel angle in every iteration of the loop. For this, the model observes two objects: 1) a point at the center at the lane, which is ca. 10m away and 2) the lead car driving in front at ca. 100m distance. The model then calculates a steering wheel angle that minimizes the visual angle between the near point and the lead car's position.

Similarly, the driving loop incorporates adjustments for longitudinal control. The implementation used for this model attempts to follow a lead car, which drives a fixed speed without breaking or changing lanes. To do this, the model adjusts its accelerator and brake pedal by an adjusted version of the control law that attempts to follow the lead car at a specified distance. Both the longitudinal and lateral control mechanisms are described in more detail by (Salvucci, 2006).

3.2.4 Mind wandering model

For the second model, we combined an existing model of mind-wandering (van Vugt et al., 2015; Moye and van Vugt, 2021; van der Velde, 2018) with the *focused driving model* to simulate the negative effect of mind-wandering on driving performance. In the *MW + driving model*, the goal chunk in ACT-R contains a slot, which can be in the state “drive” or “mind-wander”. At the end of each driving loop, the model issues a retrieval request for a chunk that encodes the next goal state. Among others, there are two chunks in declarative memory, one for each goal state, which can be retrieved via this request with equal probability. Upon retrieval of either chunk, the model incites another iteration of the driving loop or begins to mind-wander.

When the model is mind-wandering, it executes no driving productions and consequently no control updates to maintain its longitudinal and lateral position at the center of the lane. Instead, the model continuously issues retrieval requests for chunks in declarative memory. The retrieval requests are not specific to any kind of content in memory but request any chunk in declarative memory. This mechanism is akin to remembering an event or situation previously encountered, which is still active in memory. When the chunk is retrieved from declarative memory, which takes a specific amount of time, the model issues another retrieval request for another chunk in declarative memory. This results in continuous retrievals similar to the concept of a “train-of-thoughts”. This implementation decision is in line with the existing model by van Vugt et al. (2015) and based on the assumption that mind-wandering while driving appears to induce periods, where no updates are made (see assumption four) and lowers the (visual) attentional involvement in the driving task (see assumption one).

The model also has a chance to retrieve a chunk that encodes changing the goal state to “drive” (i.e., remembering to drive) to not endlessly mind-wander. In total, the model’s declarative memory contains 30 chunks that will incite further mind-wandering and a single chunk that will cause the model to re-engage in the driving task (Moye and van Vugt, 2021). To maintain comparability with previous models, the models used in this work use the same mechanism. In addition to the first mechanism, mind-wandering can also be interrupted by surpassing a lateral threshold towards the lane edges. This mechanism is based on the finding that drivers interrupt mind-wandering episodes based on sensory triggers in the driving environment (see assumption two). Previous models have shown that a similar mechanism can account for differences in steering performance with different lane widths (Held et al., 2024b).

Multiple tasks that are actively pursued are commonly interleaved in ACT-R using threaded cognition. However, as previously stated, mind-wandering seems to exhibit many differences to standard multi-tasking. Therefore, according to the model by van Vugt et al. (2015), mind-wandering occurs when the goal is in the state “wander” and driving occurs when it is in the state “drive”. Using this describes mechanism, mind-wandering and driving can effectively not be efficiently interleaved. Instead, mind-wandering leads to periods of inactivity during which no active changes to the steering are performed. In contrast, listening to the radio is a common secondary task and, as such, is pursued via a separate goal chunk and interleaved with driving using threaded cognition. In other words, the models can interleave either driving or mind-wandering with listening to music but cannot interleave mind-wandering and driving. This implementation is based on the difference between (auditory) secondary auditory tasks compared to mind-wandering (see assumption three).

3.2.5 HCPS intervention models

To test the effects of a simulated HCPS, we contrasted four models simulating different interventions by an HCPS. All HCPS intervention models perform the driving task and engage in mind-wandering according to the mechanisms described above. However, in addition, each model simulates the effect of a different intervention strategy to prevent mind-wandering (Table 3.1). The HCPS intervention models combine the *MW + driving model* with a listening model developed by Borst et al. (2010, exp. 3), who implemented a simplified model of sentence processing (Lewis et al., 2006). The *MW + driving model* productions and the auditory processing streams are interleaved using threaded cognition.

To cover a range of possible interventions, we first focused on replicating the beneficial effect of mild cognitive load when drivers are prone to mind-wandering. Furthermore, to explore the impact of increasing the cognitive load and show possible adverse effects, we implemented a model with increased cognitive load. While these models frequently engage in mind-wandering episodes, there are also periods of focused driving during which the interventions are mere distractors. For this reason, we simulated a more conservative system that adjusts the intervention to the cognitive state of the model in two adaptive models.

Table 3.1. Overview of the mental workload induced in the different HCPS intervention models. Mild load is referring to the load imposed by the superficial listening stream (step 3-4 in Figure 3.4). Intermediate load refers to the listening stream accessing the content of the speech (step 3-7 in Figure 3.4).

	mild load model	intermediate load model	warning model	mild load + warning
during driving	mild load	intermediate load	none	mild load
during mind-wandering	mild load	intermediate load	intermediate load	intermediate load

The four HCPS interventions are the following:

1. In the *mild load model*, the audio signal does not contain any content and is therefore only superficially processed. This model can be thought of as acoustic music playing to keep the driver alert.

2. In the *intermediate load model*, the audio signal induces a higher mental load by containing spoken words. The model processes the content of the audio signal by issuing a retrieval requests for the meaning of the words from declarative memory. This model can be thought of as listening to an engaging news segment on the radio.

3. In the *warning model*, the audio signal contains spoken words needed to be processed via the lexical processing stream, but these are only presented when the model is mind wandering. This model simulates the effect of an HCPS that displays a verbal warning signal to get the driver's attention and redirect them to the driving task when mind wandering is detected.

4. In the *mild load + warning model*, there are two different audio signals depending on the cognitive state of the model. During driving, the signal does not contain any content and is processed superficially, akin to the *mild load model*. During mind-wandering the audio signal contains spoken words that need to be processed, which is identical to the *warning model*. This model simulates the effect of an HCPS that presents light music to keep the driver alert during the driving segments and a warning signal when mind-wandering is detected.

When an audio event is encountered in the simulation (step 2 in Figure 3.4), there are two possible streams of processing depending on the signal: a) superficial processing for simple audio signals, which guides the attention of the model towards the sound (steps 3-4 in Figure 3.4) and b) deep processing, which, in addition, attempts to access the content of the audio signal (3-7 in 3.4). After the model starts mind-wandering (step 1) and a new audio event is presented in the environment (step 2), it is automatically placed in the aural-location buffer (step 3). During superficial processing, the model does not engage with the audio signal but merely clears the signal from the aural-location buffer (step 4), which can be thought of as passively listening to the audio without attempting to interpret the content. The *mild load model* performs this processing stream and resumes driving after clearing the aural-location buffer.

However, all other HCPS intervention models process the content of the audio signal, which induces an additional processing cost on the models and only resume driving after the last processing step (step 7). During processing of the content, the models do not simply clear the aural-location buffer (step 4), but decode the audio signal, which occupies the aural buffer (step 5). In addition, the model issues a retrieval request for the meaning of the aforementioned chunk (step 6). Upon retrieval of the chunk from declarative memory, the model clears the retrieval buffer (step 7). In the current implementation, we set the activation of these 'meaning chunks' very high, such that these chunk can always be successfully retrieved, as the audio content was simulated to be a familiar language for which the meaning of the words is readily available.

After the HCPS intervention models process the audio signal, be it superficially or further, mind-wandering is interrupted if it has been ongoing. All listening streams redirect the goal state to drive, either after clearing the aural-location buffer (step 4) in the *mild load model* or after clearing the retrieval buffer (step 7) in the remaining models. The simulated interruption of mind-wandering is based on our assumption that (auditory) secondary tasks can prevent mind-wandering (see assumption two).

In all models, auditory stimuli interrupt mind-wandering. While such a deterministic effect is likely unrealistic and drivers may be effectively able to "tune out" the audio signal, we believe that modeling the relationship between auditory features and their (in)ability to interrupt mind-wandering is out of scope for this paper.

Each model run simulated five minutes of highway driving and runs were repeated 50 times for each model.

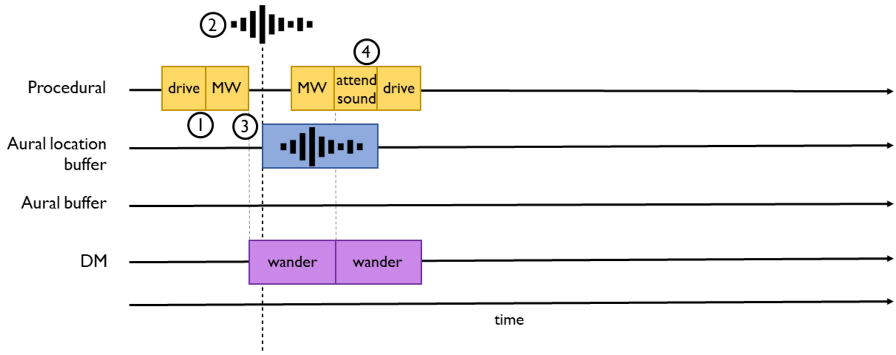


Figure 3.3. Superficial listening stream in the ACT-R architecture

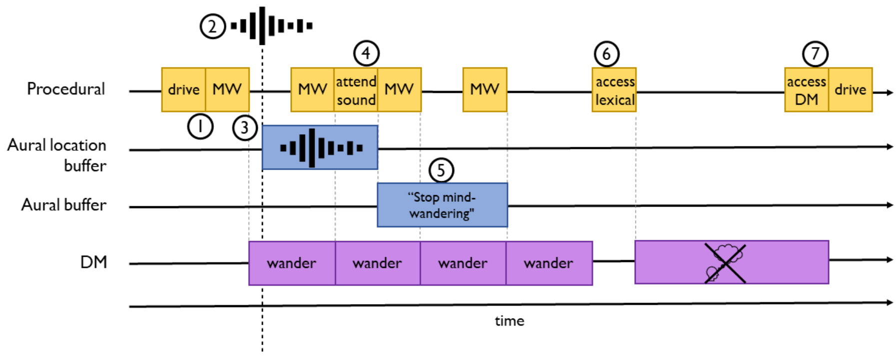


Figure 3.4. Deep processing stream in the ACT-R architecture

3.3 Results

3.3.1 Driving performance

As a measurement for driving performance, we calculated the standard deviation of the lateral position (SDLP, Figure 3.5) and the steering reversal rate (SRR, Figure 3.6) for all six models. SRR has shown to increase with effort spent to perform the driving task and to decrease with time spent on the secondary task (Markkula and Engström, 2006; McLean and Hoffmann, 1975; Held et al., 2024b). As can be observed in Figure 3.5, the *focused driving model* exhibits very steady driving performance with minimal SDLP. At the same time, it exhibits a relatively high SRR compared to the other models (Figure 3.6), implying that while it does correct its steering often, the individual steering movements do not end in large corrections regarding its lateral position on the lane. In contrast, the *MW + driving model* shows a low SRR but relatively high SDLP, implying that it does not perform as many steering corrections but the respective steering corrections are bigger. Thus, mind wandering causes the model swerve more, which can be dangerous in actual driving situations.

Figure 3.5. Standard deviation of lateral position.

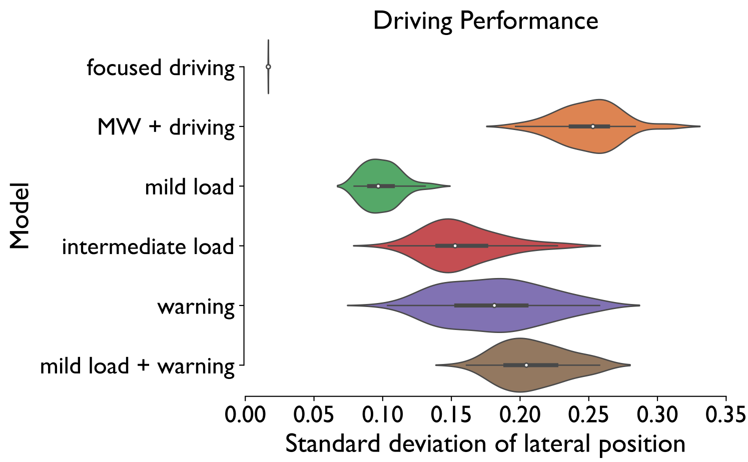
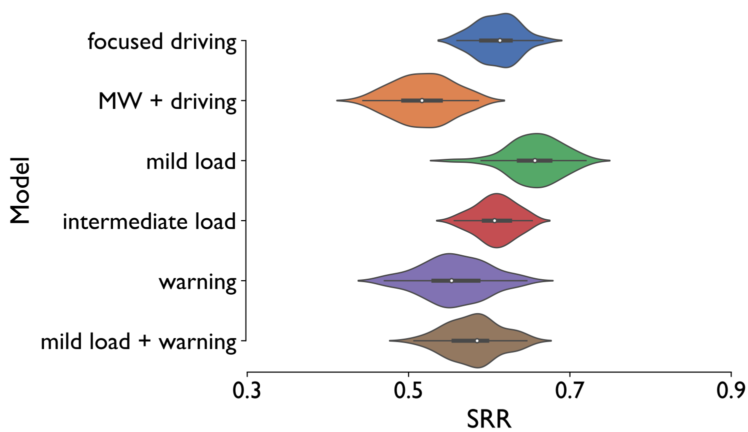


Figure 3.6. Average steering reversal rate in Hz.



The HCPS intervention models attempt to reverse this effect by refocusing the model's attention toward the driving task through the means of a secondary task.

The *mild load model* shows a low SDLP implying that the model is able to stay relatively close to the lane center. At the same time, it shows the highest number of steering reversals surpassing even the *focused driving model*, which only executes driving productions. Taken together, these results imply that the *mild load model* corrects the steering angle frequently, but in small steps. The *intermediate load model* shows similar behavior but incurs an additional cost from engaging with the deeply processed audio signal that influences driving performance negatively. This model shows both fewer steering corrections compared to the *mild load model* and a higher SDLP indicating that the driving performance worsens as the increased processing time competes with the execution of driving control operations.

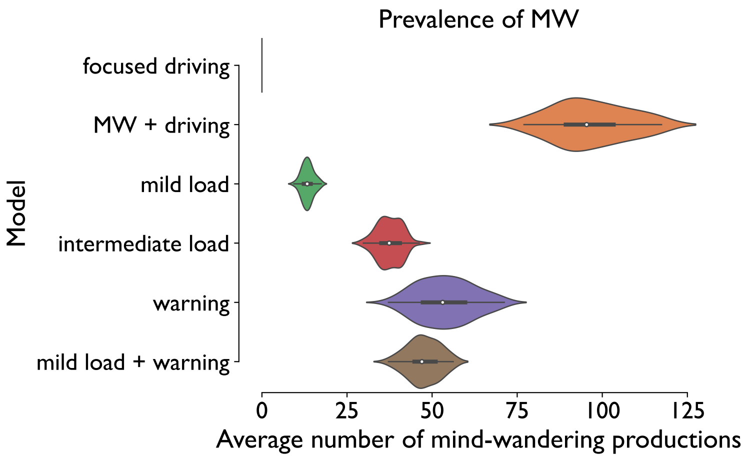
The two HCPS intervention models that adapt to the cognitive state of the model show an even greater cost to driving performance. The *warning model* shows the lowest SRR out of all HCPS intervention models, despite showing a similar SDLP as the *intermediate load model* but with greater variability. During driving segments, the *warning model* performs the same actions as the *focused driving model* but evidently, suffers a great performance cost by the warning signal during the mind-wandering segments that make the total SDLP roughly equivalent to the intermediate load model.

The *mild load + warning model* seems to suffer a similar performance loss as the *warning model* but additionally incurs a cost due to superficial engagement during the driving segments, similar to the drop in performance from the *mild load model* from the *intermediate load model* making *mild load + warning model* the worst performing HCPS intervention model. Notably, the increased SRR compared to the *warning model* is similar to the increase in steering reversals from the *focused driving model* to the *mild load model* implying a flat cost of the mild load induced by the audio signal in both situations.

3.3.2 Mind-wandering

In order to set the effect of mind-wandering on driving into context, we also evaluated how often the individual models would engage in mind-wandering. For this, we counted the number of mind-wandering productions (Figure 3.7) and the length of each mind-wandering episodes per minute (Figure 3.8). Mind-wandering episode is here defined as a period of consecutive mind-wandering productions with no driving productions in between (i.e., a ”train-of-thought”). As we did not implement any mind-wandering productions in the *focused driving model*, it never engages in mind-wandering. In contrast, we implemented mind-wandering in the *MW + driving model* but did not implement an intervention in this model result-

Figure 3.7. Average number of mind-wandering episodes.



ing in many mind-wandering episodes (Figure 3.7. Instead, mind-wandering can only be interrupted in the *MW + driving model* by spontaneously refocusing on the driving task ("remembering to drive") or driving over the simulated rumble strips, the model mind-wanders frequently. The *mild load model* interrupts mind-wandering almost always after only one mind-wandering production resulting in a low number of mind-wandering productions being executed. The *intermediate load model* implements additional processing of the audio signal leading to delayed resumption to driving. In the simulation of the warning model, the warning signal is played at the start of mind-wandering episodes simulating an HCPS that detects mind-wandering episodes and reacts with a warning signal. This results in a higher number of mind-wandering productions and longer mind-wandering episodes compared to the intermediate load model. Finally, the *mild load + warning model* appears to mind-wander less than the *warning model* with a slightly lower average length of each mind-wandering episode.

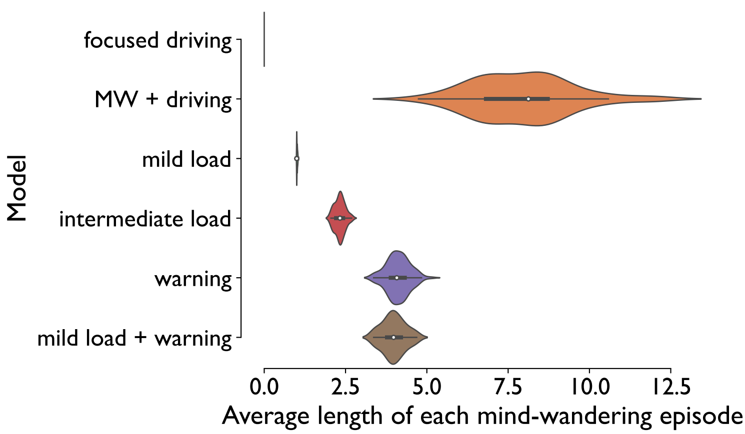
As there were two stopping criteria for mind-wandering (i.e., "remembering to drive" and exceeding a lateral threshold) we also analyzed the proportion mind-wandering episodes that are interrupted or prevented by exceeding a lateral threshold (Table 3.2). As the *MW + driving model* has the longest mind-wandering episodes on average and shows the greatest SDLP, mind-wandering is interrupted mostly by the lateral threshold. However, inducing mild load reduces SDLP and therefore the number of times mind-wandering is interrupted by exceeding the lateral threshold. Similarly, the *intermediate load model* shows an increase in the

Table 3.2. Average percentage of mind-wandering episodes that are stopped by exceeding a lateral threshold.

model	% of episodes
focused driving	0
MW + driving	0.75
mild load	0.05
intermediate load	0.12
warning	0.07
mild load + warning	0.1

lateral stopping criterion. Importantly, the warning model, shows a higher SDLP than the previous intervention models but mind-wandering was interrupted less often by deviating too far from the middle of the road. Finally, this percentage increases in the *mild load + warning model* indicating that although the length of the mind-wandering seems to be similar to the warning model, the *mild load + warning model* does not engage in mind-wandering as often as it exceeds the lateral threshold a greater number of times.

Figure 3.8. Average length of each mind-wandering episode.



We also investigated differences in mind-wandering between the models that involve the lexical processing stream as they each show different mind-wandering behavior despite ending mind-wandering after the same audio processing. Table

3.3 shows the average time that elapses between the start of a mind-wandering episode and the full processing of the audio signal. As can be observed, the *intermediate load model* shows a shorter time interval then the warning and *mild load + warning model* until the audio content is processed, implying an additional cost to attending a new stimulus compared to a continuously displayed one.

Table 3.3. Average time of a mind-wandering episode until audio content is processed.

model	delay in seconds
intermediate load	0.55
warning	0.78
mild load + warning	0.75

3.4 Discussion

In this study, we contrasted six different models to show the effects of different interventions designed to prevent harmful mind-wandering during driving. Although cognitive load tends to influence driving performance negatively in most cases, several studies have observed that low amounts of cognitive load can have a protective effect in mundane driving situations. To investigate how low-effort task may prevent mind-wandering, we first corroborated the hypothesis by Nijboer et al. (2016b) by showing that the *MW + driving model* exhibits decreased driving performance due to mind-wandering compared to a *focused driving model*. Furthermore, we contrasted different intervention strategies by an HCPS designed to prevent the driver from mind-wandering and thereby improve driving performance. Overall, the results indicated that an audio signal imposing minor cognitive load may improve driving performance by interrupting the mind-wandering process. However, when the audio signal induces more cognitive load and the content of the audio signal is processed, this protective effect is mitigated. Finally, we tested two models that adapt the audio signal to the cognitive state of the model and show that adapting to momentary changes incurs high processing costs, which may substantially decrease driving performance bringing the benefits of injecting cognitive load during mind-wandering episodes into question. Together our findings have implications for the design of HCPS that aim at mitigating the safety risks of mind wandering.

Out of all modeled interventions, the *mild load model* shows the best driving performance as it shows the lowest lane deviation with a high number of steering reversals. When this model starts mind-wandering, it clears the content of the aural-location buffer and refocuses on the driving task very shortly after. Evidently, this happens mostly after the first mind-wandering production (see Figure 3.8) leading to no consecutive mind-wandering productions. However, when the model restarts the driving loop, a new steering angle is calculated without knowledge of the previous iteration of the loop as interrupting the driving loop essentially "resets" it. This mechanism leads to a very tight steering control resulting in an even higher number of reversals than the *focused driving model*. Correcting the steering when the car crosses the lane center may lead to higher SDLP as a more gradual change in steering angle can lead to a smoother steering profile.

In the *intermediate load model*, driving performance suffers from the additional processing cost of the audio signal. As productions can only be initiated serially at the procedural module, which leads to a central bottleneck in ACT-R (Anderson et al., 2005; Held et al., 2024b), additional processing of the audio signal competes with the execution of driving productions (see Figure 3.4). As a consequence, the *intermediate load model* executes fewer steering operations leading to a lower SRR and higher lane deviation. As the model only refocuses to driving after the content has been processed, there is also a greater delay until the model resumes driving, which decreases driving performance further.

In this work, we also tested two HCPS intervention models that adapt to the cognitive state. Both the *warning model* and the *mild load + warning model* show a worse driving performance than the other intervention models. At first glance, this may be surprising as the *warning model* follows the same processing as the *intermediate load model* but does not interfere with driving during the driving state. Intuitively, this would lead to less interference overall. However, the timing of the processing may be critical. When the *warning model* starts to mind-wander, it also draws the attention towards the warning signal at the same moment (step 1 in Figure 3.4) and later analyzes the audio signal. In the *intermediate load model*, this process can already be ongoing (e.g., step 3 or 5 in Figure 3.4) when the model starts mind-wandering leading to a faster interruption. However, in the *warning model*, this process starts always from the beginning as soon as the model starts mind-wandering. Thus, the model takes a longer time to resume driving on average.

The *intermediate load model*, shows the largest lane deviation out of all tested models with a slightly higher SRR than the *warning model*. In contrast to the *warning model*, processing the audio signal does not line up with the start of the mind-wandering episode as the *mild load + warning model* tests two different levels of processing depending on the cognitive state. Although, the model attends the audio signal superficially throughout the simulation, it cannot make use of this mechanism. While driving, the aural-location buffer is cleared immediately after the audio signal is perceived without processing the content of the audio signal, which leads to the audio information being lost. Consequently, the model must re-attend the audio signal to initiate the same processing stream as in the *warning model* and *intermediate load model* and suffers a similar cost as the *warning model*. However, due to the additional cost of "mode-switching" between the levels of processing, the re-attending of the audio signal may be delayed when mind-wandering starts shortly after the aural-location was cleared during the driving state. Lastly, the *mild load + warning model* also superficially engages in the audio signal while driving leading to interference with the driving productions during driving segments. Combined, these mechanisms lead to a high lane deviation compared to the rest of the HCPS intervention models causing the model to exceed the lateral threshold that interrupts mind-wandering more often. As the model is redirected to the driving state in theses instances, the number of mind-wandering productions and the length of each episode is relatively low on average compared to the *warning model*.

Taken together, the models tested in this study corroborate the hypothesis by Nijboer et al. (2016b) who proposed that low-effort mental tasks improve driving performance by reducing mind-wandering and, furthermore, show the cost-benefit trade-off between different interventions inducing different levels of cognitive load with regard to driving performance. These findings indicate that when drivers are in danger of mind-wandering, driving performance can increase by interventions of systems that mildly engage the drivers. Moreover, the relatively poor performance of the *warning model* and the *mild load + warning model* indicate that these systems also face the danger of "over calibration", that is, attempting to adapt to momentary changes on a small scale.

3.4.1 Evaluation & Real-life implications

The *MW + driving model* showed an increase in lane deviation as well as a decrease in SRR compared to the *focused driving model*. While the difference between the two models highlights the negative effect that mind-wandering can have on driving, it has to be stated that in a real-life scenario this effect may be exaggerated. This is because focused driving, during which drivers exclusively perform steering and adjusting the accelerator, is unlikely to occur in real life as people perform various other control operations related to driving (such as observing surrounding traffic) in addition to driving-unrelated tasks (such as mind-wandering).

To evaluate the predictions we made in this work, one has to measure mind-wandering while driving, and the effect of interventions. Classifying mind-wandering while driving provides a substantial challenge. However, some researchers have made successful attempts, for example, using EEG both outside and inside of a driving simulator (Jin et al., 2019, 2020; Tang et al., 2023; Baldwin et al., 2017; Pepin et al., 2021). Above-chance level classification has also been shown using functional near-infrared spectroscopy (e.g., Liu et al., 2021b; Durantin et al., 2015), physiological parameters (e.g., Blanchard et al., 2014), and even behavioral driving data (Beninger et al., 2021). Detecting mind-wandering can also be aided by cognitive models that are leveraged to directly inform about the cognitive state of the driver. For example, such attempts have been made by Klaproth et al. (2020), who used an ACT-R model in combination with EEG data to reduce uncertainty about the cognitive state of pilots or Schwerd and Schulte (2021), who estimated situation awareness of pilots using a cognitive model-based state estimation framework. Although to our knowledge there is no research that has successfully made online predictions about mind-wandering while driving to this date, Damm et al. (2019) have made steps towards demonstrating the general feasibility of such an approach by classifying periods of frustrations while driving to facilitate merging through intersections.

In real-life driving scenarios, avoiding undesirable mental states, such as mind-wandering is highly sought (e.g., Unni et al., 2017; Damm et al., 2019) as it unlocks the potential for HCPSs to issue specific interventions to counteract safety-critical cognitive states. However, our work highlights that HCPSs that adapt to mind-wandering need to account for the cost of switching modes of engagement in the secondary task. We show that these adaptations to momentary cognitive changes might incur too high costs to have real-life benefits in some circumstances. Furthermore, our models indicate that inducing mild cognitive load continuously in mundane driving situations may have the best overall effect.

3.4.2 Limitations

In this study, we made predictions about different interventions by HCPSs that adapt to undesirable cognitive states such as mind-wandering. While the outcome of the models are plausible and in accordance with what multitasking theories predict, empirical observations are necessary to strengthen the conclusions we drew from the models.

In this study, we measured driving performance by means of SRR and lane deviation, in an effort to evaluate driving performance similarly to the work by

Nijboer and colleagues (2016b). However, mind-wandering typically occurs in low-stake situations where increased lane deviation or decreased steering operations do not pose an immediate threat. In addition, with increasing automation that can regulate driver behavior in common and trained situations and only needs human intervention in unseen situations, reaction times to changing traffic events or hazard detection might play a more important rule in the future. While our work showed a general effect of driving performance by mind-wandering that might lead to a more specific effect in different driving scenarios, future work might uncover shortcomings that are specific to mind-wandering when explicitly modeling such scenarios.

3.4.3 Conclusion

In this paper, we tested the effect of different interventions to prevent mind-wandering, which has a harmful effect on driving performance. To this end, we first tested the hypothesis by Nijboer and colleagues (2016b), who proposed that low-effort mental tasks could prevent mind-wandering during driving and thereby have an overall positive effect on driving performance. Furthermore, we showed that this effect can be mitigated by increasing the cognitive load or attempting to adapt to small-scale changes of the cognitive state. Further studies could attempt to investigate different driving scenarios that capture safety-critical aspects of mind-wandering such as hazard detection. Ultimately, these models could be used to inform the design of future automation systems that attempt to increase safety by lowering mind-wandering during driving.

4

A Prototype for a Workload Management System

Abstract

While increasing levels of automation often seem to make human contributions obsolete, humans and machines are characterized by different strengths and weaknesses. However, many Human-Cyber-Physical Systems attempting to exploit their individual strengths for safety or performance gains do not take the dynamic capabilities of the human into account. Using the showcase of semi-autonomous driving, we present a concept for a cooperative envisioned control system that adapts to the human state using behavioral and (neuro-)physiological data and integrates cognitive and machine learning based modeling to optimize interventions by adaptive systems. Moreover, we test a first prototype in a low-fidelity driving simulator, which integrates physiological sensors and cognitive modeling to detect extraneous cognitive workload and derives appropriate intervention to alleviate workload. We show that by increasing the level of automation when necessary, the system is able to keep cognitive workload steady in demanding task conditions.

4.1 Introduction

Many engineering approaches aim at cooperatively integrating humans and machine into joint human-cyber-physical systems, in particular in safety-critical applications such as driving Rajkumar et al. (2010). Increasing levels of automation continuously exploit the immense capabilities of machines to analyze complex situations and proposing adequate behavioural strategies within miliseconds. Because of this, integrating machines into safety-critical applications is envisioned to achieve higher levels of safety than would be possible by humans alone. However, while automated systems often seem to replace humans at first glance, at the moment, they cannot compete with human capabilities in unprecedented and therefore unmodeled situations. For example, while an autopilot can control steering operations on common highways, it is the unrivaled capability of the human to flexibly react to situations outside the machine's conception, which causes regulative authorities to insist on engaging drivers in the driving task to this day. For the foreseeable future, humans and machines are therefore often envisioned as two parts of a common system characterized by different strengths and weaknesses forming a *Human-Cyber-Physical Systems* (HCPS) (Hancock et al., 2013). However, only few current designs for HCPSs have information about human capabilities, human understanding of the situation or take the dynamic changes of human capabilities into account Emmanouilidis et al. (2019). Motivated by these needs, our aim is to sketch a model that provides tighter integration of humans and cyber-physical systems into cooperative HCPS. In the showcase we discuss here, we focus on semi-autonomous driving. However, it is our opinion that the general approach is applicable to other areas such as aircraft or power grid control.

One factor of high relevance in the design of cooperative human-machine systems in semi-autonomous driving is the avoidance of cognitive overload. Excessive workload can affect drivers in all situations where the cognitive demand of one task or its combination among multiple parallel tasks exceeds cognitive resources. Cognitive overload poses important safety risks since drivers reportedly have reduced visual capabilities (Lee et al., 2007), increased fatigue (Saxby et al., 2013) as well as delayed or reduced cognitive processes inducing degradation of vehicle control (Engström et al., 2017). It is therefore of great importance for future assistive and automated systems to recognize excessive workload and employ counteractive measures, for example, by supporting or taking over parts of the driving task. At the same time, the introduction of cooperative systems must be attentive towards the potential of introducing novel cognitive load due to information displays and interactions between the human and the system.

4.2 Setting

A common approach to assess human states in a task, such as cognitive processing load during driving, is by training machine learning models on behavioral data obtained in experiments in which cognitive load is manipulated (Yoshida et al., 2014). For human state recognition in driving tasks, data on steering, accelerating or braking behavior are commonly used. To ensure that the model correctly generalizes to real-life driving situations, additional context information, such as traffic or demographic information, can be incorporated into the model (Trende et al., 2022).

Following this argument, adding sensor data pertaining to the human state is another step to improve the performance of the human-state recognition model. Physiological measures like heart rate variability, skin conductance or eye movements and pupil dilation (e.g., Engström et al., 2005) have been widely used to classify human states like cognitive workload. Additional measurements of the states are brain activation measurements like functional near-infrared spectroscopy (fNIRS) (e.g., Liu et al., 2021a; Unni et al., 2017) or electroencephalography (EEG) (e.g., Jin et al., 2020).

Such an idea has been prototyped by Damm et al. (2019) using functional near-infrared spectroscopy (fNIRS) to classify stress and frustration of a driver in a manually operated car. In this work, the trained machine-learning model was used to provide behavioral predictions of human drivers and has been further exploited to time defensive control operations of surrounding automated traffic with the goal to (a) avoid collisions in case the human is about to engage in risky driving manoeuvres while (b) not sacrificing performance by defensive driving when it is unnecessary. This example has shown great potential in increasing safety by an approximately three-fold reduction of human driver's risk of traversing through too short gaps in an oncoming traffic stream.

However, HCPSs that rely solely on behavioral or neurophysiological markers provide rather unspecific information about the human state that is dependent on the continuous functionality of sensors resulting in high epistemic and aleatoric uncertainties in sensing and interpreting these markers.

To compensate these deficiencies, we envision the integration of explainable, cognitive models in such a system, which provide observable behavior and states to evaluate mechanisms that stay constant across different domains. In the context of driving, they could be used to carry out the same tasks as the driver in a real-life driving environment, and inform the HCPS about impending failure due to a critical human mental state such as cognitive overload. For example, the cognitive model could predict delayed reaction times to task-relevant stimuli such as traffic signs (Borst et al., 2010; Held et al., 2024b,a) or reduced steering control Salvucci and Beltowska (2008). The HCPS could then evaluate and validate this state assessment using the machine-learning model classifications, which are based on context information as well as behavioral and brain data of the human driver.

4.3 Envisioned System Structure

In our vision, HCPSs should immediately and sensibly react to — and vice versa influence — human assessment of the situation and impending human behavior, even if these have not been expressed explicitly. The cyber-physical components of such HCPSs shall therefore maintain a domain-appropriate 'mental' image of the states and plans of involved humans that is of comparable quality to a human's mental image of the state and future behavior of the technology and the fellow humans it interacts with. In our showcase of automated driving, the system would maintain a representation that reflects the cognitive workload of the driver as well as how each traffic component contributes to the total amount of workload. The envisioned HCPS of the future, in its domain of operation, exploits that image for comfortable, predictable, and provably safe human-cyber-physical cooperation, thus being able to bridge the dividing line between humans and machines in

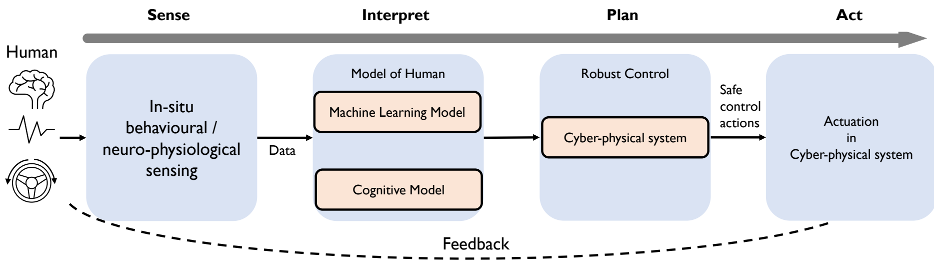


Figure 4.1. A generic HCPS system architecture exploiting in-situ assessment of human state for safe operation.

sensing the environment, behavioral planning and control, and shared action.

To fully integrate the different information sources and react appropriately, we therefore state more formally (see also Figure 4.1) that the HCPS shall comprise the four modules of

Sense: behavioral and (neuro-)physiological sensors to track some — in general rather unspecific — physiological markers correlated with human state,

Interpret: executable, cognitive models of human state permitting to disambiguate and interpret those generally ambiguous markers by relating the observed time series to known human state dynamics and thus filtering the time series in a cognitively plausible way,

Plan: robust embedded control deriving adequate, that is, justifiably safe reactions of the technical, that is, cyber-physical components in the system, and

Act: the cyber-physical technology to implement the selected actions.

The sphere of control in this sense-interpret-plan-act cycle depicted in Figure 4.1 would thereby primarily cover the technical system components, where it implements control actions that are favourable for the human given the perceived and predicted course of the human state.

4.3.1 Cognitive model

We envision the cognitive model to be designed in the Adaptive Control of Thought-Rational (ACT-R) cognitive architecture (Anderson, 2007). ACT-R is a psychological theory implemented as a computer simulation, which allows for the construction of executable, rule-based models. ACT-R consists of multiple, specialized modules (e.g., the procedural module responsible for procedural memory), which may interact via the execution of production rules. Production rules are if-then rules that modify extensions of the modules (the so-called buffers) if specific conditions are met in the environment.

Furthermore, the cognitive model does not merely provide additional data for the system to evaluate, instead, it offers *explainable* predictions that are categorically different to the black-box classifications of mental states by machine-learning models. A clear communication to the driver based on explainable predictions in the context of HCPS is desirable for trust in semi-autonomous systems (Oliveira et al., 2020; Ruijten et al., 2018) and to facilitate the generalization of the HCPSs' predictions regarding regulatory actions to alleviate cognitive load.

In addition, cognitive models can make predictions about human states more robust as they do not rely on momentary data from the human to be available at all times. Thus, in cases of noisy or missing data, cognitive models enable a fail-safe recognition of cognitive workload. A combined approach of cognitive models and machine-learning models could also be beneficial to facilitate the correct generalization of the HCPS to unforeseen situations. As cognitive architectures employ general principles set out by the modeler, the model generalizes predictively to hitherto unseen, rare or borderline cases, which can be helpful when trying to constrain or correct the output of machine-learning models.

4.4 Prototype

4.4.1 Overview

To evaluate our envisioned system structure, we developed a first prototype that incorporated and tested the four modules described in section 4.3, albeit in simplified form. In a low-fidelity driving simulation, human drivers were tasked to drive along a multi-lane highway while performing a strenuous working memory task with five different workload levels. Pupil size was continuously measured via an eye-tracking device (*Sense*). It was then evaluated with respect to its elevation indicating potentially increased cognitive workload (*Interpret*). Finally the system decided between three levels of control input to optimally adapt to the human's momentary cognitive workload (*Plan*), which the human-cyber-physical system realized by diving the shared control of the lateral and longitudinal control of the vehicle (*Act*).

4.4.2 Simulation Environment

The driving experiment, including the adaptive automation system, was programmed in Java building on the code framework by Held et al. (2024b); Kujala and Salvucci (2015). It was run on a 1920x1080 px monitor running Microsoft Windows. To steer, the participants used a Logitech steering wheel in combination with throttle and brake pedal. The behavioral data was sampled at a rate of 200Hz. Eye-tracking was conducted using the Portable EyeLink Duo 2 (SR Research Ltd., Ottawa, Canada) and sampled at a rate of 500Hz. We used nine-point calibration and recorded mono-ocularly (left eye) in remote tracking mode. In this simple prototype, we used the ACT-R model (see below) that performed the same task as the human drivers, as driving automation.

The simulation environment is a task design used by Held et al. (2024b), who adapted a design by Unni et al. (2017). The study consists of a 2-factor within-subject design manipulating the factors of driving difficulty and working memory load.

Driving difficulty was manipulated by the road design, which consisted of either a three lane highway with 3.5m lane width or a two lane construction site with 2.5m lane width. In either condition, the lane was completely straight with surrounding traffic driving according to the speed limit. For this initial demonstration of the prototype, we did not further analyse the effect of road design on the automation level.

Working memory load was manipulated using an modified n-back task using speed signs. Depending on the difficulty of the n-back task, ranging from 0-back to 4-back, participants were instructed to drive according to the n-th sign back. In other words, participants had to continuously watch out for speed signs on the right side of the road, memorize the speed displayed, update a mental list of task-relevant speed signs and recall the appropriate speed. The speed signs consisted of speeds of base ten ranging from 40 km/h to 120 km/h. An overview of this task is displayed in Figure 4.2.

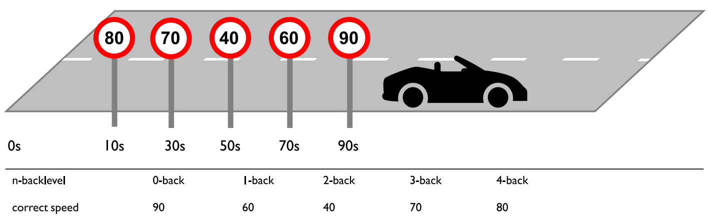


Figure 4.2. Overview of the n-back task. Figure taken from Held et al. (2024b)

4.4.3 Test group

For this paper, we have evaluated the data of 18 volunteers from an ongoing test procedure. The participants were aged between 18 and 27 (mean = 21.5; SD = 2.95). Participants were recruited in the Groningen area and gave informed consent prior to starting the experiment. This research complied with the American Psychological Association Code of Ethics and this experiment was approved by the Ethics Committee of the University of Groningen. Due to faulty measurements of the eye-tracker we had to exclude one participant. Another two participants had to be excluded due to the ACT-R model taking over in out-of-bounds situations, which crashed the simulation.

After completing a training period, participants started the experiment, which consisted of 20 consecutive blocks with a small break in between each block. Each block paired an n-back level with either a highway scenario or a construction site and consisted of 160s of being actively performing the n-back task. The blocks were pseudo-randomized such that each n-back level occurred once in combination with a highway scenario and a construction site scenario resulting in ten blocks. The second half of the experimented consisted of the ten blocks in reverse order.

4.4.4 Adaptive automation

The levels of our adaptive automation system were *no automation*, *partial automation* and *full automation* and determined which responsibilities were distributed to the human and which were distributed to an ACT-R model running real-time next to the simulation. When the automation level was at *no automation*, test users had to perform all driving-related tasks. Increases in automation occurred after a brief warning period of five seconds to either *partial automation*, during which the ACT-R model took over the steering control such that users could fully focus on keeping the correct speed according to the working memory task or *full automation*, during which the ACT-R model performed all driving related tasks, that is, both steering control and driving at the task-appropriate n-back speed.

The automation level was determined by how much the current pupil size exceeded the baseline of the block (cf. Katidioti et al., 2016), which was determined at the beginning of each block. The baseline period began 10 seconds after the block started to ensure that the pupil size had fully adjusted to the visual input until 30 seconds until the first speed sign appeared. The default automation level was *no automation* leaving the participants in full control. The two decision thresholds to increase the level of automation were determined to be $t_{partial} = 1.025 * (baseline + RMSE)$ and $t_{full} = 1.05 * (baseline + RMSE)$, where the baseline period began 10 seconds after the block started to ensure that the pupil size had fully adjusted to the visual input until 30 seconds until the first speed sign appeared and RMSE was a moving root-mean-square error with a moving window of 10 seconds. The thresholds were based off the work by Held et al. (2024b). To suppress a high number of changes in a short time period (typically happening when the pupil size was close to a threshold), we established a period of 20 seconds after every automation level change that prevented additional changes to the automation level.

4.4.5 ACT-R Model

The ACT-R model was a model used in previous work by (Held et al., 2024b). The model combines an extension of the seminal driving model by Salvucci (2006) with an n-back model determining the appropriate speed.

The driving part of the model utilizes five production rules that operate in a loop to observe and evaluate a near and far point in the road. Using the two-point steering model, the model calculates a new steering angle in every iteration of the driving loop designed to maintain a centre position in the lane.

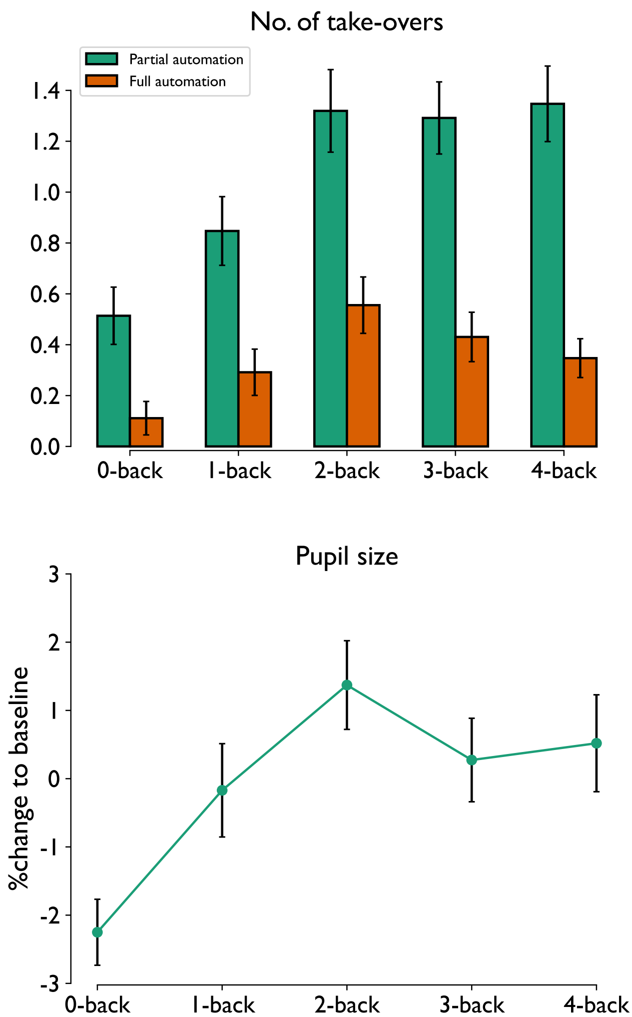
The n-back part of the model maintains a linked list of the task-relevant speed signs by rehearsing the signs starting with the most recent sign (Held et al., 2024b). To then recall or rehearse a speed sign in a 4-back task, the model goes through its rehearsed list until it has reached the target sign.

4.5 Results

In a first analysis, we investigated the number of times the system increases the level of automation across the different working memory load levels (n-back task). As is depicted in Figure 4.3 on the left, we could observe a higher number of increases in the automation in higher n-back difficulties as compared to easier levels of the n-back task. In addition, the system increased the level of automation substantially more times to partial automation than full automation, which indicates, in most cases, cognitive workload did not increase after an initial increase to partial automation. Interestingly, the number of times the automation takes over did not increase past the 2-back, both for partial and full automation, indicating that pupil size and consequently cognitive workload did not further increase in the 3-back and 4-back.

To corroborate our results, we also analyzed the percentage increase of pupil size of participants compared to the baseline period, which reflects cognitive work-

Figure 4.3. Left: Average number of automation increases per block. Right: Average percentage change to baseline of pupil size per block.



load. As can be observed in Figure 4.3 on the right, pupil size increased until the 2-back condition but remained stable in the 3-back and 4-back, indicating that cognitive workload did not steadily across n-back levels but high n-back conditions imposed similar workload with the assistance of the system.

4.6 Discussion

In this work, we presented an early prototype for an HCPS architecture. Our envisioned HCPS utilizes both machine-learning and cognitive models to disambiguate measured sensor data, classify undesirable mental states and finally derive adequate control actions to bring humans to a more task-appropriate mental state. The prototype integrates physiological sensing of cognitive workload via eye-tracking with online cognitive modeling of the human state using the cognitive architecture ACT-R, and derives and communicates appropriate changes to the level of automation to the drivers in a low-fidelity driving simulator. Preliminary analysis of the results show that the systems reacts appropriately to the human driver by increasing automation whenever necessary, thereby decreasing cognitive workload in more demanding circumstances, in effect keeping workload steady across different task conditions – which was the goal of the envisioned HCPS. This contrasts with earlier results by (Held et al., 2024b), who found that, using the same simulation but without an adaptive HCPS, workload steadily increased across n-back levels, resulting in increasingly worse driving performance.

Regarding automation takeover, the current prototype took over control more often in the higher n-back levels compared to the 1-back and 2-back, indicating that the system already identifies dangerous workload level in a low-fidelity driving environment. In addition, the number of take-overs stays constant in higher n-back levels, which could indicate that cognitive workload was already stabilized. Indeed, Figure 4.3 (right) shows that the pupil size and consequently the cognitive workload is stable across higher n-back levels, which is in contrast to earlier results by (Held et al., 2024b), who found that, using no adaptive HCPS, pupil size rises steadily across n-back levels. While this is a simple prototype of our envisioned architecture, it already illustrates two major findings: a) the system detects and reacts appropriately to increased cognitive workload levels in situ and b) extraneous workload can be avoided by interventions of the system.

4.6.1 Outlook: Extending the robust control

In the current prototype, the ACT-R model was only used to take over driving tasks when necessary. However, in our envisioned HCPS, it is also used for online estimation of cognitive workload. A particularly intriguing use of cognitive models in embedded control applications for HCPSs is to not only exploit them for detecting and adapting to a human's state, but to use the model itself for reasoning about the impact of cyber-physical control actions. Exploiting the model of the human driver for model-predictive control within the embedded controller in the driving application, would advance the HCPS to the next level by not only adapting the control actions to the current human state but also to the modeled future state of human driver.

We envision this verification of the control actions to be an extension of the *plan* module in the architecture and be integrated by interpreting the interaction between environment and human as a two-player reactive game graph (Alur, 2004) in the timed game form (Behrmann et al., 2007). Here, one player is the cyber-physical system generating the inputs to the cognitive model, that is, adaptive control actions to prevent undesirable mental states and the other player is the human 'deciding' about internal human-state changes and observable reactions visible to the other player, that is, changing or not changing to a more desirable mental state. Winning-strategy construction in such a reactive game would provide a reliable way of driving a human into a set of (in the imminent situation or generally) desired states.

In order to automatically synthesize the embedded controller for the safety-critical human-centered systems, we would first use the ACT-R model of human behavior. The model, including the architectural components and task-related knowledge, can then be translated into a network of Timed Automata (Alur and Dill, 1992). The approach to formalize the ACT-R cognitive model by Timed Automata networks, called TA-ACT-R, has previously been introduced by Langenfeld et al. (2019). The second player, i.e. the control player, is then introduced by partitioning the actions of the TA-ACT-R model into environmental actions and human state changes. This leads to transitions of the automata network being split into two parts, where one part is controllable by the human and one is controllable the cyber-physical system (essentially the inputs to the human model's perceptive components), yielding a timed game. We then employ reachability and safety properties to define the control objectives. The control synthesis for the HCPS is realized by finding winning strategies in the timed game employing existing on-the-fly algorithms for strategy construction within timed games (Cassez et al., 2005). Ultimately, the generated HCPS control strategy comes in the form of a function that maps the current state of the network of timed automata into control actions.

4.6.2 Limitations

While our prototype demonstrates the integration of all four modules of our envisioned system architecture, the current version simplifies the procedure in many aspects, which carries obvious limitations. For example, acquiring data from multiple modalities can make sensing more robust in cases of missing or faulty sensor data. In addition, further optimizations to the signal processing can be made to disambiguate the signal, for example in the case of eye-tracking employing Kalman filtering to reduce variance (Pillai et al., 2021).

Furthermore, we only use the ACT-R output in this work to take over the driving task and in future analysis to generate post-hoc estimations of cognitive workload. While it could in principle be used already to estimate workload in situ, the current prototype does not include the translation into Timed Automata networks. Though it becomes obvious from the above that we currently have a consolidated idea how to handle symbolic models (in particular, cognitive architectures) in such procedures, the caveat here is that major epistemic uncertainty about the level of correspondence between actual human behavior and the cognitive model employed as a game graph is unavoidable in such a setting. Strategies that work perfectly on the model may consequently fail in practice. However, hybrid-AI models combining (symbolic) cognitive architectures with (subsymbolic) machine-learnt models could also provide significant gains here, because their hybrid nature may help detecting and flagging epistemic uncertainty — in which case robust control can alleviate the problem — or even trigger learning-on-demand effectively reducing epistemic uncertainty on future encounters of similar situations.

4.6.3 Conclusion

In this work, we show the first prototype for an envisioned system architecture for an adaptive Human-cyber-physical system incorporating sensing physiological data, deriving the human state, planning and actuating control operations to bring human drivers to a more task-appropriate mental state. As envisioned, the prototype resulted in steady cognitive workload for the users, even though task conditions became increasingly more demanding.

5
Situation Awareness and Decision Making

This chapter is currently being prepared for submission. MH, JW and JB planned and conceptualized the research including the experimental design and the analysis of the results. MH co-developed experiments. MH conducted the experiments and carried out the analysis. MH wrote the initial draft of the manuscript. JW and JB provided critical feedback and helped shape the research, analysis and manuscript.

Abstract

Situation awareness (SA) and decision making are critical cognitive processes during complex maneuvers such as left turns at intersections. However, studying their neural basis under realistic driving conditions remains challenging due to high technical requirements. In this study, we used eye-tracking and an fMRI-compatible virtual reality driving simulator to investigate the neural correlates of SA and decision making during left-turn scenarios with varying levels of cognitive load. Participants performed a left-turn maneuver through a file of cars with varying gaps between the cars while also performing a concurrent working memory task. Our results show an increased pupillary response when participants approached the intersection and, again, when they decided to cross. Additionally, we observed a decline in the secondary working memory task performance around the intersection event. Using eye-tracking to identify relevant stages of situation awareness and decision making, we found that the visual cortex is activated early during a left-turn maneuver. Furthermore, we found sustained activation in the precuneus, ventromedial prefrontal cortex and temporoparietal junction while participants evaluated traffic and crossed the intersection. As such, this study provides (neuro)physiological evidence for theoretical models that have proposed a sequence of cognitive stages of perception, comprehension and projection in a realistic scenario.

5.1 Introduction

Although driving is a daily activity for much of the population, it remains one of the most dangerous tasks people regularly undertake. Among the many challenges drivers face, left-turn maneuvers are particularly hazardous and prone to human error (Harding et al., 2014). Although there is a belief that increasing automation will eliminate human participation in traffic, many researchers predict that traffic will consist of mixed traffic between semi-autonomous vehicles that automate some but not all driving tasks, and human-driven vehicles in the foreseeable future (e.g., Guériau and Dusparic, 2020; Fernandez et al., 2021). In order for machines and humans to cooperatively interact as human-cyber-physical systems, we require machines that understand the limitations and capabilities of humans situation awareness (Hancock et al., 2013; Damm et al., 2019; Bengler et al., 2023). For this, we need basic research in realistic situations to understand the neuronal basis of such safety critical actions like left-turn maneuvers and inform future technical systems.

The concepts of situation awareness and decision making have a long history in human factors research as they are believed to be major contributors to human failure in safety-critical scenarios like turns through oncoming traffic. The most well-known conceptual framework of situation awareness has been given by Endsley (1995). Endsley defines situation awareness as a hierarchical process consisting of three stages. The first stage, *perception*, comprises gathering of task relevant information in the scene, for example, looking at a traffic sign or other traffic members. The second stage, *comprehension*, refers to a process of integrating the perceived stimuli into a cohesive mental image of the world, possibly building on stored knowledge from prior experience. For example, understanding the crossing layout, the positions of other cars and how they relate to one's planned trajectory. Lastly, *projection*, describes a stage of mentally forecasting the future to predict upcoming changes in the environment, for example, by predicting the behavior of others. This awareness of dynamic situations can serve as a basis for a decision, for example, to turn through a specific gap between oncoming cars. Although empirical evidence that directly validates this framework remains elusive, numerous studies have characterized factors that influence situation awareness. For example, impairing the perception by making relevant vehicles only appear in the peripheral view or reducing the contrast of the scene has shown to decrease situation awareness (Park et al., 2022; Jia et al., 2024). Similarly, increasing traffic density or making agents less predictable has shown to decrease situation awareness, suggesting that integrating the stimuli and predicting their trajectory is vital for situation awareness (Park et al., 2022; Van De Merwe et al., 2024).

Despite the evident usefulness of the framework, fundamental challenges remain in operationalizing and measuring these internal cognitive stages in the real-world or in high fidelity simulations. To this date, the most widely used method to assess SA is the Situation Awareness Global Assessment Technique (SAGAT) questionnaire (Endsley, 2020, 1988). However, the SAGAT relies on stopping the simulation to question participants about the scene, making it impractical for real-life assessment. In contrast, (neuro)physiological measurements have shown promise to provide time resolved and specific indicators of cognitive states in realistic driving scenarios that can comprise a mixture of concurrently changing and emotional processes.

Researchers have successfully used physiological signals to predict cognitive states such as frustration or cognitive load, which adversely affect driving performance (Trende et al., 2022; Unni et al., 2017; Held et al., 2024b; Damm et al., 2019). Yet, as well-defined (neuro)physiological correlates of SA are lacking, physiological measures to assess SA remain largely underutilized. In practice, the technical requirements to investigate neurophysiological structures in a realistic driving scenario are high, which is why many researchers rely mostly on eye-tracking, which is easier to obtain. Eye-tracking gives access to overt attention patterns and can serve as a proxy for information sampling. However, while it may offer crucial insight into what drivers look at, it remains ambiguous with regard to the levels of situation awareness achieved (Salmon et al., 2008; Zhang et al., 2023).

To address this, we propose a combined approach using both eye-tracking and functional magnetic resonance imaging (fMRI) to investigate the neural mechanisms underlying SA and decision making. Based on the Endsley model, we conceptualize situation awareness in the context of a left-turn maneuver as the product of a sequence of partially overlapping cognitive phases: 1) information sampling, that is perceiving the surrounding traffic and road, 2) comprehension of the scene, that is understanding the crossing layout, the position of relevant agents and their spatiotemporal relation to one’s own desired trajectory 3) predicting the future state, that is anticipating the behavior and trajectory of cars and evaluating the risk of crashes for upcoming gaps. This sequence is followed by making the decision and performing the action, referring to the initiation and execution of the left-turn maneuver. We used eye-tracking and behavioral data to temporally distinguish intervals of the described sequence during left-turn maneuvers and further used these intervals to analyze concurrently recorded fMRI images with the aim of identifying distinct neural correlates of situation awareness and decision making.

Left-turn intersections are among the most extensively researched driving scenarios due to their high contribution to vehicle accidents (Harding et al., 2014). A previous study by Schweizer et al. (2013) used a virtual reality driving simulator combined with fMRI to investigate neural activity during left-turn decisions in traffic under varying levels of risk. The authors compared the brain activity when turning at an intersection with and without traffic against driving on a straight road. Their findings revealed that left-turn scenarios activated posterior regions including the precuneus, visual and parietal cortices and the cerebellum compared to straight driving. Schweizer et al. (2013) concluded that left-turn scenarios engage the posterior brain areas due to increased demands of visual-motor integration.

In addition, the authors also investigated the effect of an auditory secondary task, in which participants were instructed to answer true or false questions while driving. This is relevant as, driving, including turning at intersections, is often comprised of multiple sub tasks that have to be performed concurrently and there is broad evidence that human decision making at intersections may be inconsistent when the tasks exceed their cognitive capabilities (e.g., Zgonnikov et al., 2022; Ratcliff and Vanunu, 2022). Under additional cognitive load, Schweizer et al. (2013) found increased activation in the dorsolateral prefrontal cortex (dlPFC) in left-turn scenarios as opposed to the ventrolateral prefrontal cortex (vlPFC) in straight driving situations. They concluded that the presence of a distracting auditory task enacted a shift of activation towards anterior brain regions such as the dlPFC, which has been linked to a variety of functions such as attention and working memory processes but also to automated decision making (Sakagami et al., 2006). This conclusion aligns with evidence from controlled experimental studies that have suggested that when cognitive resources are exhausted, humans may not be able to maintain a fully rational, analytic approach to decisions but instead may rely on heuristics or simplified mental models based on an accuracy-effort trade-off, which can lead to suboptimal or riskier decisions (Gigerenzer and Gaissmaier, 2011).

However, when mono-tasking, results by Vorobyev et al. (2015) revealed increased activation in the dorsalmedial and medial prefrontal cortex (dmPFC, mPFC; BA9 and BA10, respectively) during risky crossing decisions compared to cautious stopping and waiting for the traffic to pass. Interestingly, the effect size was increased for participants who were identified as low-risk takers, leading Vorobyev et al. (2015) to infer that increased cognitive effort is reflected in a higher activation of the dmPFC and the mPFC. This conclusion aligns with prior research that shows that activation in the mPFC predicts comparatively risky decisions that presumably need more cognitive effort to choose (Matthews et al., 2004). In other words, risky decisions due to a lack of available cognitive resources may predominantly activate lateral prefrontal areas (vlPFC, dlPFC), risky decisions accompanied by increased cognitive effort may be reflected by activation in medial prefrontal areas (dmPFC, mPFC).

To summarize, the assessment of situation awareness based on neurophysiological sensors is difficult due to the lack of well-defined and unambiguous neurophysiological markers. Furthermore, these markers, when identified, may be subject to change when drivers use alternate strategies due to limited cognitive resources. The current study therefore aimed to investigate the neural correlates of situation awareness during left-turn maneuvers under varying levels of cognitive load. In an fMRI-compatible virtual reality driving simulator, participants were instructed to perform a fast but safe left turn at a busy Y-intersection with continuous traffic but varying gap sizes between vehicles. While executing this maneuver, participants also performed a working memory task (easy vs. hard). Our primary goal was to determine how different phases of SA acquisition and subsequent decision-making could be inferred from their neural correlates. We hypothesized that under high working memory load, drivers would rely more on fast, heuristic decision-making rather than slow, analytical evaluation of gaps. At the behavioral level, this would result in reduced time to reach a decision to cross the intersection and accepting smaller gap sizes during the hard working memory task. At the neural level, we aimed to characterize the brain regions involved in left-turn decision-making using fMRI. Based on previous studies, we expected left-turn maneuvers to activate posterior brain areas, including the occipital-parietal regions, cerebellum and the precuneus, which are involved in visual-spatial processing and visuomotor integration. Additionally, we predicted activation in the dlPFC and vlPFC, which may reflect increased engagement of working memory and attentional control as participants need to manage their cognitive resources.

5.2 Methods

5.2.1 Participants

We recruited 30 subjects. All participants were in possession of a valid driver's licence in Germany at the time of the experiment. They gave their informed consent prior to the experiment and received 12€/hour as a reimbursement. The experiment complied with the American Psychological Association Code of Ethics and was approved by the Ethics Committee of the Carl von Ossietzky University Oldenburg. All participants had normal or corrected-to-normal eyesight.

5.2.2 Experimental Design

The experiment was conducted with an fMRI compatible driving simulator (Figure 5.1). The driving simulation was constructed using the driving simulation software SILAB (Würzburger Institut für Verkehrswissenschaften), and the simulated car was controlled using a steering wheel and two pedals for braking and accelerating, respectively. As opposed to the norm in real driving, the brake had to be operated with the left foot to restrict movement within the MRI machine. In addition, the simulator consisted of a steering wheel with two response buttons that was placed above the participant's stomach. The experiment was projected in 1280 x 1024 (120 Hz) resolution on a screen ca. 50cm behind the participants that was visible via a mirror. The oval screen had a width of 53cm and a height of 28cm at the center resulting in a visual angle of ca. $55°$ horizontally and ca. $31°$ vertically.

The experiment used a within-subject design in which the factor working mem-

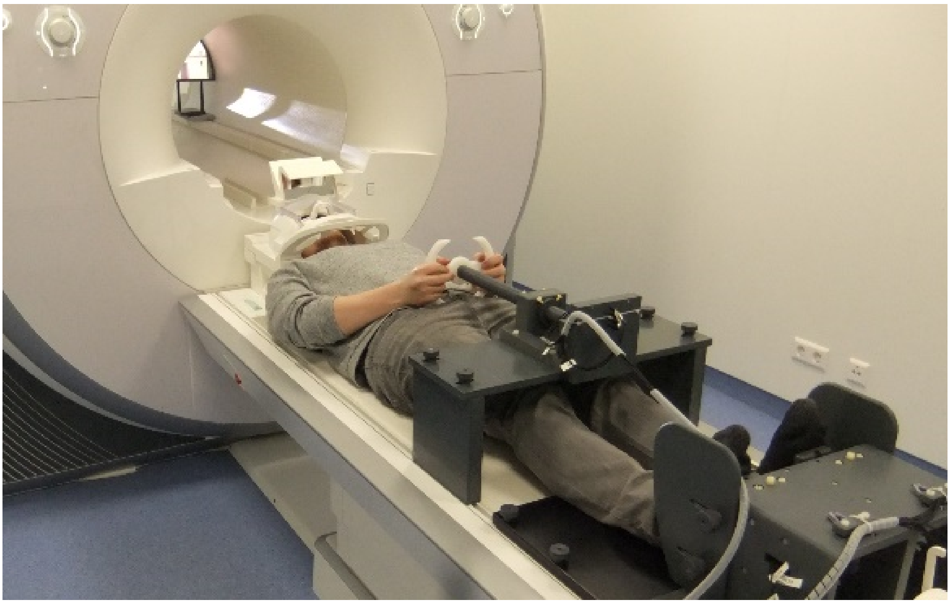
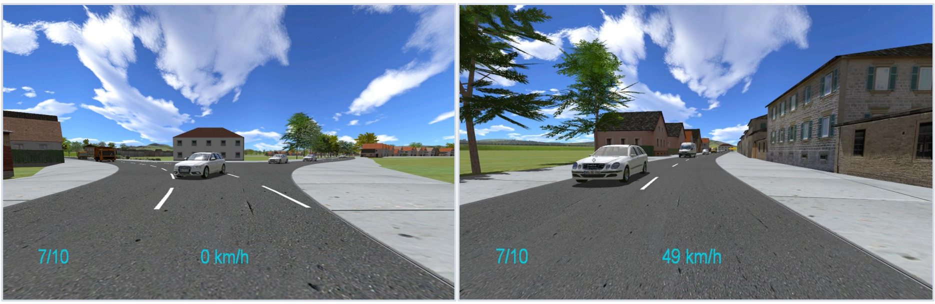


Figure 5.1. Setup of the MR compatible driving simulator

ory load was varied. Participants drove on a quasi-circular track along an urban road and intermittent intersections. While driving, they performed an auditory n-back working memory task. At all times during the experiment there was light traffic in the opposite direction to motivate participants to stay in the right lane. During the driving part of the experiment the participants were instructed to maintain a constant speed of 50 km/h until they reached the next intersection. The intersections had a Y-layout in which participants had to perform a left turn through traffic crossing from the right (see Figure 5.2). At each intersection, participants were instructed to come to a full stop before crossing. To enforce this behavior, the first gap between approaching cars from the right was prohibitively small (15m) such that participants had to stop at the intersection.

After stopping, participants had to decide when to cross the intersection through an appropriate gap in the row of cars that was crossing the intersection from the right. The opposing traffic drove at a constant speed with varying gap sizes between vehicles. Participants were instructed to cross the intersection by finding an appropriately sized gap between the cars as soon as possible while remaining safe and complying to all traffic rules. To ensure that participants could not make an illegal maneuver to cross the intersection by momentarily swerving into the other lane, we added a stationary construction vehicle at the opposite lane of the target direction. By pressing a button on the steering wheel, participants indicated the time point when they made a decision on which gap to take. Note that this did typically *not* coincide with the point at which they resumed driving; they were explicitly instructed to press the button at the moment of the decision. They only started driving when the gap they decided for was close enough.

Figure 5.2. Screenshot of an example trial.



Participant's view when evaluating gaps at the intersection (left). Participant's view when driving between intersection (right).

Each crossing maneuver involved 16 oncoming cars, which resulted in 15 potential gaps to cross the intersection. If participants were unable to cross in between the row of cars, they could wait until all opposing vehicles had crossed the intersection, though this rarely occurred outside the training sessions. We designed the gap sequence with the goal to maximize variability in the waiting time at the intersection while still ensuring that participants needed to evaluate every seen gap. Our aim was to generate gap sequences for which the cumulative probability to cross after all gaps were seen was between 95% and 100%. To accomplish this, we first calculated the probability of crossing given a certain gap size based on the results of a pilot experiment with 10 participants. Afterwards, we sampled gaps at each intersection from a gamma distribution as our intention was to simulate crossing scenarios in which most gaps are small but some are wide enough to cross through. The gamma distribution was fitted to chosen gap width data from ten pilot participants and cut off at 10m and 70m as these gaps represented the extreme edges of uncertainty towards gap acceptance. Next, we sampled sequences from the distribution and selected those sequences that included gap sequences that the cumulative probability to cross the intersection given the 14 sampled gap sizes was 95%-100% (see Figure 5.3).

Working memory load was manipulated by an auditory n-back task with two possible difficulties (0-back vs. 3-back) that were varied between blocks. Participants were listening to an audio recording of numbers between zero and nine. After the start of the experiment, a number was played via headphones every five seconds throughout the whole trial. In the 0-back condition, participants were instructed to press the right button on the steering wheel every time they heard a zero. In the 3-back condition, participants needed to react by pressing the right button of the steering wheel if the last number was identical to the number they heard 3 numbers ago. In other words, in a sequence of *3-4-7-6-4-7* participants needed to react to the second four and the second seven. They did not need to give a response to the other stimuli. We selected a challenging 3-back task because a pilot experiment revealed that a 2-back task did not reach cognitive processing capacity and most participants achieved very high performance in both tasks. On average, 30% of n-back stimuli were targets, which participants needed to respond to in either condition. We rewarded a monetary bonus of 0.50€ if the participants made no collisions with other cars and three or fewer mistakes in the n-back task.

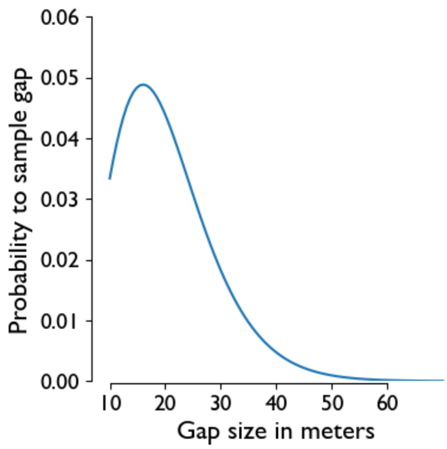


Figure 5.3. Probability to sample a gap.

5.2.3 fMRI Scanning and eye-tracking

The brain images were acquired using a 3T Siemens Magnetom Prisma scanner equipped with a 20-channel head coil. The functional images were acquired through 48 axial slices with a multiband echo planar imaging sequence (repetition time = 850ms; echo time = 30ms; voxel resolution = 2.53x2.53x2.50mm; field of view = 192mm; flip angle = 62°; multiband factor = 4). Anatomical T1-weighted images were acquired by 224 saggital slices using an MPRAGE-Sequence (repetition time = 2000ms; echo time = 2.07ms; inversion time = 952ms; voxel size = 0.75x0.75x0.75mm; field of view = 240mm; field angle = 9°).

In addition, eye-tracking data were acquired using an MRI compatible Eyelink 1000 device (SR Research Ltd., Ottawa, Canada). For this set-up we selected nine-point calibration with mono-ocular tracking (left eye) in remote tracking mode with a sampling rate of 1000Hz via the mirror in the scanner.

5.2.4 Procedure

First, participants were asked to give informed consent to participate in the study. After a brief introduction to the task, we conducted a training session outside of the fMRI scanner room in a separate environment using a steering wheel and gas pedals in a seated position. Participants were free to train as much as they needed to get comfortable with the controls and the task. The training session involved five intersections in the 0-back condition and five intersections in the 3-back condition. Participants could voluntarily repeat the training.

Afterwards, we prepared participants for the fMRI scanner. After safety instructions were given, we placed the participants within the fMRI scanner and assisted them in practicing using the controls while lying down. Finally, we calibrated the eye-tracker and started the experiment.

Before the experiment began, a structural T1-weighted scan was recorded. The main experiment lasted approximately 70 minutes with eight blocks and a small break between blocks. Each block of the experiment lasted about seven minutes and consisted of ten intersections with intermittent driving segments to get to the next intersection. The working memory load level was counterbalanced and changed between blocks.

After the experiment, participants were asked to fill out a questionnaire, which obtained demographic information as well as subjectively perceived working memory load levels and driving experience.

5.2.5 Analysis

We excluded all fMRI runs during which participants showed excessive movement ($> 3mm$ movement along one axis). This led to the exclusion of twelve runs out of 240. In addition, we excluded the data of all intersection trials during which the eye-tracker lost the signal due to participants not fully opening their eyes. We further excluded 38 trials using this criterion. Thus, in total, we excluded 158 trials

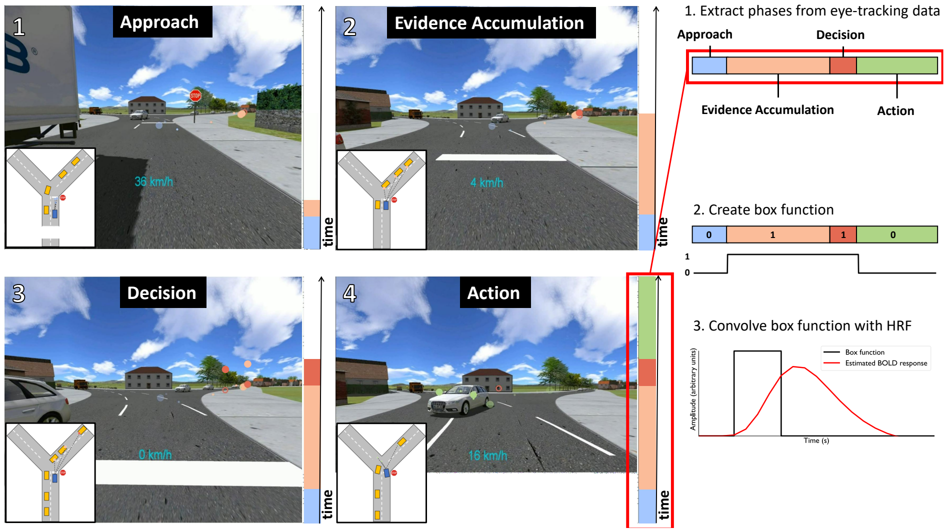


Figure 5.4. Classification of phases during crossing. Colors represent the presumed phase of decision making. blue = Orange = evidence accumulation, red = moment of decision, green = planning and executing action. An illustration of how the decision making regressor was generated is depicted on the right.

out of 2400 or 6.5% of the data.

For the analysis of the intersection crossing behavior, we evaluated the gaps that participants rejected or accepted. As participants drove different speeds and arrived at different times at the intersection, in many cases, they already missed a few potential gaps before coming to a full stop. Thus, we only evaluated those gaps that were visible after participants stopped at the intersection. We analyzed the gap acceptance by fitting a logistic regression model on the probability to take a gap and the gap size.

Eye-tracking

Eye-tracking data were preprocessed by interpolating between eye-blinks and removing signal artifacts using the procedure described in Mathôt et al. (2013a). Furthermore, we used the eye-tracking data to build regressors for a GLM analysis of the fMRI data. Specifically, we assigned two different labels based on the time and location of the participants' gaze fixation during the intersections. When the participants fixated on the intersection, the crossing traffic or the crossing road before they made the decision, we labeled the time period of the fixation as *evidence accumulation*. The fixation during which the participants made the decision as indicated through the button press, we labeled as *decision making*. All other fixations during the intersection period did not receive a label. Fixations on other locations (e.g., stop sign, road markings) are unlikely to contribute towards making a decision to cross. Furthermore, fixations following the decision could not contribute to the decision anymore and were assumed to be contributing towards implementing and planning the action of crossing through the intersection. Figure 5.4 illustrates a showcase of this method for the different phases of an example trial. A video demonstration using an example trial can be found at the Open Science Foundation under https://osf.io/6st4f/files/uzwq9.

fMRI preprocessing

For fMRI preprocessing, we used the standardized fmriprep pipeline, which utilizes FSL and freesurfer to perform motion correction, coregistration, normalization, segmentation of the brain tissue among other things (Esteban et al., 2019). For a detailed specification of these steps, please refer to the supplementary material. Lastly, we smoothed the images using a 6mm kernel.

GLM

The nilearn software package was used to analyze the functional images using a general linear model (GLM) and to perform a first and second-level analysis to characterize the effects of the situation awareness acquisition and decision making under varying cognitive load (Abraham et al., 2014). We included 18 regressors into the first-level analysis of the GLM (eight regressors of interest and 10 nuisance regressors). Importantly, we used the labeled time periods based on the fixations to construct two regressors to model the SA acquisition and decision making phase.

In the first regressor, we coded time intervals from fixating crossing traffic including the decision with 1 thus capturing the entire period of situation awareness and decision making. This regressor served as a probe to define regions of interest that were modulated during the specified interval. The second was a modulated regressor that coded all fixation periods towards traffic as -1, except for the the fixation period during which the decision button was pressed (encoded as 1). The second regressor was then orthogonalized with respect to the first causing it to capture only the specific activation that leads to making a decision to cross. All other time periods were coded as 0 in both regressors. To model the encoding of the n-back stimuli, we added a regressor that was 1 during the presentation of the n-back stimuli. Furthermore, we added two regressors for the response buttons (left and right, respectively), and three regressors for driving actions (acceleration, breaking, steering). The regressors of interest were convolved with a hemodynamic response function. In addition, we included six movement regressors, three regressors accounting for signal drift and one constant regressor per experimental block as regressors of no interest.

After estimating the first-level model, we computed a second level GLM on the contrast images across all subjects. On the resulting z-map, we used a threshold of $p < 0.01$ testing for both positive and negative activation, a cluster threshold of $n = 20$ and corrected for multiple comparisons using false discovery rate.

In a second analysis of the fMRI data, we investigated the temporal dynamic of the BOLD response in the significant regions of interest for the previously made contrast, that is, *SA & DM*. To do this, we calculated the percentage signal change around the time of the intersection event averaged across participants. First, we used each significant cluster from the second-level analysis as a mask for the single subject t-maps. As we previously used smoothed data to generate the t-maps and clusters, we selected the coordinates from the voxel with the highest t-value in the t-maps for each participant and each cluster. Next, we extracted the timeseries for each of these voxels and calculated a percentage change from the average signal strength (here acting as a baseline) across each run. Lastly, we averaged the all timeseries across the intersection trials for each participant and across participants. Using this procedure, we extract the BOLD response to the intersection event expressed as a percentage signal change. To compare the BOLD response across different brain regions, we normalized the percentage signal strength such that the distance from the onset of the BOLD response to the peak of the BOLD response of the averaged timeseries within a cluster was equal to 1.

5.3 Results

5.3.1 Driving Behavior

In both n-back conditions participants reached a decision after approximately nine seconds ($t_{0back} = 9.27s, t_{3back} = 9.12s$) and accelerated approximately after 14 seconds ($t_{0back} = 14.22s, t_{3back} = 13.89s$) after they stopped at the intersection (Figure 5.9). Using a paired t-test, we found no significant difference with regard to the time participants took from arrival at the intersection to decide which gap to take ($t(29) = 0.62, p = 0.54$) and no significant differences regarding gap acceptance between the different n-back conditions ($t(29) = 0.66, p = 0.51$)

(Figure 5.5).

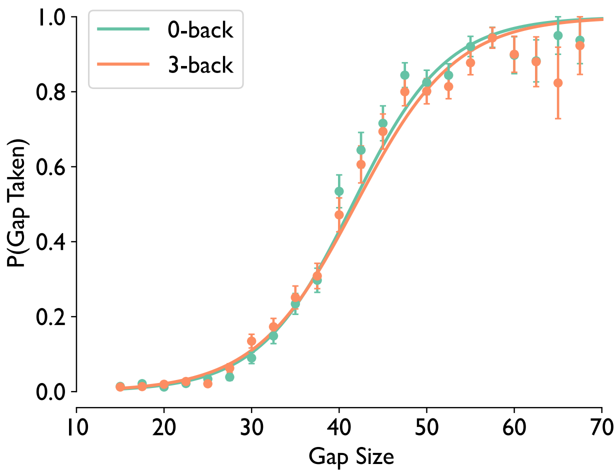


Figure 5.5. Logistic regression of crossing probability depending on gap size.

5.3.2 Workload

We observed a higher error rate on the n-back task in the high workload condition (3-back) compared to low workload (0-back) ($m_{0-back} = 1.3\%, m_{3-back} = 12\%; t(29), p < 0.01$). In addition, the error rate starts increasing at the start of the intersection period (Figure 5.6) and reaches its peak around the time of the decision (Figure 5.7) giving insight that reaching the decision to cross may free up cognitive resources while having to evaluate gaps interfere with the n-back task. This result is in line with our prediction that the n-back task and the gap acceptance task may interfere with each other. However, it should be noted that an n-back error may be the result of the most-recent number being missed but also a previous number being missed or a sequencing error. It follows that a distracting event may affect the error rate not just around the event but also for a longer period until the missed item is no longer relevant to the task, that is, maximally 15 seconds in case of the 3-back task. Consequently, in the 3-back, the peak error rate may spread out temporarily. In addition, the driving segment between the two intersections lasted around 30-40s, which likely explains the increased error rate towards at around -20s in 5.6 as it corresponds to the previous intersection.

We also analyzed the pupil dilation, which is often interpreted as a an indica-

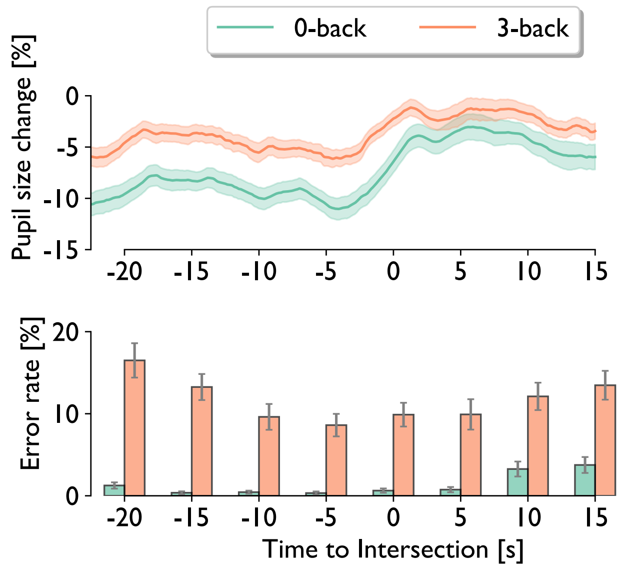


Figure 5.6. Pupil size and error rate on the n-back task centered around entering the intersection.

tor for cognitive workload (Kahneman and Beatty, 1966; Marquart et al., 2015a). We found a significant difference between the average pupil size between n-back levels ($t(29) = 2.35, p = 0.02$) (see Figure 5.6 & 5.7). In Figure 5.6, data are aligned such that time zero corresponds to the moment participants could first view upcoming gaps between cars. The figure also includes a screenshot of an example trial to show a representative field of view at this time point. As can be seen, as participants approached intersections, pupil dilation increases. In addition, pupil dilation remained elevated as participants presumably observed the vehicle gaps and navigated through the traffic. Notably, the difference in pupil dilation between 0-back and 3-back is reduced during the intersection periods, which may indicate that total cognitive workload levels are more similar.

In Figure 5.7, we show pupil dilation centered around making the decision to cross. Here, pupil dilation increased around the decision time, peaks shortly after the decision and then decreases. Again, the effect of n-back level on pupil dilation is virtually absent around maximum dilation. Together, the analyses of pupil dilation suggests that as drivers are entering the intersection, their mental workload increases compared to the driving section. In addition, making the decision to cross increases the mental workload substantially, even compared to the already

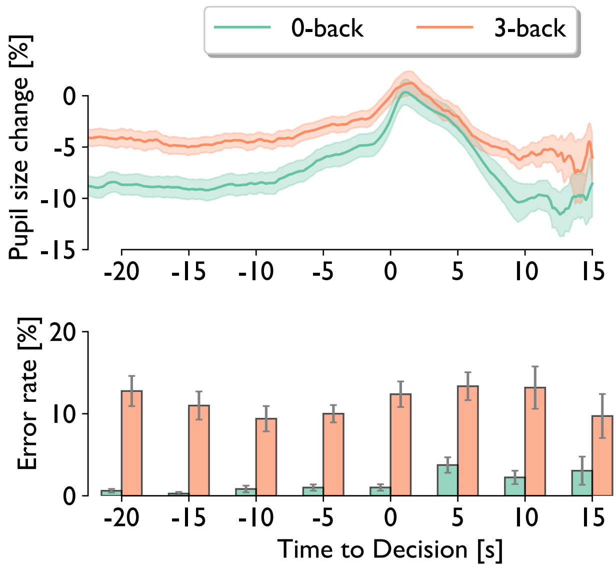


Figure 5.7. Pupil size and error rate in the n-back task centered around making the decision

elevated workload when entering the intersection.

In sum, both n-back error rates and pupil dilation data indicate that higher n-back levels increased cognitive load. The increased load in the 3-back task interfered with the cognitive demands imposed by crossing through oncoming traffic. However, driving parameters like waiting time to enter the crossing were not affected, the error rate in the n-back task increases while the difference in pupil dilation between n-back conditions is reduced. Taken together, these results may indicate a strategy change where participants focused cognitive resources on driving at the crossings at the cost of neglecting the n-back task.

5.3.3 fMRI Results

First, we contrasted the decision-making period in the 3-back condition to the decision-making period in the 0-back condition ($DM_{3\text{-back}} > DM_{0\text{-back}}$). However, we found no active clusters using this contrast, corroborating a possible strategy change at the intersection prioritizing driving. This parallels the behavioral result, which showed that participants show no change in gap size acceptance depending on n-back difficulty. Consequently, we contrasted the entire decision making period against zero regardless of n-back condition (*SA & DM*). The most relevant clusters that the contrast revealed lie in the left and right temporal lobe, occipital cortex, temporal parietal junction (TPJ), precuneus (Pcn), hippocampus, amygdala and the ventromedial prefrontal cortex (vmPFC; Figure 5.8). In addition, we also observed a significant cluster in the corpus callosum and bilaterally in the temporal lobes. Regarding negative activation, the most prominent clusters were found in the occipital lobe, cerebellum and motor cortex among others. The maxima and size of all significant clusters are reported in Table 5.1.

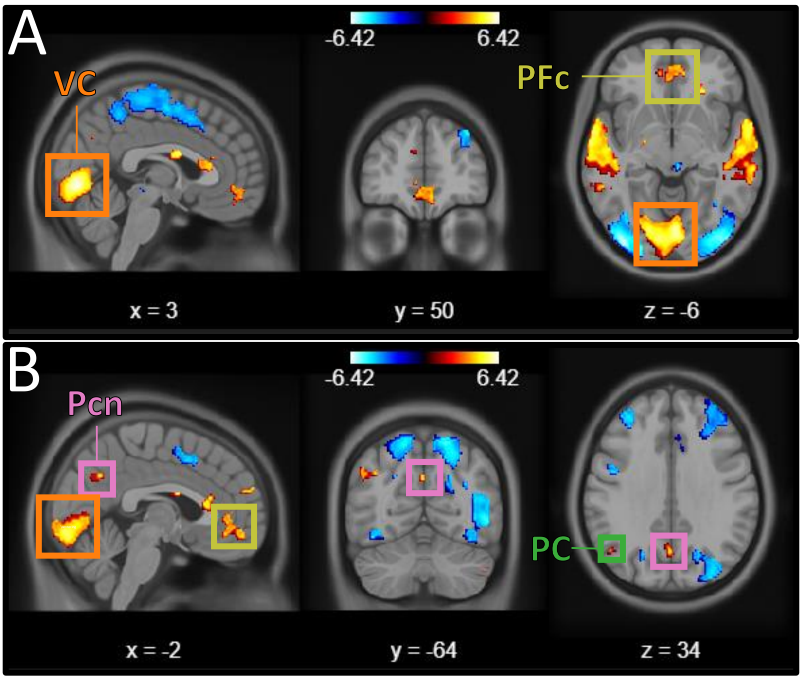


Figure 5.8. Whole-brain GLM results for the *SA & DM* contrast. Coordinates are in MNI space. All results are corrected with a $p = .01$ FDR and a minimal cluster size of 20. The most prominent areas are highlighted by color. Magenta = Pcn, orange = occipital cortex, green = TPJ, yellow = ventromedial prefrontal cortex. Colorbar depicts range of t-values.

Next, we aimed to investigate the temporal dynamics of brain areas related to intersection crossing decisions. Thus, we calculated the percentage change signal across the intersection period for the precuneus is associated with (higher) visual

Brain region	X	Y	Z	Peak Stat	Cluster Size (mm^3)
Temporal lobe (l)	-52	-30	2	6.42	21200
Occipital Cortex	4	-78	-4	6.39	17632
Temporal lobe (r)	58	-26	0	6.09	16096
Motor Cortex (l)	-50	-18	56	5.86	8968
Corpus Collosum	0	0	22	5.50	680
Dorsal Cerebellum (r)	16	-52	-20	5.45	3296
Anterior Corpus Callosum	6	18	14	4.88	1960
vlPFC (r)	24	32	-6	4.55	184
Anterior Cingulate Cortex	-10	34	8	4.50	3304
Hippocampus	-36	-28	-14	4.43	184
mPFC	-8	58	24	4.36	872
Temporal Pole	46	12	-24	4.35	648
Amygdala (l)	-26	-14	-16	4.32	1536
Posterior Cerebellum (r)	20	-74	-36	4.29	2392
Posterior Cerebellum (l)	-24	-76	-36	4.21	1048
Dorsal Cerebellum (l)	-16	-48	-18	4.16	672
Precuneus	-2	-64	34	4.11	224
Head of Caudate Nucleus	20	-16	30	4.09	296
Amygdala (r)	24	-8	-18	4.01	1384
Ventral Cerebellum (r)	20	-58	-48	3.84	336
Ventrolateral Cerebellum (r)	48	-66	-40	3.75	176
vlPFC (r)	24	40	4	3.61	208
TPJ (l)	-46	-64	36	3.60	512
Occipital Cortex (l)	-40	-88	-10	-6.39	14584
Occipital Cortex (r)	42	-84	-10	-6.01	94256
Superior Parietal Lobule (l)	-18	-62	62	-5.11	8560
dlPFC (r)	36	48	38	-4.69	4432
dlPFC (l)	-34	42	34	-4.64	2208
Caudate Nucleus (r)	20	10	6	-4.37	568
Insular Cortex (r)	34	26	6	-4.28	1536
Insular Cortex (l)	-32	24	0	-4.26	1848
Ventral Cerebellum (l)	-14	-50	-54	-4.21	672
Parahippocampal Gyrus (r)	4	-30	-6	-4.18	184
Mortor Cortex (l)	-46	0	34	-4.17	488
Cerebellum (l)	-40	-54	-32	-4.03	504
Anterior Cerebellum (l)	-10	-40	-26	-3.83	424
Inferior Frontal Gyrus (r)	48	6	4	-3.83	344
Anterior Cerebellum (r)	42	-38	-34	-3.74	400

Table 5.1. Cluster maxima of the *SA & DM* contrast. Coordinates are in MNI space. All results are corrected with a p=.01 FDR and a minimal cluster size of 20.

processing, and the vmPFC and TPJ have been asssociated with thinking about others and their intentions or actions (Ruff and Fehr, 2014) (Figure 5.9). In Figure 5.9, the BOLD responses are time-locked to the presumed start of the information acquisition for situation awareness buildup, that is, the time 0 represents the time of the first fixation towards oncoming traffic. The first fixation typically occurs

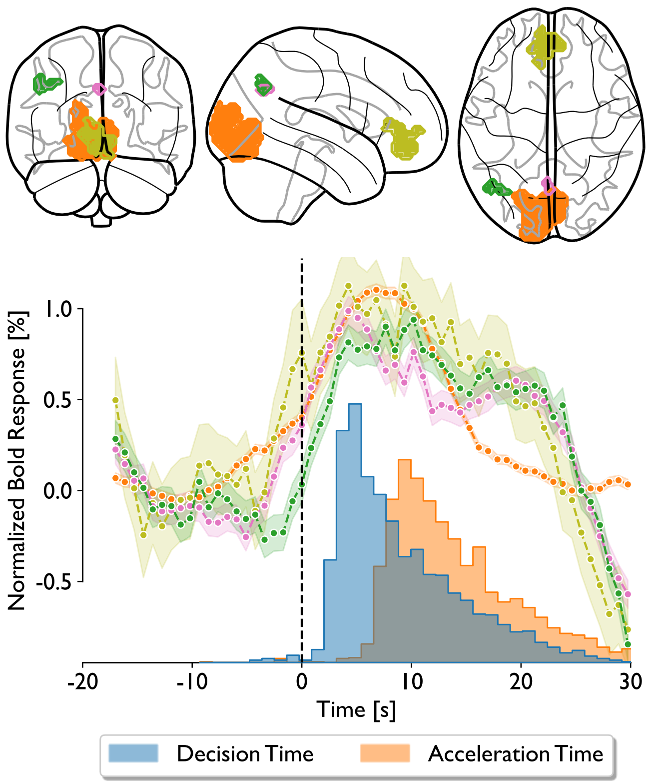


Figure 5.9. Bold response in the regions of interest. Magenta = Pcn, orange = visual cortex, green = TPJ, yellow = vmPFC. Time 0 represents the first fixation towards oncoming traffic. The blue bars display the moment of decision to cross. The orange bars display the moment when participants are initiating the crossing maneuver.

after participants have fixated the stop line ahead of them as they are slowing down and coming to the stop at the intersection. The colored dashed lines display the percentage signal change in the peak voxel of this cluster across the intersection period. Note that due to the smoothing, the peak voxel represents the weighted average of 27 voxels. To relate the brain activation with the participants' behavior, the histogram shows the distribution of response times when participants reached a decision to cross (blue) and when the participants started to accelerate with the intention to cross (orange).

We distinguish between two patterns. On the one hand, the BOLD signal increases as participants start looking into traffic and presumably evaluate gaps. The onset of the increase differed between regions. The visual cortex has the earliest onset with an initially shallow and then steep slope. The response peaks around six seconds after the begin of the SA acquisition phase and decreases shortly after the peak. This pattern is in concordance with the assumption that the visual cortex is particularly active during during the initial information sampling. Precuneus and vmPFC activation begins with intermediate latency but rises steeply. The precuneus is implicated in the analysis of spatiotemporal information and spatial layout processing. The vmPFC has been shown to be active in social decision making during the information processing and decision phase. Activation in the TPJ is the last to rise with a delay of approximately three seconds to precuneus and vmPFC. The TPJ has been suggested to play a role in reasoning about others like perspective taking and predicting goals and states of other persons (e.g., Saxe and Kanwisher, 2003).

In addition, the BOLD activation time courses in the precuneus region (magenta in Figure 5.9), TPJ (green) and the ventromedial prefrontal cortex (yellow) show a markedly different pattern from the visual cortex. In these regions, the BOLD signal remains elevated until approximately 20 seconds after participants first enter the intersection, that is well into the time interval of decision and action. These patterns suggest that the precuneus, ventromedial prefrontal cortex and parietal cortex support the early phases of evaluating the gap such as visual processing and estimating the distance, but also support in planning the potential trajectory and executing the action (*projection* in the Endsley model), decision making and executing the action. Notably, the BOLD response in the TPJ shows the latest onset, which may indicate that the TPJ is only activated after a potential gap is identified and the participants judge if taking the gap is feasible given the behavior of the oncoming cars. In sum, we have identified four regions in the cortex whose activation time course and known functional specificity are in broad congruence with the processes suggested by situation awareness theory and decision making.

5.4 Discussion

We investigated the influence of cognitive load on situation awareness and decision making in a realistic fMRI driving simulator aiming to find the behavioral and neural correlates of situation awareness and decision making and how they may be affected by cognitive load. Participants showed an increased pupillary response when they approached the left-turn intersection and made the decision to cross the intersection. In addition, we observed that during intersections differences in pupil dilation between n-back conditions were diminished while the performance in the n-back task decreased, indicating that drivers demote priority of distracting secondary tasks to make safety-critical decisions at intersections. We found no significant effect of cognitive load on the accepted gap threshold or brain activation despite our initial hypothesis.

Further, we identified relevant periods of evidence accumulation and decision making from eye-tracking data and used these periods to analyze fMRI BOLD data using a GLM approach. We found significant clusters in the visual cortex, Pcn and vmPFC and TPJ among other brain areas when participants were assessing whether to take a gap at an intersection. Lastly, we investigated the temporal dynamics of the activation using the percentage change of the BOLD signal around the intersection event and found a different activation pattern between the visual cortex and the precuneus and medial frontal cortex with respect to onset the length of the BOLD response. The visual cortex was activated early followed by vmPFC and Pcn. The TPJ showed a delayed onset compared to other brain areas. At the same time, the activation in the visual cortex decreased shortly after the peak, while the other relevant brain areas showed a sustained activation across the intersection period. These different patterns may be related to the different underlying processes of SA acquisition: The active brain areas' functions are in concordance with theoretical models of situation awareness, which propose a sequence of cognitive stages of perception, comprehension and projection followed by a decision.

The brain areas that were active during the intersection period align with theoretical models of situation awareness such as the Endsley model, which proposes a sequence of cognitive stages to acquire situation awareness and make a decision (Endsley, 1995). Specifically, we found a significant cluster for the *SA & DM > 0* contrast in the occipital cortex. In addition, we found negative activation in the lateral occipital lobe suggesting a shift from lateral towards medial brain areas within the occipital lobe during intersections. Navigational subtasks, such as turning at intersections, require extensive visual scanning. Although the visual cortex is generally engaged during driving, greater activation is observed when visual demands increase, such as at intersections (Gharib et al., 2020; Schweizer et al., 2013). Similarly, Vorobyev et al. (2015); Callan et al. (2009) have found that the occipital cortex is a crucial component situations that involve resolving uncertainty in ambiguous intersection scenarios during which drivers may need to cross or stop at an intersection. The shift from lateral towards medial areas is indicative of the behavioral change from actively driving towards watching traffic that has been documented by previous studies (e.g., Calhoun et al., 2002). This interpretation of the increased activation in the visual cortex is further supported by the rise in pupil dilation around the intersection event as pupil dilation has been shown to increase due to visual load as well (e.g., visual search difficulty Stolte et al. (2020)). The early onset of physiological and neural markers as participants enter the intersection aligns with the initial perception phase in the Endsley model of situation awareness.

Moreover, Endsley's model predicts the step of comprehension, which is described as a process of integrating the perceived stimuli into a cohesive mental image of the world around us. In the context of a left-turn intersection, this model likely involves the surrounding cars, which need to be integrated together with their anticipated trajectory. In our study, we found a significant cluster in the precuneus, which lies in Brodmann area 7 (medial precuneus) and Brodmann area 31 (dorsal precuneus). More specifically, the active region lies in the medial posterior region of the precuneus (peak voxel coordinate: -2, -64, 32), which has shown activation in previous studies when subjects were attentively tracking moving targets Culham et al. (1998). Furthermore, in an experiment by Malouin et al. (2003), participants imagined themselves to be performing various actions such as walking (with obstacles), initiating gait and standing. Importantly, the authors instructed participants to mentally replay previously watched scenes from a first-person perspective. In all three conditions they found activity in the posterior precuneus region. Thus, a common understanding of the precuneus' function is integrating visual information and relating spatial information to one's position or, in other words, first person perspective scene processing Al-Ramadhani et al. (2021); Foster et al. (2023). In our study, we observed that the activation in the precuneus clusters increased later than in the visual cortex and remained active for a longer period until the crossing maneuver was completed (Figure 5.9). Based on our results, the precuneus may be involved in the described comprehension stage of the Endsley model, that is, constructing a representation the visual stimuli, that is, the queue of oncoming cars into a holistic view of of the scene. The sustained activation suggests that the precuneus may support the continuous updating as the cars continue to pass and the integration of relevant visual information calculate and track the target gap participants intend to navigate through.

Furthermore, we observed a significant cluster in the vmPFC, which is a key structure in social decision making (Hiser and Koenigs, 2018; Heekeren et al., 2008; Ruff and Fehr, 2014). Lesion studies have shown that patients with defects in the vmPFC show deficits in assessing risk, probabilistic reinforcement learning and reward processing (Pujara et al., 2015; Wheeler and Fellows, 2008).

Importantly, Ruff and Fehr (2014) found that the vmPFC may evaluate decisions independently of the currency of the outcome. That is, it encodes the decision also to forms of reward like social consequences for oneself and others. Crucially, the authors highlight that the value computation may happen at the time of the decision rather than upon receiving the reward. As participants in this experiment were instructed to complete the course quickly but without causing accidents, they need to continuously evaluate the risk and reward of taking a specific gap. In other words, the vmPFC may facilitate the prediction of future states based on possible decisions and evaluate the outcome. In the context of the Endsley model, the stage of projection involves predicting future states of the surroundings to build situation awareness.

Finally, we identified a significant cluster in the TPJ, exhibiting the latest onset in the BOLD response for the SA & DM > 0 contrast. The TPJ is known to support a range of functions that vary according to hemispheric lateralization (e.g., Corbetta and Shulman, 2002). In this study, we observed significant activation in the left TPJ (peak voxel: -46, -64, 36), which previous research has associated with matching relevant episodic memory content to the current context (Geng and Vossel, 2013). Saxe and Kanwisher (2003) linked the TPJ to the process of reasoning about other minds and intentions. Moreover, the authors showed that activation in TPJ is independent of the visual appearance of other humans and merely requires participants to think about other people's beliefs, intentions or mental states. In the present experiment, the TPJ may integrate the oncoming traffic and their intended trajectory and match present gaps with representations formed during earlier trials and experiences.

To summarize, our analysis of the brain activation does not only give insight into which brain regions were active during the crossing decision but as we used the eye-tracking data to precisely identify the situation awareness acquisition and decision making period, we can utilize the BOLD response to investigate the temporal change across this period. First, we observed that BOLD responses in different brain regions have different onsets, suggesting that there is a stage-based process where some functions precede others. Specifically, the visual cortex has the earliest onset and regions involved in stimulus integration and decision have a later onset comparatively. Second, over the course of the intersection crossing, certain brain regions and thereby functions associated with those regions are engaged for different time periods. The visual cortex is primarily engaged at the start of the intersection, whereas the precuneus, vmPFC and TPJ have their peak shortly after reaching the decision with the TPJ having the latest onset. Importantly, they remain active until participants have left the intersection. This suggests that self-referential integration, the valuation of the prediction and decision making is a vital part throughout the whole intersection period. As such, these structures may serve a role in continuous reevaluation of the decision.

The findings in this study suggest that some phases in the situation awareness process are active simultaneously over a temporally extended interval with differing onsets. However, based on the current study, it is difficult to further delineate the presumed phases of situation awareness due to the sluggishness of the BOLD signal. In addition, the driving environment is constantly changing with multiple decisions needed to be made simultaneously or in quick succession. For example, at an intersection, drivers need to decide when to brake in order to slowly come to a stop at a good viewing angle, evaluate oncoming traffic, find the correct gap and decide when to accelerate in order to safely cross.

We also observed two significant clusters in the white matter of the corpus callosum. Due to fMRI being sensitive to grey matter activation and white matter typically showing reduced metabolism, significant areas in the white matter have historically often been considered artifacts D'Arcy et al. (2006). However, Fraser et al. (2012) have explored white matter activation in the corpus callosum in interhemispheric visuo-motor tasks. Though most participants in their study showed significant activation in the isthmus of the corpus callosum, which is located in the posterior third of the corpus callosum, they found a significant cluster in anterior regions of the corpus callosum on the group level as well. Our findings align with this work, suggesting that white matter activation in the corpus callosum may play a role in interhemispheric coordination during the task in this study. As the crossing traffic appears from the right side, participants attention is right-lateralized in order to observe the upcoming gaps. In contrast, the response button to indicate a crossing decision is on the left and planned trajectory and eventual action, including turning the wheel, is towards the left supporting the notion that the corpus callosum may facilitate communication between hemispheres.

Lastly, we found large significant clusters bilaterally in the temporal lobes (Figure 5.8), where the primary auditory cortices are located (e.g., Yi et al., 2019). In our study, the n-back task was presented auditorily via headphones through which participants also perceived environmental sounds such as engine noise. However, at the intersection, there are no additional auditory stimuli present, which makes this a surprising result. However, a common strategy to successfully manage the n-back task is to mentally rehearse the to-be-remembered sequence of n-back stimuli (e.g., Held et al., 2024b). Furthermore, we also observe an increase in n-back error rate and an increase in pupil dilation at the intersection periods, indicating that the difficulty to manage the n-back task and thereby the cognitive workload may increase. Thus, we conclude that the BOLD response in the temporal lobes may also be a result of enhanced effort towards the nonverbal rehearsal, which has been linked to the superior temporal lobe though its involvement has been inconsistent (Buchsbaum and D'Esposito, 2008; Nijboer et al., 2014).

5.4.1 Limitations and Outlook

While there is a plethora of evidence for the role of the precuneus in the integration of visual spatial information, this link does not remain exclusive. On the contrary, Lyu et al. (2021) investigated the precuneus and its role in the default-mode-network, ascertaining that the dorsal precuneus is also related to cognitive control networks involving executive control and goal-directed behavior. They found that the dorsal precuneus was more active in difficult conditions that imposed higher cognitive workload compared to easy conditions. As such, the activation in the precuneus that we observed during the intersection period may be related to increased task difficulty while crossing the intersection.

As our experimental design favored realism in lieu of strict experimental control, some trials were characterized by participants being indecisive and correcting previously made decisions. In other words, participants saw a gap they intended to take, pressed the button indicating a decision on the steering wheel but in the end did not cross when the gap came up. Instead, they waited for another gap, pressed the button again and crossed, essentially correcting themselves after reevaluating their decision. Although there were few such trials in this study, future studies may systematically investigate this behavior. Assuming that participants have built a misguided representation of their surrounding, meaning they have insufficient situation awareness, future studies may investigate which aspects lead to 1) a faulty representation and 2) which brain processes are essential in evaluating previously made decisions.

5.4.2 Conclusion

As summarized in Figure 5.10, this paper investigates the neural correlates of situation awareness during left-turn decisions in driving. First, we analyzed the time course of recorded eye-tracking data and thereby inferred the onset and duration of different phases of crossing a left-turn intersection. Using the onsets and durations, we formed regressors used in subsequent fMRI analysis. We found a pattern of activation in line with predictions from theoretical models such as the Endsley model of situation awareness. This research lays the theoretical groundwork for

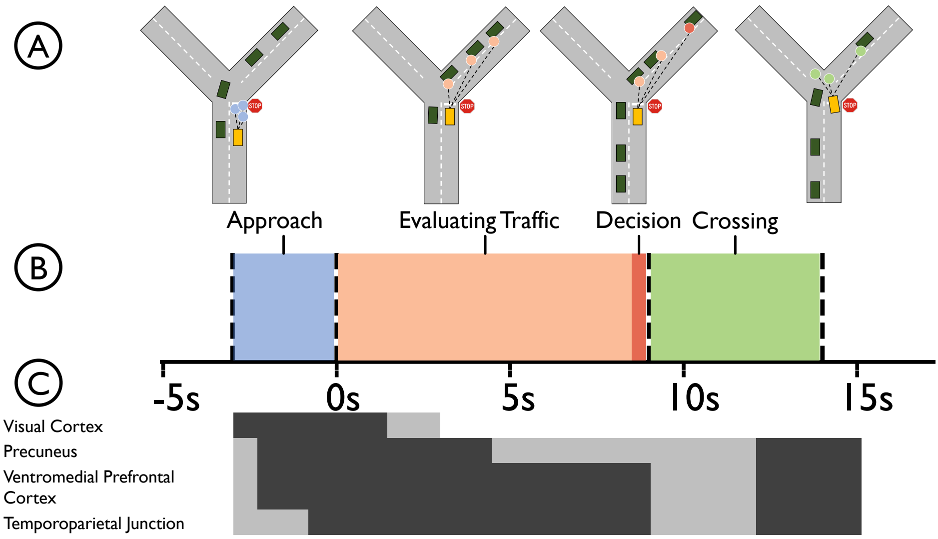


Figure 5.10. Graphical summary of the analysis and results used in this study to infer the cognitive states of drivers using eye-tracking data and utilizing these results for further fMRI analysis. The current driving situation is displayed at the top (A). Based on the eye-tracking gaze data (black dotted lines in A), we inferred the cognitive state of the driver (colored sections in B). The grey bars (C) depict the simplified time course of activated brain areas from no activation (white) to high activation (dark grey).

future studies that may wish to develop automation systems utilizing neurophysiological measurements to make predictions about human states, with the aim of improving safety in crossing-related decisions. Further studies could attempt to delineate the different stages of situation awareness further to ultimately estimate the state of situation awareness based on neurophysiological data.

Acknowledgments

This work was supported by the DFG-grant RI 1511/3-1 to J. Rieger. We would like to express our gratitude to Jooris Mettler for his technical expertise and support throughout this project. We would also like to thank Sina Khajei and Sude Sarayköylü for their assistance during data acquisition. Furthermore, we would

like to thank Benedikt Kretzmeyer, Lars Weber and Anirudh Unni for their work on the pilot experiment.

5.5 Appendix

Anatomical data preprocessing

A total of 1 T1-weighted (T1w) images were found within the input BIDS dataset.The T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) with `N4BiasFieldCorrection` (Tustison et al., 2010), distributed with ANTs (version unknown) (Avants et al., 2008, RRID:SCR_004757), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped with a *Nipype* implementation of the `antsBrainExtraction.sh` workflow (from ANTs), using OASIS30ANTs as target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using `fast` (FSL version unknown), RRID:SCR_002823, Zhang et al., 2001). Brain surfaces were reconstructed using `recon-all` (FreeSurfer 7.3.2, RRID:SCR_001847, Dale et al., 1999), and the brain mask estimated previously was refined with a custom variation of the method to reconcile ANTs-derived and FreeSurfer-derived segmentations of the cortical gray-matter of Mindboggle (RRID:SCR_002438, Klein et al., 2017). Volume-based spatial normalization to two standard spaces (MNI152NLin6Asym, MNI152NLin2009cAsym) was performed through non-linear registration with `antsRegistration` (ANTs (version unknown)), using brain-extracted versions of both T1w reference and the T1w template. The following templates were were selected for spatial normalization and accessed with *TemplateFlow* (23.0.0, Ciric et al., 2022): *FSL's MNI ICBM 152 non-linear 6th Generation Asymmetric Average Brain Stereotaxic Registration Model* [Evans et al. (2012), RRID:SCR_002823; TemplateFlow ID: MNI152NLin6Asym], *ICBM 152 Nonlinear Asymmetrical template version 2009c* [Fonov et al. (2009), RRID:SCR_008796; TemplateFlow ID: MNI152NLin2009cAsym].

Functional data preprocessing

For each of the 8 BOLD runs found per subject (across all tasks and sessions), the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated by aligning and averaging 1 single-band references (SBRefs). Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using `mcflirt` (FSL , Jenkinson et al., 2002). BOLD runs were slice-time corrected to 0.38s (0.5 of slice acquisition range 0s-0.76s) using `3dTshift` from AFNI (Cox and Hyde, 1997, RRID:SCR_005927). The BOLD time-series (including slice-timing correction when applied) were resampled onto their original, native space by applying the transforms to correct for head-motion. These resampled BOLD time-series will be referred to as *preprocessed BOLD in original space*, or just *preprocessed BOLD*. The BOLD reference was then co-registered to the T1w reference using `bbregister` (FreeSurfer) which implements boundary-based registration (Greve and Fischl, 2009). Co-registration was configured with six degrees of freedom. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep*. Several confounding time-series were calculated based on the *preprocessed BOLD*: framewise displacement (FD), DVARS and three region-wise global signals. FD was computed using two formulations following Power (absolute sum of relative motions, Power et al. (2014)) and Jenkinson (relative root mean square displacement between affines, Jenkinson et al. (2002)). FD and DVARS are calculated for each functional run, both using their implementations in *Nipype* (following the definitions by Power et al., 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. Additionally, a set of physiological regressors were extracted to allow for component-based noise correction (*CompCor*, Behzadi et al., 2007). Principal components are estimated after high-pass filtering the *preprocessed BOLD* time-series (using a discrete cosine filter with 128s cut-off) for the two *CompCor* variants: temporal (tCompCor) and anatomical (aCompCor). tCompCor components are then calculated from the top 2% variable voxels within the brain mask. For aCompCor, three probabilistic masks (CSF, WM and combined CSF+WM) are generated in anatomical space. The implementation differs from that of Behzadi et al. in that instead of eroding the masks by 2 pixels on BOLD space, a mask of pixels that likely contain a volume fraction of GM is subtracted from the aCompCor masks. This mask is obtained by dilating a GM mask extracted from the FreeSurfer's *aseg* segmentation, and it ensures components are not extracted from voxels containing a minimal fraction of GM. Finally, these masks are resampled into BOLD space and binarized by thresholding at 0.99 (as in the original implementation). Components are also calculated separately within the WM and CSF masks. For each CompCor decomposition, the k components with the largest singular values are retained, such that the retained components' time series are sufficient to explain 50 percent of variance across the nuisance mask (CSF, WM, combined, or temporal). The remaining components are dropped from consideration. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al., 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardized DVARS were annotated as motion outliers. Additional nuisance timeseries are calculated by means of principal components analysis of the signal found within a thin band (*crown*) of voxels around the edge of the brain, as proposed by (Patriat et al., 2017). The BOLD time-series were resampled into standard space, generating a *preprocessed BOLD run in MNI152NLin6Asym space*. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep*. All resamplings can be performed with *a single interpolation step* by composing all the pertinent transformations (i.e. head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using `antsApplyTransforms` (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos, 1964). Non-gridded (surface) resamplings were performed using `mri_vol2surf` (FreeSurfer).

Many internal operations of *fMRIPrep* use *Nilearn* 0.10.1 (Abraham et al., 2014, RRID:SCR_001362), mostly within the functional processing workflow. For more details of the pipeline, see the section corresponding to workflows in *fMRIPrep*'s documentation: .

Copyright Waiver

6
General Discussion

This dissertation applied a multi-method approach to investigate task interference in realistic scenarios using the example of driving under varying levels of cognitive load. To address this objective, we combined eye-tracking, cognitive modeling, and functional magnetic resonance imaging (fMRI). Each method contributed distinct but complementary insights into how cognitive workload manifests during driving and how it may interact with driving performance. Thus, the concluding synthesis of the results in the following chapter is organized according to the methodological approach rather than by cognitive construct. This structure reflects the unusually broad methodological scope of the work and underscores how each method contributed unique insights into the broader theoretical question of how cognitive load shapes behavior in complex, dynamic environments. The findings presented in this dissertation may inform future research aimed at designing automated systems with the goal of maintaining an optimal level of cognitive load based on (neuro)physiological data.

6.1 Behavior

The first contribution of this dissertation is the demonstration that even basic driving tasks, such as steering on a straight highway with little traffic, require working memory. While earlier studies have found that driving performance, measured by steering reversals, typically decreases when the demands of secondary tasks increase (Macdonald and Hoffmann, 1977, 1980), this relationship has not been clear, as many studies have also suggested the opposite (Scheunemann et al., 2019; Mclean and Hoffmann, 1973; Greenshields, 1963). However, in chapter 2, we observed that as working memory load increased, drivers exhibited fewer steering actions and deviated more from the center of the road consistently across n-back levels. Based on the behavioral performance, we suggest that the n-back task and steering performance on a straight highway rely on overlapping resources and thus exhibit effects of task interference, as there are fewer resources available to perform steering actions when the working memory load is high.

Perhaps somewhat surprisingly, in a more complex task, we did *not* observe a significant effect of working memory load, as participants showed no difference in gap taking behavior during intersection turning across working memory load levels (chapter 5). Although we observed a higher error rate in the 3-back task compared to the 0-back task when participants were actively driving and turning at an intersection, the increased working memory load did not result in a decrement in gap taking performance. One possible explanation for this result is that participants may have deprioritized the distracting secondary task in order to safely perform a left turn. This explanation is in line with previous results from Unni et al. (2017); Scheunemann et al. (2019), who concluded that by increasing task difficulty beyond the ability of participants, drivers may flexibly disengage from the task to maintain driving performance at a sufficient level. In the case of steering, although drivers deviated more from the center of the road under high load conditions, they were still driving safely.

Taken together, these results provide evidence that working memory is essential for both basic driving control tasks, such as lane keeping, and for more complex scenarios, such as intersection turning. Moreover, when working memory load exceeds drivers' capacity, they may abandon secondary tasks to prioritize safety. These findings highlight a potentially dangerous level of cognitive overload when working memory load is manageable, this comes with substantial decreases in driving performance, potentially leading drivers to overestimate their ability to multitask. Notably, interpreting driving behavior in isolation is ambiguous, leading to mostly inconclusive evidence regarding the effect of cognitive load on driving performance (Engström et al., 2017; Nijboer et al., 2016b; Scheunemann et al., 2019). This is why this dissertation also recorded multiple (neuro)physiological measurements and employed cognitive models, which may disambiguate the behavioral responses by providing information about the functional mechanisms of the observed behavior.

6.2 Cognitive Modeling

Analysis of the cognitive models in chapter 1 substantiates our result that simple steering control may require working memory due to a bottleneck at the problem state (Borst et al., 2010; Nijboer et al., 2016a). We concluded that the control loop involving steering and speed control requires working memory at least once per cycle. Consequently, as the working memory demands increase and secondary tasks occupy more working memory resources, this competition causes a bottleneck, resulting in the control loop being executed less frequently. Thus, latitudinal control (steering movements) and longitudinal control (number of speedometer checks) decrease in human participants, leading to decreased driving performance. Notably, although speedometer checks were not modeled in chapter 2 and thus cannot be used to compare to human behavior, Salvucci et al. (2006) have modeled learning appropriate timings to check one's own speed utilizing the declarative module of ACT-R. In the study described in chapter 1, the secondary working memory task would directly compete for the declarative module, leading to delayed or fewer executions of memory retrievals pertaining to speed control, resulting in fewer speedometer checks.

Utilizing a cognitive architecture may not only help us understand the negative effects of secondary tasks on driving but also enable us to investigate the effects secondary tasks may have on driving performance without testing them experimentally. In chapter 3, we extended the ACT-R model that we developed in chapter 2 to investigate the often-observed phenomenon that low amounts of cognitive load can increase driving performance by refocusing drivers and preventing mind-wandering. First, we implemented a tested model of mind-wandering to simulate mind-wandering as repeated memory retrievals and showed how the disconnect from the current task can impact driving performance (van Vugt et al., 2015). Measured by increased lane deviation and decreased steering actions, prolonged periods of mind-wandering lead to a decrease in driving performance. This result mirrors our findings from chapter 2, suggesting that mind-wandering engages cognitive resources, which lead to fewer control updates in the driving task. In fact, other studies have highlighted the similarity of performance decrements when drivers are mind-wandering versus dual-tasking (Yanko and Spalek, 2014). Our results substantiate this notion. However, Yanko and Spalek (2014) also emphasize that while mind-wandering and dual-tasking both impact driving negatively, they differ with respect to the compensatory mechanisms that drivers engage. Similarly, we found that drivers suffer performance decrements when they were driving under manageable cognitive load (chapter 2) but they neglected the secondary task when safety was at stake (chapter 5).

Second, we showed how driving performance may increase when secondary tasks are minor and are presumably preventing the negative effects of mind-wandering, which is an effect that has often been observed in experimental studies (Nijboer et al., 2016b; He and McCarley, 2011; Cao and Liu, 2013; Fitch et al., 2014). To accomplish this, we leveraged ACT-R as a predictive tool: In chapter 3, we devised multiple possible intervening mechanisms designed to disrupt mind-wandering and refocus drivers towards driving. While all simulated mechanisms increased driving performance when compared to a mind-wandering driving model, we demonstrated a relationship between the invasiveness of the external intervention and its effect on driving performance. Due to the observation that interventions themselves can be considered distractions that require cognitive resources, we concluded that successful interventions minimize the cognitive effort required to process them and are only effective when drivers exhibit dangerous levels of mind-wandering.

The results from chapters 2 and 3 established the utility of ACT-R to model potential behavioral interventions of assistive systems by modeling cognitive workload during driving with respect to overload and underload. Thus, in chapter 4, we applied our findings from chapter 2 and chapter 3 and, in the first part of the chapter, described a vision of a future human-cyber-physical system (Hancock et al., 2013). The proposed system would utilize cognitive models alongside (neuro)physiological signals to evaluate interventions that steer the human driver towards a state of mind more appropriate for safe driving, as suggested by previous work by Damm et al. (2019). In the second part of chapter 4, we devised a basic prototype based on estimating cognitive workload by means of pupil dilation and the concurrently running cognitive model. We tested the prototype using the same experimental setup as in chapter 2 in an exploratory experiment. Although the prototype was simple, to our knowledge, it is the first implementation of a system that sustains a continuous cognitive model throughout the experiment to model the drivers cognitive state. The exploratory experiment we conducted with the prototype showed that by dynamically adapting the driving requirements as subjective cognitive load increased, pupil dilation reached an early plateau and maintained a stable level under higher working memory conditions. This is a noticeable contrast to the results in chapter 2 during which we observed a continuous rise in pupil dilation as working memory demands increased. These results indicate that an assistive system based on the modeled cognitive load may aid in regulating the cognitive workload of drivers and lead to increased driving performance.

This result is in line with previous ACT-R models that have shown the impact of manual tasks or memory rehearsal on steering performance and extends their findings by demonstrating the continuous increase as working memory load levels increase (Salvucci and Macuga, 2002; Salvucci and Beltowska, 2008).

6.3 Eye-tracking

Analysis of concurrently recorded eye-tracking data provided two further insights into the cognitive states of drivers. First, pupil dilation was consistently affected by cognitive workload during driving in the studies covered by this thesis (chapters 2, 4, and 5). Although the link between pupil size and the content size of participant's working memory has long been established in controlled experimental environments (Kahneman and Beatty, 1966), this dissertation demonstrated the robustness of this effect in various driving situations. Pupil size increased under higher workload conditions compared to low workload conditions (chapters 2, 4, and 5). Furthermore, this effect remained consistent for both binary comparisons (low vs. high; chapter 5) as well as for gradual increases across multiple levels (5-level n-back; Chapters 2 and 4). In addition, participants exhibited performance decreases due to working memory load in both simple highway driving and complex intersection scenarios (chapters 2 and 5). Moreover, participants' pupil size was shown to be sensitive to the workload induced by driving demands, as pupil dilation increased both with respect to arriving at the intersection as well as to making a decision to cross the intersection. While Marquart et al. (2015b) have previously suggested that pupil size can be used to measure mental workload while driving, these findings highlight that pupil dilation may serve as a robust physiological marker of cognitive workload across different levels or types of workload in dynamic driving scenarios.

The second unique insight that eye-tracking recordings provided was the gaze position of participants, which may be useful for interpreting participants behavior. In chapter 2, we observed that participants check their own speed less often as working memory load increases, which is in line with our interpretation of the behavioral results. As working memory load increases, more resources are engaged towards retaining the required items in working memory, which leads to speed-tracking being neglected.

Moreover, analysis of gaze position can be used to infer cognitive states. In chapter 5, we utilized eye-tracking to infer stages of situation awareness acquisition by analyzing when participants started looking at the traffic and used the identified time periods to analyze the fMRI BOLD data.

In the previous chapters, we showed the consistency of pupil dilation in estimating cognitive workload. While the effect was robust across different experiments, participants, and workload levels, pupil dilation remains an ambiguous signal and is not specific to cognitive workload (Einhäuser, 2017). In contrast, brain imaging techniques such as fMRI enable a more fine-grained interpretation that is essential for understanding the neural mechanisms underlying complex real-world tasks, like driving.

6.4 fMRI

In Chapter 5, we therefore investigated the impact of cognitive load on driving performance using fMRI to identify both cortical and subcortical structures involved in navigating challenging scenarios such as left-turn intersections. Our results revealed a clear temporal sequence of activation: early engagement of the visual cortex as participants approached the intersection, followed by activation in the precuneus (Pcn) and ventromedial prefrontal cortex (vmPFC) during gap evaluation, and a later onset of activity in the temporoparietal junction (TPJ). The identified regions are related to functions consistent with theoretical models of situation awareness. The early activation in the occipital cortex indicates an initial stage of perception (Vorobyev et al., 2015; Callan et al., 2009). Further, the sustained Pcn and vmPFC activity have been linked to target tracking, moving around objects, and integrating spatial information from a first-person perspective, suggesting a stage of integrating the traffic around the driver into a comprehensive image of the scene (Culham et al., 1998; Malouin et al., 2003; Al-Ramadhani et al., 2021; Foster et al., 2023). Lastly, the relatively late activation of the TPJ around the intersection suggests a stage of reasoning about the intentions of other drivers and future trajectories of the surrounding traffic (Saxe and Kanwisher, 2003; Geng and Vossel, 2013). This temporal cascade not only provides novel evidence for the sequential engagement of distinct neural systems during safety-critical driving decisions under varying cognitive load but also suggests neural markers that could be integrated to evaluate the cognitive state of drivers.

6.5 Synthesis of the Methods

A central strength of this dissertation lies in the integration of behavioral measures, eye-tracking, cognitive modeling, and fMRI to build a multi-layered understanding of the neurocognitive mechanisms underpinning driving under cognitive load. Each method addressed the effects of cognitive load on driving performance from a different vantage point: behavioral data revealed performance decrements and compensatory strategies. Eye-tracking provides continuous, non-invasive indices of cognitive state and attentional allocation. Cognitive modeling offers a mechanistic explanation of these patterns and predictive capability for untested scenarios. And finally, fMRI uncovered the spatial and temporal neural dynamics underlying situational awareness and decision making in complex driving situations. By combining these approaches, this dissertation demonstrates how converging evidence from multiple modalities can yield a richer and more precise account of complex real-world behavior than any single method in isolation.

For example, in chapter 5, errors in the n-back task during intersections suggested an increase in cognitive workload. The analysis of pupil dilation showed that pupil size reacted to two events: namely, approaching the intersection and evaluating traffic. Furthermore, eye-tracking served as a marker for cognitive events, which enabled an informed design of the fMRI analysis centered around functionally similar situations. That is, instead of using vehicle information such as the distance to the intersection or the time before making a turn, by using eye-tracking, we were able to define critical temporal periods and temporally align inferred cognitive events. Consequently, fMRI analysis revealed a similar sequence of events to which different brain regions were sensitive.

Using another example from chapter 2, we used cognitive modeling to explain an observed interaction between a visuo-spatial driving task and a working memory task. Previous work had suggested an interaction between these two cognitive concepts using behavioral and neurophysiological measurements (Scheunemann et al., 2019). However, while these methods permit insight into the activation patterns, allowing the authors to map functions to brain regions, they do not explain the functional mechanisms that drive behavior (Kriegeskorte and Douglas, 2018, 2019). This thesis utilized cognitive models to close this gap. By explicitly modeling the cognitive mechanisms of performing the described tasks concurrently, we identified a bottleneck at a task-specific resource related to working memory. By providing explainable predictions, cognitive modeling adds to previous results to ultimately enable researchers to infer modes of intervention aimed at alleviating mental load on drivers.

As such, integrating continuous physiological signals (pupil dilation, gaze patterns), computational models of cognition (ACT-R), and temporally resolved neural activation (fMRI) patterns creates a holistic framework not only for understanding how cognitive load impacts driving but also for informing adaptive driver assistance systems that can anticipate and respond to dangerous levels of cognitive demand.

6.6 Limitations and Future Research

While the multi-method approach employed in this dissertation advanced our understanding of cognitive workload during driving, it also underscored several challenges inherent in studying complex, real-world scenarios. First, naturalistic driving environments are highly dynamic, evolving rapidly and offering multiple valid strategies to solve the task. For example, though it was not the focus of our study conducted in chapter 5, some participants exhibited similar behavior by deciding to cross between two cars only to correct themselves after reevaluating the scene. Assuming that participants had built an inadequate representation of the scene before correcting themselves, it is a highly relevant situation to investigate, as such behavior is important with respect to safety. However, collecting a large enough sample size to investigate these trials experimentally is challenging due to their relative infrequency and the risk of confounds, such as training effects, which become especially problematic and difficult to control in complex scenarios.

Further, although fMRI provided valuable insights into the neural substrates of situation awareness and decision making, the sluggishness of the BOLD signal and the resulting poor temporal resolution remained a challenge in driving scenarios that are quickly developing and continuously changing. To align the neural activation we found here to cognitive stages of situation awareness and decision making at intersections, future studies should consolidate our findings with (neuro)physiological recordings that are more temporally sensitive such as EEG or MEG. Such methods could benefit from the spatial precision we provided here and aid in disentangling the cognitive stages of situation awareness and decision making.

6.7 Final Remarks

In closing, central to this thesis was the investigation of task interference in complex, realistic scenarios by employing multiple, complementary methods in the showcase scenario of driving on highways and through intersections. To this end, we recorded eye-tracking, behavior, and fMRI, as well as functionally modeled the behavior and cognitive system using cognitive modeling across four independent studies. We investigated cognitive overload and underload in simple scenarios, such as straight highway driving, and extended our focus towards complex left-turn intersections. Together, our findings contribute to a more nuanced understanding of how drivers balance cognitive demands in dynamic environments, showing that cognitive load not only degrades driving performance by taking away resources from the driving task but can also have benefits or prompt adaptive shifts in task prioritization by preventing drivers from mind-wandering. Beyond the theoretical contribution, this dissertation also provides a foundation for applied systems that leverage neurophysiological recordings to assess the momentary capabilities of drivers and adapt the assistance dynamically. Although driving is the showcase scenario used here, we believe that the results can be useful for other safety-critical domains where humans must constantly allocate limited cognitive resources, such as aviation, power-grid control, or human–robot interaction.

Deutsche Zusammenfassung

Menschen führen alltäglich Aufgaben aus, die mehrere kognitive Systeme, wie zum Beispiel Wahrnehmung, Aufmerksamkeit, Gedächtnis und Motorik, zur selben Zeit beanspruchen. Eine zentrale Frage in der psychologischen Forschung ist, wie diese Funktionen unter hoher kognitiver Beanspruchung miteinander interagieren und welche Folgen dies für das menschliche Verhalten hat. Darüber hinaus ist es wichtig zu untersuchen, wie Ergebnisse dieser Forschung sich in realistische Szenarien übertragen lassen.

Eine häufige, aber anspruchsvolle Aufgabe, die wir tagtäglich meistern, ist das Autofahren. Während des Autofahrens müssen wir kontinuierlich die Umgebung beobachten, schnelle Entscheidungen treffen und die Kontrolle über das Fahrzeug behalten. Gleichzeitig ist die Sicherheit beim Autofahren maßgeblich von der kognitiven Leistungsfähigkeit des Fahrers beeinflusst, da trotz technologischer Fortschritte eine Vielzahl von Unfällen auf menschliches Versagen zurückzuführen ist. Aus diesem Grund eignet sich das Beispiel Autofahren gut, um zu untersuchen, wie kognitive Belastungen menschliches Verhalten in realistischen Szenarien beeinflussen.

Da Autofahren aus vielen dynamischen Subaufgaben besteht, reicht die reine Verhaltensbeobachtung nicht aus, um kognitive Prozesse vollständig zu erklären. In der Anwendungsforschung besteht ein Spannungsfeld zwischen dem Ziel, Situationen möglichst realistisch nachzustellen, und experimenteller Kontrolle, die uns hilft, Ergebnisse interpretierbar und verständlich zu machen. Beispielsweise wird in einfachen Kreuzungssituationen häufig die Größe der Lücke zwischen Autos des kreuzenden Verkehrs betrachtet. Die Größe der Lücke, durch die Fahrer fahren, wird als akzeptable Lückengröße gewertet. Wenn der Fokus lediglich auf der Lückengröße liegt, können kognitive Prozesse, die zur Akzeptanz oder Ablehnung der Lücke führen, allerdings nur eingeschränkt nachvollzogen werden. Welche Strategie Fahrer verfolgen, um die Verkehrssituation zu evaluieren, wie viele kognitive Ressourcen sie zu welchem Zeitpunkt aufwenden, um die Lückengröße zu evaluieren, und wie der Entscheidungsprozess abläuft, ist durch reine Verhaltensbeobachtung nur schwer zugänglich.

Diese Dissertation zeichnet sich durch den gewählten multimethodischen Ansatz aus, bestehend aus Verhaltensbeobachtung, Eye-Tracking, kognitiver Modellierung und funktionaler Magnetresonanztomographie (fMRT). (Neuro)physiologische Messmethoden wie Eye-Tracking oder fMRT können hier weitere Hinweise darauf liefern, wohin die Blicke der Fahrer fallen und welche Gehirnareale dabei aktiv sind. Dieser Ansatz beleuchtet nicht nur die neuronale Organisation der mentalen Belastung beim Fahren, sondern disambiguiert auch das menschliche Verhalten beim Autofahren. Um die zugrunde liegenden funktionalen Mechanismen der kognitiven Prozesse zu verstehen, verwendet diese Dissertation kognitive Modelle in der kognitiven Architektur ACT-R. Diese ermöglichen es, realistische Fahrszenarien als Modelle abzubilden und die kognitiven Funktionen von Perzeption zu Aktion vollständig nachzustellen. Die Arbeit konzentriert sich dabei auf zwei Fahrszenarien: das Geradeausfahren auf Autobahnen und das Linksabbiegen an Kreuzungen als typische Situationen, in denen sich automatische und komplexe kognitive Prozesse unterscheiden.

Untersuchungsmethoden

Im Rahmen dieser Dissertation nutzten wir Eye-Tracking, um eine direkte und alltagsnahe Messung von Fahreraufmerksamkeit und kognitiver Belastung durchzuführen. Eye-Tracking erfasst Blickrichtung und Pupillengröße mit einer Infrarotkamera, was Aufschluss darüber geben kann, welche Punkte in einer Szene zu welchen Zeitpunkten relevant für den Fahrer sind. Veränderungen der Pupillengröße werden bereits seit den 1960er Jahren in psychologischen Experimenten untersucht, um kognitive Belastung zu erforschen, und werden in dieser Dissertation verwendet, um auch in realistischen Fahrsituationen die kognitive Belastung der Fahrer zu ermitteln.

Zur Ergänzung der Eye-Tracking-Daten wurden kognitive Modelle der ACT-R-Architektur eingesetzt. ACT-R ist sowohl eine psychologische Theorie als auch eine kognitive Architektur, die als Computerprogramm implementiert wurde. ACT-R simuliert kognitive Prozesse mithilfe von Modulen, die Informationen in Form von *Chunks* austauschen. Unter realistischen, empirisch gestützten Einschränkungen lassen sich so verschiedene Annahmen über kognitive Prozesse beim Fahren testen, Engpässe identifizieren und sogar zukünftige Ereignisse oder die Wirkung neuer Assistenzsysteme vorhersagen. Ein kognitives Modell ist eine ausführbare Instanz, die bestimmte regelbasierte Handlungsabläufe simuliert. Sobald zum Beispiel ein Straßenschild sichtbar ist, wird die Aufmerksamkeit darauf gerichtet. Ein kognitives Modell beinhaltet eine Vielzahl solcher simplen Regeln, die in ihrer Ausführung den Regeln der Architektur unterliegen. So können beispielsweise zwei Regeln zur gleichen Zeit ausführbar sein. Sollten sie allerdings die gleichen Ressourcen verwenden (zum Beispiel das visuelle System), entsteht ein Engpass. Wie lange dieser Engpass besteht, ist empirisch validiert und wird im Modell als Verzögerung der Handlungsabfolge abgebildet. ACT-R kann somit nicht nur Einsicht in die zugrunde liegenden funktionalen Mechanismen kognitiver Prozesse geben, sondern auch zukünftige Ereignisse simulieren. Dieser Funktionsumfang macht ACT-R besonders attraktiv im Bereich des Autofahrens, wo sicherheitskritische Ereignisse simuliert werden können, ohne menschliche Fahrer zu gefährden.

Zusätzlich nutzten wir fMRT, um die räumliche Organisation der am Fahren beteiligten Gehirnfunktionen zu untersuchen. fMRT ist eine nicht-invasive Methode zur neuronalen Bildgebung, die Hirnaktivität abbilden kann, indem sie die Sauerstoffsättigung im Blut misst. Neuronale Aktivität führt durch den erhöhten Bedarf an Sauerstoff zu kurzzeitigen Veränderungen im lokalen Stoffwechsel, was zu einer Änderung der Sauerstoffsättigung im Blut führt. fMRT nutzt die unterschiedlichen magnetischen Eigenschaften von sauerstoffarmem im Vergleich zu sauerstoffreichem Blut, um eine Karte der neuronalen Aktivität zu erstellen. Aufgrund der Sensitivität von fMRT gegenüber Bewegungen wird fMRT in der Forschung zu Fahrsituationen bis dato selten genutzt. Durch unseren speziellen Versuchsaufbau waren allerdings realitätsnahe Fahrsimulationen im Scanner möglich, sodass wir fMRT nutzen konnten, um das Fahrverhalten zusammen mit den zugrunde liegenden neuronalen Prozessen zu interpretieren.

Ergebnisse

Das erste Ergebnis dieser Dissertation ist die Demonstration, dass selbst simple Fahraufgaben das Arbeitsgedächtnis in verschiedenen Versuchskontexten konstant beanspruchen. In Kapitel 1 fuhren Probanden in einem Fahrsimulator eine gerade Strecke mit minimalem Verkehr, während sie eine sekundäre Arbeitsgedächtnisaufgabe lösen mussten. Mit ansteigenden Anforderungen in der sekundären Aufgabe führten die Fahrer weniger Lenkradbewegungen durch, um das Fahrzeug in der Spur zu halten. Gleichzeitig sank die Anzahl der Blickbewegungen auf die Geschwindigkeitsanzeige, die den Fahrern helfen sollte, die Geschwindigkeitsbegrenzung einzuhalten. Wir schlossen daraus, dass die steigende Komplexität der Sekundäraufgabe dazu führte, dass Probanden weniger Zeit und kognitive Ressourcen zur Verfügung hatten, die Fahraufgabe zu meistern. Durch den Einsatz kognitiver Modelle konnten wir zeigen, dass ein Flaschenhalseffekt im sogenannten *Problem State*, einer Ressource, die eng mit dem Arbeitsgedächtnis verwandt ist, womöglich ursächlich dafür ist. Die eingesetzten Modelle simulierten Lenkbewegungen sowie die Geschwindigkeitskontrolle über einen Kontrollzyklus und konnten zeigen, dass der Kontrollzyklus das Arbeitsgedächtnis belastet und dadurch mit anderen Aufgaben um kognitive Ressourcen konkurriert.

Im weiteren Verlauf dieser Dissertation nutzten wir die etablierten Modelle, um das bekannte Phänomen zu untersuchen, bei dem Fahrer häufig eine schlechtere Fahrleistung zeigen, wenn die kognitive Belastung sehr gering ist. Hierfür kombinierten wir die Fahrmodelle aus Kapitel 1 mit etablierten Modellen aus der Literatur, die das Gedankenabschweifen (*Mind-wandering*) simulieren. Durch diese Kombination von Methoden konnten wir Forschungsergebnisse aus der Literatur simulieren und zeigen, dass auch eine sehr niedrige kognitive Belastung einen negativen Effekt auf die Fahrleistung hat, da Fahrer aufgrund der niedrigen kognitiven Belastung weniger kognitive Ressourcen für die Fahraufgabe aufwenden. Darüber hinaus bot der Einsatz von kognitiven Modellen auch die Möglichkeit, Simulationen zu erstellen, mit dem Ziel, eine Interventionsmöglichkeit zu finden, die einen positiven Effekt auf die Fahrleistung hat. Unsere Ergebnisse zeigten ein Spannungsfeld zwischen den kognitiven Kosten, die durch einen neuen Stimulus auf den Fahrer entstehen, wenn dieser beispielsweise auf ein auditorisches Warnsignal reagieren muss, und der verbesserten Fahrleistung, wenn Fahrer vom Gedankenabschweifen abgehalten werden. Erfolgreiche Interventionen müssen also den kognitiven Aufwand der Intervention minimieren und sollten möglichst nur zum Einsatz kommen, wenn sie notwendig sind, um unnötige Ablenkungen zu verhindern.

Die Ergebnisse aus den Kapiteln 2 und 3 zeigen, dass sich ACT-R gut eignet, um potenzielle verhaltensbezogene Interventionen assistiver Systeme durch die Modellierung der kognitiven Beanspruchung beim Fahren zu untersuchen. Darauf aufbauend wurde in Kapitel 4 zunächst eine Vision eines sogenannten *Human-Cyber-Physical-Systems* vorgestellt, das kognitive Modelle mit (neuro)physiologischen Signalen kombiniert. Dieses hat zum Ziel, Interventionen in Abhängigkeit des mentalen Zustands von Fahrern zu planen. Anschließend wurde ein einfacher Prototyp entwickelt, der die kognitive Belastung anhand von Pupillenerweiterung und eines parallel laufenden kognitiven Modells schätzt. Dieser Prototyp wurde in einem einfachen Experiment getestet und zeigte, dass eine dynamische Anpassung der Fahranforderungen an die subjektive kognitive Belastung zu einer Stabilisierung der Pupillendilatation führte. Diese Ergebnisse bieten erste Hinweise darauf, dass assistive Systeme auf Basis (neuro)physiologischer Messungen die Beanspruchung von Fahrerinnen und Fahrern regulieren und die Fahrleistung verbessern können.

In Kapitel 5 wurde der Einfluss kognitiver Belastung auf die Fahrleistung in einer neuen Versuchsumgebung untersucht. Anders als in den vorangegangenen Kapiteln fokussierten wir uns hier auf das Szenario des Linksabbiegens, also auf eine urbane, komplexe Situation mit vielen Verkehrsteilnehmern. Hier untersuchten und analysierten wir mithilfe von Eye-Tracking und fMRT die neuronalen Mechanismen der Situationswahrnehmung. Kreuzungen sind hochkomplexe Situationen, die experimentell nur schwierig untersucht werden können, ohne wesentliche Bestandteile der Situation zu simplifizieren. Mithilfe eines speziell angefertigten Versuchsaufbaus nutzten wir Eye-Tracking, um Zeitfenster zu identifizieren, in denen Fahrer ein Situationsbewusstsein erlangten, indem erfasst wurde, wann sie den Verkehr beobachteten. Diese Zeitfenster bildeten anschließend die Grundlage für die Auswertung der fMRT-Signale. Während frühere Kapitel zeigten, dass Pupillendilatation ein robuster, jedoch unspezifischer Indikator kognitiver Beanspruchung ist, ermöglichte die fMRT-Analyse eine differenziertere Interpretation der zugrunde liegenden neuronalen Prozesse. Die Ergebnisse zeigten eine klare zeitliche Abfolge neuronaler Aktivierung in anspruchsvollen Fahrsituationen wie Linksabbiegekreuzungen: eine frühe Aktivierung des visuellen Kortex als Ausdruck der Wahrnehmung, gefolgt von anhaltender Aktivität im Precuneus und im ventromedialen präfrontalen Kortex, die mit der Integration räumlicher und verkehrsbezogener Informationen in Verbindung steht, sowie einer späteren Aktivierung der temporoparietalen Übergangsregion, die auf das Schlussfolgern über die Intentionen anderer Verkehrsteilnehmender hindeutet. Diese Aktivierungskaskade stimmt mit theoretischen Modellen der Situationswahrnehmung überein und liefert Hinweise auf neuronale Marker zur Bewertung des kognitiven Zustands von Fahrerinnen und Fahrern.

Fazit

In dieser Dissertation stand die Untersuchung von Interferenzen in komplexen, realitätsnahen Szenarien im Mittelpunkt, exemplarisch am Fahren auf Autobahnen und an Kreuzungen. Hierzu wurden in vier unabhängigen Studien komplementäre Methoden eingesetzt, darunter Verhaltensmessungen, Eye-Tracking, kognitive Modellierung sowie fMRT, um das Verhalten und die kognitiven Prozesse abzubilden. Untersucht wurden sowohl kognitive Über- als auch Unterforderung in einfachen Fahrsituationen wie dem Geradeausfahren auf der Autobahn sowie komplexen Fahrsituationen wie dem Linksabbiegen an einer Kreuzung. Die durch die Kombination der Methoden ermöglichten Ergebnisse tragen zu einem differenzierten Verständnis bei, wie Fahrerinnen und Fahrer kognitive Anforderungen in dynamischen Umgebungen ausbalancieren. Gleichzeitig zeigen sie, dass kognitive Belastung die Fahrleistung nicht nur durch eine Konkurrenz um Ressourcen negativ beeinträchtigen kann, sondern auch positive Effekte haben kann, etwa durch die Reduktion von Gedankenabschweifen. Über den theoretischen Beitrag hinaus liefert die Arbeit eine Grundlage für anwendungsorientierte Assistenzsysteme, die (neuro)physiologische Signale nutzen, um die momentane Leistungsfähigkeit von Fahrern zu erfassen und die Unterstützung durch automatisierte Systeme dynamisch anzupassen. Die gewonnenen Erkenntnisse sind dabei nicht auf den Anwendungsfall Fahren beschränkt, sondern lassen sich auch auf andere sicherheitskritische Bereiche wie die Luftfahrt, die Steuerung von Stromnetzen oder die Mensch-Roboter-Interaktion übertragen.

English Summary

Every day, people perform tasks that require the simultaneous use of several cognitive systems, such as perception, attention, memory, and motor skills. A central question in psychological research is how these functions interact under high cognitive load and what consequences this has for human behavior. Furthermore, it is important to investigate how the results of this research can be transferred to realistic scenarios.

A common but demanding task that we master every day is driving a car. While driving, we must continuously observe our surroundings, make quick decisions, and maintain control of the vehicle. At the same time, driving safety is significantly influenced by the driver's cognitive performance, as despite technological advances, a large number of accidents are attributable to human error. For this reason, driving serves as a showcase example for investigating how cognitive load may influence human behavior in realistic scenarios.

Since driving consists of many dynamic subtasks, simply observing behavior is often not enough to fully explain cognitive processes. In applied research, there is a tension between aiming to recreate situations as realistically as possible and experimental control, which helps researchers to make results interpretable and understandable. For example, in simple intersection situations, the size of the gap between cars in crossing traffic is often considered. The size of the gap through which drivers pass is considered an acceptable gap size. However, if the focus lies solely on gap size, cognitive processes that contribute towards accepting or rejecting a gap can only be understood to a limited extent. For example, the strategy drivers employ to evaluate the traffic situation, how many cognitive resources they expend at what point in time, and how the decision-making process works is often not clear from behavioral analysis alone.

This dissertation is characterized by its multi-method approach, consisting of behavioral observation, eye-tracking, cognitive modeling, and functional magnetic resonance imaging (fMRI). (Neuro)physiological measurement methods such as eye-tracking or fMRI can provide further clues as to where drivers' eyes fall and which areas of the brain are active in the process. This approach not only sheds light on the neural organization of cognitive load while driving, but also disambiguates human behavior while driving. To further understand the underlying functional mechanisms of cognitive processes, we used cognitive models in

the ACT-R cognitive architecture. These enable realistic driving scenarios to be modeled computationally and the cognitive functions from perception to action to be fully simulated. The work focuses on two driving scenarios: driving straight ahead on highways and turning left at intersections as typical situations in which automatic and complex cognitive processes differ.

Research Methods

In this dissertation, we used eye-tracking to conduct a direct and realistic measurement of driver attention and cognitive load. Eye-tracking records gaze direction and pupil size using an infrared camera, which can provide information about which points in a scene are relevant to the driver at which points in time. Furthermore, changes in pupil size have been studied in psychological experiments since the 1960s to investigate cognitive load and were used in this work to determine the cognitive load of drivers in realistic driving situations.

Cognitive models based on the ACT-R architecture were used to supplement the eye-tracking data. ACT-R is both a psychological theory and a cognitive architecture that has been implemented as a computer program. ACT-R simulates cognitive processes using modules that exchange information in the form of *chunks*. A cognitive model is an executable instance that simulates certain rule-based sequences of actions. Under realistic, empirically supported constraints, this method allows various assumptions about cognitive processes while driving to be tested, bottlenecks to be identified, and even future events or the effect of new assistance systems to be predicted. For example, as soon as a road sign becomes visible, attention is directed to it. A cognitive model contains a large number of such simple rules, which are subject to the rules of the architecture in their execution. For example, two rules can be executed at the same time. However, if they use the same resources (e.g., the visual system), a bottleneck occurs. The duration of this bottleneck is empirically validated and is represented in the model as a delay in the sequence of actions. Thus, ACT-R cannot only provide insight into the underlying functional mechanisms of cognitive processes but also simulate future events. This range of functions makes ACT-R particularly attractive in the field of driving, where safety-critical events can be simulated without endangering human drivers.

In addition, we used fMRI to investigate the spatial organization of brain functions involved in driving. fMRI is a non-invasive method of neural imaging that can map brain activity by measuring oxygen saturation in the blood. Neural activity leads to short-term changes in local metabolism due to increased oxygen demand, which results in a change in blood oxygen saturation. fMRI uses the different magnetic properties of oxygen-depleted blood compared to oxygen-rich blood to create a map of neural activity. Due to the sensitivity of fMRI to movement, fMRI has rarely been used in research on driving situations to date. However, our special experimental setup enabled realistic driving simulations in the scanner, allowing us to use fMRI to interpret driving behavior alongside the underlying neural processes.

Results

The first result of this dissertation is the demonstration that even basic driving tasks may constantly engage working memory in different experimental setups. In Chapter 1, subjects drove on a straight highway with minimal traffic in a driving simulator while having to solve a secondary working memory task. As the demands of the secondary task increased, drivers made fewer steering wheel movements to keep the vehicle in its lane. At the same time, the number of glances at the speedometer, which helped drivers comply with the speed limit, decreased. We concluded that the increasing complexity of the secondary task meant that subjects had less time and fewer cognitive resources available to accomplish the driving task. Using cognitive models, we were able to show that a bottleneck effect in the so-called *problem state*, a resource closely related to working memory, may be the cause. The models used simulated steering movements and speed control by a control loop and were able to show that the control loop engages working memory, thus competing with other tasks for cognitive resources.

In the further course of this dissertation, we used the established models to investigate the well-known phenomenon whereby drivers often perform worse when cognitive load is very low. To achieve this, we combined the driving models from Chapter 1 with established models from the literature that simulate mind-wandering. This combination of models enabled us to simulate behavioral findings from the literature and showed that very low cognitive load can negatively affect driving performance, as drivers devote fewer cognitive resources to the driving task. In addition, the use of cognitive models also offered the opportunity to create simulations with the aim of finding an intervention option that has a positive effect on driving performance. Our results showed a conflict between the cognitive costs incurred by a new stimulus to the driver, for example when they have to react to an auditory warning signal, and the improved driving performance when drivers are prevented from letting their minds wander. Therefore, successful interventions must minimize the cognitive effort required and, as far as possible, should only be used when necessary to prevent unnecessary distractions.

The results from chapters 2 and 3 show that ACT-R is well suited for investigating potential behavioral interventions of assistive systems by modeling cognitive load during driving. Building on this, Chapter 4 first presented a vision of a so-called *human-cyber-physical system* that combines cognitive models with (neuro)physiological signals. The aim of this system is to plan interventions depending on the mental state of drivers. Subsequently, a simple prototype was developed that estimates cognitive load based on pupil dilation and a concurrently running cognitive model. This prototype was tested in a simple experiment and showed that dynamically adapting driving requirements to subjective cognitive load led to stabilization of pupil dilation. These results provide initial indications that assistive systems based on (neuro)physiological measurements can regulate driver stress and improve driving performance.

In Chapter 5, we investigated the influence of cognitive load on driving performance in a new test environment. Unlike in the previous chapters, we focused on the scenario of turning left, that is, an urban, complex situation with many road users. Using eye-tracking and fMRI, we examined and analyzed the neural mechanisms of situation awareness. Intersections are highly complex situations that are difficult to study experimentally without simplifying essential components of the situation. Using a specially designed experimental setup, we used eye-tracking to identify time windows in which drivers gained situational awareness by recording when they observed traffic. These time windows then formed the basis for the evaluation of the fMRI signals. While earlier chapters showed that pupil dilation is a robust but nonspecific indicator of cognitive load, fMRI analysis allowed for a more nuanced interpretation of the underlying neural processes. The results showed a clear temporal sequence of neural activation in challenging driving situations such as left-turn intersections: early activation of the visual cortex as an expression of perception, followed by sustained activity in the precuneus and ventromedial prefrontal cortex, which is associated with the integration of spatial and traffic-related information, and later activation of the temporoparietal junction, which indicates reasoning about the intentions of other road users. This activation cascade is consistent with theoretical models of situational perception and provides clues to neural markers for assessing the cognitive state of drivers.

Conclusion

This dissertation focused on the investigation of interference in complex, realistic scenarios, using driving on highways and at intersections as examples. To this end, complementary methods were used in four independent studies, including behavioral measurements, eye-tracking, cognitive modeling, and fMRI, to map behavior and cognitive processes. Both cognitive overload and underload were investigated in simple driving situations such as driving straight ahead on the highway as well as complex driving situations such as turning left at an intersection. The results obtained by combining these methods contribute to a differentiated understanding of how drivers balance cognitive demands in dynamic environments. At the same time, they show that cognitive load can not only negatively affect driving performance by competing for resources, but can also have positive effects by reducing mind-wandering. Beyond its theoretical contribution, the work provides a basis for application-oriented assistance systems that use (neuro)physiological signals to record the current performance of drivers and dynamically adjust the support provided by automated systems. The findings are not limited to the application of driving, but can also be transferred to other safety-critical areas such as aviation, power grid control, or human-robot interaction.

Nederlandse Samenvatting

Mensen voeren elke dag taken uit die het gelijktijdig gebruik van meerdere cognitieve systemen zoals perceptie, aandacht, geheugen en motoriek vereisen. Een centrale vraag in psychologisch onderzoek is hoe deze functies onder hoge cognitieve belasting met elkaar interacteren en welke gevolgen dit heeft voor het menselijk gedrag. Verder is het belangrijk om te onderzoeken hoe de resultaten van dergelijk onderzoek kunnen worden toegepast in realistische scenario's.

Een voorbeeld van zo'n veelvoorkomende maar veeleisende taak is autorijden. Tijdens het autorijden moeten we voortdurend onze omgeving observeren, snelle beslissingen nemen en de controle over het voertuig behouden. Tegelijkertijd wordt de verkeersveiligheid in belangrijke mate beïnvloed door de cognitieve prestaties van de bestuurder, aangezien ondanks technologische vooruitgang een groot aantal ongevallen te wijten is aan menselijk falen. Daarom dient autorijden als een goed voorbeeld om te onderzoeken hoe cognitieve belasting het menselijk gedrag in realistische scenario's beïnvloedt.

Aangezien autorijden uit veel dynamische subtaken bestaat, volstaat het observeren van gedrag niet om cognitieve processen volledig te verklaren. In toegepast onderzoek bestaat er een spanningsveld tussen het doel om situaties zo realistisch mogelijk na te bootsen en experimentele controle, die ons helpt om resultaten interpreteerbaar en begrijpelijk te maken. In eenvoudige kruispuntsituaties wordt bijvoorbeeld vaak gekeken naar de grootte van de ruimte tussen auto's van het kruisende verkeer. De grootte van de opening waar bestuurders doorheen rijden wordt beschouwd als een acceptabele opening. Als de focus echter uitsluitend op de grootte van de opening ligt, kunnen cognitieve processen die leiden tot acceptatie of afwijzing van de opening slechts in beperkte mate worden begrepen. Het is moeilijk om door alleen gedragsobservatie te achterhalen welke strategieën bestuurders gebruiken om de verkeerssituatie te beoordelen, hoeveel cognitieve middelen ze op welk moment besteden om de grootte van de opening te beoordelen en hoe het besluitvormingsproces werkt.

Dit proefschrift onderscheidt zich door de interdisciplinaire benadering, bestaande uit gedragsobservatie, eye-tracking, cognitieve modellering en functionele MRI (fMRI). (Neuro)fysiologische meetmethoden zoals eye-tracking of fMRI kunnen verdere aanwijzingen geven over waar de blik van de bestuurders naartoe gaat en welke hersengebieden daarbij actief zijn. Deze benadering belicht niet alleen de neurale organisatie van cognitieve belasting tijdens het rijden maar maakt ook het menselijk gedrag duidelijker. Dit proefschrift maakt gebruik van cognitieve modellen in de ACT-R-cognitieve architectuur om de onderliggende functionele mechanismen van cognitieve processen te begrijpen. Hiermee kunnen realistische rijsituaties als model worden weergegeven en de cognitieve functies, van perceptie tot actie, worden gesimuleerd. Het werk richt zich daarbij op twee rijscenario's: rechtdoor rijden op snelwegen en linksaf slaan op kruispunten als typische situaties waarin automatische en complexe cognitieve processen van elkaar verschillen.

Onderzoeksmethoden

In dit proefschrift gebruikten we eye-tracking om een directe en realistische meting van de aandacht en cognitieve belasting van bestuurders uit te voeren. Eye-tracking registreert de blikrichting en pupilgrootte met behulp van een infraroodcamera, wat informatie kan geven over welke punten in een rijsituatie op welk moment relevant zijn voor de bestuurder. Veranderingen in de pupilgrootte worden al sinds de jaren zestig in psychologische experimenten bestudeerd om de cognitieve belasting te onderzoeken. In dit proefschrift worden ze gebruikt om de cognitieve belasting van bestuurders in realistische rijsituaties te bepalen.

Ter aanvulling aan de eye-trackinggegevens gebruikten we cognitieve modellen op basis van de ACT-R-architectuur. ACT-R is zowel een psychologische theorie als een cognitieve architectuur die als een computerprogramma is geïmplementeerd. ACT-R simuleert cognitieve processen met behulp van modules die informatie uitwisselen in de vorm van *chunks*. Onder realistische, empirisch onderbouwde beperkingen kunnen zo verschillende aannames over cognitieve processen tijdens het rijden worden getest, knelpunten worden geïdentificeerd en zelfs toekomstige gebeurtenissen of het effect van nieuwe assistentiesystemen worden voorspeld.

Een cognitief model is een uitvoerbare instantie die bepaalde op regels gebaseerde handelingsprocessen simuleert. Zodra bijvoorbeeld een verkeersbord zichtbaar is, wordt de aandacht erop gericht. Een cognitief model bevat een groot aantal van dergelijke eenvoudige regels, die in hun uitvoering onderworpen zijn aan de regels van de architectuur. Zo kunnen bijvoorbeeld twee regels tegelijkertijd worden uitgevoerd. Als ze echter dezelfde middelen gebruiken (bijvoorbeeld het visuele systeem), ontstaat er een knelpunt. De duur van dit knelpunt is empirisch gevalideerd en wordt in het model weergegeven als een vertraging in de handelingsprocessen. ACT-R kan dus niet alleen inzicht geven in de onderliggende functionele mechanismen van cognitieve processen, maar ook toekomstige gebeurtenissen simuleren. Deze functionaliteit maakt ACT-R bijzonder aantrekkelijk op het gebied van autorijden, waar veiligheidskritische gebeurtenissen kunnen worden gesimuleerd zonder menselijke bestuurders in gevaar te brengen.

Daarnaast maakten we gebruik van fMRI om de ruimtelijke organisatie van hersenfuncties die bij het autorijden betrokken zijn te onderzoeken. fMRI is een niet-invasieve methode voor neurale beeldvorming waarmee hersenactiviteit in kaart kan worden gebracht door de zuurstofsaturatie in het bloed te meten. Neurale activiteit leidt tot kortstondige veranderingen in het lokale metabolisme als gevolg van een verhoogde zuurstofbehoefte, wat de zuurstofsaturatie in het bloed verandert. fMRI maakt gebruik van de verschillende magnetische eigenschappen van zuurstofarm bloed in vergelijking met zuurstofrijk bloed om een kaart van neurale activiteit te maken. Vanwege de gevoeligheid van fMRI voor beweging wordt fMRI tot nu toe in onderzoek naar rijsituaties zelden gebruikt. Door onze speciale proefopstelling waren realistische rijsimulaties in de scanner echter mogelijk, zodat we fMRI konden gebruiken om het rijgedrag samen met de onderliggende neurale processen te interpreteren.

Resultaten

Het eerste resultaat van dit proefschrift is de demonstratie dat zelfs eenvoudige rijtaken het werkgeheugen in verschillende experimentele contexten voortdurend aanspreken. In hoofdstuk 1 reden proefpersonen een rechte route met minimaal verkeer in een rijsimulator, terwijl ze een secundaire werkgeheugentaak moesten uitvoeren. Naarmate de eisen van de secundaire taak toenamen, maakten de bestuurders minder stuurbewegingen om het voertuig in zijn rijstrook te houden. Tegelijkertijd nam het aantal blikken op de snelheidsmeter, die bestuurders moest helpen zich aan de snelheidslimiet te houden, af. We concludeerden dat de toenemende moeilijkheid van de secundaire taak betekende dat proefpersonen minder tijd en cognitieve middelen beschikbaar hadden om de rijtaak uit te voeren. Met behulp van cognitieve modellen konden we aantonen dat een bottleneck-effect in de zogenaamde *probleemtoestand*, een middel dat nauw verband houdt met het werkgeheugen, hier mogelijk de oorzaak van is. De gebruikte modellen simuleerden stuurbewegingen en snelheidsregeling via een controlecyclus en konden aantonen dat de controlecyclus een belasting voor het werkgeheugen vormt en dus met andere taken om cognitieve middelen concurreert.

In het verdere verloop van dit proefschrift maakten we gebruik van de gevestigde modellen om het bekende fenomeen te onderzoeken waarbij bestuurders vaak slechter presteren als de cognitieve belasting zeer laag is. Hiervoor combineerden we de rijmodellen uit hoofdstuk 1 met gevestigde modellen uit de literatuur die het afdwalen van gedachten (mind-wandering) simuleren. Door deze combinatie van methoden konden we onderzoeksresultaten uit de literatuur simuleren en aantonen dat zelfs een zeer lage cognitieve belasting een negatief effect heeft op de rijprestaties, omdat bestuurders door de lage cognitieve belasting minder cognitieve middelen aan het rijden besteden. Bovendien was het door het gebruik van cognitieve modellen ook mogelijk om simulaties te maken met als doel een interventieoptie te vinden die een positief effect heeft op de rijprestaties. Onze resultaten toonden een spanningsveld aan tussen de cognitieve kosten die een nieuwe stimulus voor de bestuurder met zich meebrengt, bijvoorbeeld wanneer de bestuurder moet reageren op een auditief waarschuwingssignaal, en de verbeterde rijprestaties wanneer bestuurders worden verhinderd om hun gedachten te laten afdwalen. Succesvolle interventies moeten daarom de vereiste cognitieve inspanning tot een minimum beperken en, voor zover mogelijk, alleen worden toegepast als ze nodig zijn om onnodige afleiding te voorkomen.

De resultaten uit hoofdstukken 2 en 3 tonen aan dat ACT-R geschikt is voor het onderzoeken van mogelijke gedragsinterventies van ondersteunende systemen door de cognitieve belasting tijdens het rijden te modelleren. Voortbouwend hierop werd in hoofdstuk 4 eerst een visie gepresenteerd van een zogenaamd Human-Cyber-Physical System dat cognitieve modellen combineert met (neuro)fysiologische signalen. Het doel hiervan is om interventies te plannen op basis van de mentale toestand van bestuurders. Vervolgens werd een eenvoudig prototype ontwikkeld dat de cognitieve belasting op basis van pupilverwijding en een parallel cognitief model schat. Dit prototype werd getest in een eenvoudig experiment en toonde aan dat een dynamische aanpassing van de rijvereisten aan de subjectieve cognitieve belasting leidde tot stabilisatie van de pupilverwijding. Deze resultaten geven een eerste aanwijzing dat ondersteunende systemen op basis van (neuro)fysiologische metingen de belasting van bestuurders kunnen reguleren en de rijprestaties kunnen verbeteren.

In hoofdstuk 5 hebben we de invloed van cognitieve belasting op rijprestaties in een nieuwe testomgeving onderzocht. Anders dan in de vorige hoofdstukken hebben we ons hier gericht op het scenario van links afslaan, d.w.z. een stedelijke, complexe situatie met veel verkeersdeelnemers. Met behulp van eye-tracking en fMRI onderzochten en analyseerden we de neurale mechanismen van situatieperceptie. Kruispunten zijn zeer complexe situaties die moeilijk experimenteel te bestuderen zijn zonder essentiële componenten van de situatie te vereenvoudigen. Met behulp van een speciaal ontworpen proefopstelling identificeerden we middels eye-tracking tijdvensters waarin bestuurders zich bewust werden van de situatie door te registreren wanneer ze het verkeer observeerden. Deze tijdvensters vormden vervolgens de basis voor de evaluatie van de fMRI-signalen.

Terwijl eerdere hoofdstukken aantoonden dat pupilverwijding een robuuste maar niet-specifieke indicator is van cognitieve belasting, maakte fMRI-analyse een meer gedifferentieerde interpretatie van de onderliggende neurale processen mogelijk. De resultaten toonden een duidelijke opeenvolging van neurale activering in uitdagende rijsituaties, zoals linksaf slaan op een kruispunt: vroege activering van de visuele cortex als uitdrukking van perceptie, gevolgd door aanhoudende activiteit in de precuneus en ventromediale prefrontale cortex, die geassocieerd wordt met de integratie van ruimtelijke en verkeersgerelateerde informatie, en latere activering van de temporopariëtale overgangsregio, die wijst op het redeneren over de intenties van andere verkeersdeelnemers. Deze activeringscascade komt overeen met theoretische modellen van situatiebewustzijn en biedt aanwijzingen voor neurale markers voor het beoordelen van de cognitieve toestand van bestuurders.

Conclusie

Dit proefschrift richt zich op het onderzoek naar interferentie in complexe, realistische scenario's, met als voorbeelden het rijden op snelwegen en kruispunten. Hiervoor werden in vier onafhankelijke studies complementaire methoden gebruikt, waaronder gedragsmetingen, eye-tracking, cognitieve modellering en fMRI, om gedrag en cognitieve processen in kaart te brengen. Zowel cognitieve overbelasting als onderbelasting werden onderzocht in eenvoudige rijsituaties zoals rechtdoor rijden op de snelweg, en in complexe rijsituaties zoals linksaf slaan op een kruispunt. De resultaten die door het combineren van deze methoden zijn verkregen dragen bij aan een gedifferentieerd begrip van hoe bestuurders cognitieve eisen in dynamische omgevingen in evenwicht brengen. Tegelijkertijd laten ze zien dat cognitieve belasting niet alleen een negatieve invloed kan hebben op de rijprestaties door te concurreren om middelen, maar ook positieve effecten kan hebben, bijvoorbeeld door het verminderen van afdwalen van gedachten. Naast de theoretische bijdrage vormt het werk een basis voor toepassingsgerichte assistentiesystemen die (neuro)fysiologische signalen gebruiken om de huidige prestaties van bestuurders te registreren en de ondersteuning door geautomatiseerde systemen dynamisch aan te passen. De bevindingen zijn niet beperkt tot de toepassing van autorijden, maar kunnen ook worden toegepast op andere veiligheidskritische gebieden zoals de luchtvaart, de controle van elektriciteitsnetten of de interactie tussen mens en robot.

Declaration of Originality

I certify that I have written this thesis independently, that I have not used any sources or aids other than those indicated, and that I have followed the general principles of scientific work and publications as laid down in the guidelines of good scientific practice.

Bibliography

Abraham, A., Pedregosa, F., Eickenberg, M., Gervais, P., Mueller, A., Kossaifi, J., Gramfort, A., Thirion, B., and Varoquaux, G. (2014). Machine learning for neuroimaging with scikit-learn. *Frontiers in Neuroinformatics*, 8.

Al-Ramadhani, R. R., Shivamurthy, V. K. N., Elkins, K., Gedela, S., Pedersen, N. P., and Kheder, A. (2021). The Precuneal Cortex: Anatomy and Seizure Semiology. *Epileptic disorders : international epilepsy journal with videotape*, 23(2):218–227.

Alm, H. and Nilsson, L. (1995). The effects of a mobile telephone task on driver behaviour in a car following situation. *Accident Analysis and Prevention*, 27(5).

Alsaid, A., Lee, J. D., Roberts, D. M., Barrigan, D., and Baldwin, C. L. (2018). Looking at mind wandering during driving through the windows of PCA and t-SNE. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 62(1).

Alur, R. (2004). Games for formal design and verification of reactive systems. In Wang, F., editor, *Automated Technology for Verification and Analysis*, Lecture Notes in Computer Science. Springer.

Alur, R. and Dill, D. (1992). The theory of timed automata. In de Bakker, J. W., Huizing, C., de Roever, W. P., and Rozenberg, G., editors, *Real-Time: Theory in Practice*, Lecture Notes in Computer Science. Springer.

Anderson, J. R. (2007). *How Can the Human Mind Occur in the Physical Universe?*, volume 148. Oxford Univ Pr. Publication Title: How Can the Human Mind Occur in the Physical Universe?

Anderson, J. R., Taatgen, N. A., and Byrne, M. D. (2005). Learning to achieve perfect timesharing: Architectural implications of hazeltine, teague, and ivry (2002). *Journal of Experimental Psychology: Human Perception and Performance*, 31(4):749–761.

Aricò, P., Borghini, G., Di Flumeri, G., Colosimo, A., Bonelli, S., Golfetti, A., Pozzi, S., Imbert, J. P., Granger, G., Benhacene, R., and Babiloni, F. (2016). Adaptive automation triggered by EEG-based mental workload index: A passive brain-computer interface application in realistic air traffic control environment. *Frontiers in Human Neuroscience*, 10. Publisher: Frontiers Media S. A.

Atchley, P. and Chan, M. (2011). Potential benefits and costs of concurrent task engagement to maintain vigilance: A driving simulator investigation. *HUMAN FACTORS*, 53(1).

Avants, B., Epstein, C., Grossman, M., and Gee, J. (2008). Symmetric diffeomorphic image registration with cross-correlation: Evaluating automated labeling of elderly and neurodegenerative brain. *Medical Image Analysis*, 12(1):26–41.

Baldwin, C. L., Roberts, D. M., Barragan, D., Lee, J. D., Lerner, N., and Higgins, J. S. (2017). Detecting and quantifying mind wandering during simulated driving. *Frontiers in Human Neuroscience*, 11:406.

Behrmann, G., Cougnard, A., David, A., Fleury, E., Larsen, K. G., and Lime, D. (2007). UPPAAL-tiga: Time for playing games! In Damm, W. and Hermanns, H., editors, *Computer Aided Verification*, Lecture Notes in Computer Science. Springer.

Behzadi, Y., Restom, K., Liau, J., and Liu, T. T. (2007). A component based noise correction method (CompCor) for BOLD and perfusion based fmri. *NeuroImage*, 37(1):90–101.

Bencich, E., Gamboz, N., Coluccia, E., and Brandimonte, M. A. (2014). When the mind “flies”: the effects of mind-wandering on driving. *EUT Edizioni Università di Trieste*.

Bengler, K., Damm, W., Luedtke, A., Rieger, J., Austel, B., Biebl, B., Fränzle, M., Hagemann, W., Held, M., Hess, D., Ihme, K., Kacianka, S., Kerscher, A. J., Forrest, L., Lehnhoff, S., Pretschner, A., Rakow, A., Sonntag, D., Sztipanovits, J., Schwammberger, M., Schweda, M., Unni, A., and Veith, E. (2023). A References Architecture for Human Cyber Physical Systems - PART II: Fundamental Design Principles for Human-CPS Interaction. *ACM Transactions on Cyber-Physical Systems*. Just Accepted.

Beninger, J., Hamilton-Wright, A., Walker, H. E. K., and Trick, L. M. (2021). Machine learning techniques to identify mind-wandering and predict hazard response time in fully immersive driving simulation. *Soft Computing*, 25(2).

Biondi, F. N., Lohani, M., Hopman, R., Mills, S., Cooper, J. M., and Strayer, D. L. (2018). 80 MPH and out-of-the-loop: Effects of real-world semi-automated driving on driver workload and arousal. In *Proceedings of the human factors and ergonomics society annual meeting*, volume 62, pages 1878–1882. SAGE Publications Sage CA: Los Angeles, CA. Issue: 1.

Blanchard, N., Bixler, R., Joyce, T., and D'Mello, S. (2014). Automated physiological-based detection of mind wandering during learning. In Trausan-Matu, S., Boyer, K. E., Crosby, M., and Panourgia, K., editors, *Intelligent Tutoring Systems*, volume 8474. Springer International Publishing. Series Title: Lecture Notes in Computer Science.

Borst, J. P. and Anderson, J. R. (2017). A step-by-step tutorial on using the cognitive architecture ACT-r in combination with fMRI data. *Journal of Mathematical Psychology*, 76. Publisher: Elsevier Inc.

Borst, J. P., Taatgen, N. A., and van Rijn, H. (2010). The problem state: A cognitive bottleneck in multitasking. *Journal of Experimental Psychology: Learning Memory and Cognition*, 36(2):363–382.

Borst, J. P., Taatgen, N. A., and Van Rijn, H. (2011). Using a symbolic process model as input for model-based fMRI analysis: Locating the neural correlates of problem state replacements. *NeuroImage*, 58(1).

Bosch, V. and Mecacci, G. (2023). Eyes on the road: Brain computer interfaces and cognitive distraction in traffic. *Frontiers in neuroergonomics*, 4:1171910.

Broadbent, D. P., D'Innocenzo, G., Ellmers, T. J., Parsler, J., Szameitat, A. J., and Bishop, D. T. (2023). Cognitive load, working memory capacity and driving performance: A preliminary fNIRS and eye tracking study. *Transportation Research Part F: Traffic Psychology and Behaviour*, 92:121–132.

Brookhuis, K. A., de Vries, G., and de Waard, D. (1991). The effects of mobile telephoning on driving performance. *Accident Analysis and Prevention*, 23(4).

Buchsbaum, B. R. and D'Esposito, M. (2008). The search for the phonological store: From loop to convolution. *Journal of Cognitive Neuroscience*, 20(5).

Bunce, S. C., Izzetoglu, K., Ayaz, H., Shewokis, P., Izzetoglu, M., Pourrezaei, K., and Onaral, B. (2011). Implementation of fNIRS for monitoring levels of expertise and mental workload. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 6780 LNAI. Springer, Berlin, Heidelberg. ISSN: 03029743.

Burdett, B. R., Charlton, S. G., and Starkey, N. J. (2018). Inside the commuting driver's wandering mind. *Transportation Research Part F: Traffic Psychology and Behaviour*, 57:59–74.

Burdett, B. R., Charlton, S. G., and Starkey, N. J. (2019). Mind wandering during everyday driving: An on-road study. *Accident Analysis & Prevention*, 122:76–84.

Byrne, E. A. and Parasuraman, R. (1996). Psychophysiology and adaptive automation. *Biological Psychology*, 42(3).

Byrne, M. D. and Anderson, J. R. (2001). Serial modules in parallel: the psychological refractory period and perfect time-sharing. *Psychological review*, 108(4).

Calhoun, V. D., Pekar, J. J., McGinty, V. B., Adali, T., Watson, T. D., and Pearlson, G. D. (2002). Different activation dynamics in multiple neural systems during simulated driving. *Human Brain Mapping*, 16(3). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hbm.10032.

Callan, A. M., Osu, R., Yamagishi, Y., Callan, D. E., and Inoue, N. (2009). Neural correlates of resolving uncertainty in driver's decision making. *Human Brain Mapping*, 30(9). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hbm.20710.

Cao, S. and Liu, Y. (2013). Concurrent processing of vehicle lane keeping and speech comprehension tasks. *Accident Analysis & Prevention*, 59:46–54.

Cassez, F., David, A., Fleury, E., Larsen, K. G., and Lime, D. (2005). Efficient on-the-fly algorithms for the analysis of timed games. In Abadi, M. and de Alfaro, L., editors, *CONCUR 2005 – Concurrency Theory*, Lecture Notes in Computer Science. Springer.

Chai, T. and Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)? – arguments against avoiding RMSE in the literature. *Geoscientific Model Development*, 7(3).

Chooi, W. T. and Logie, R. (2020). Changes in error patterns during n-back training indicate reliance on subvocal rehearsal. *Memory and Cognition*, 48(8). Publisher: Springer.

Cina, M. and Rad, A. B. (2023). Categorized review of drive simulators and driver behavior analysis focusing on ACT-r architecture in autonomous vehicles. *Sustainable Energy Technologies and Assessments*, 56.

Ciric, R., Thompson, W. H., Lorenz, R., Goncalves, M., MacNicol, E., Markiewicz, C. J., Halchenko, Y. O., Ghosh, S. S., Gorgolewski, K. J., Poldrack, R. A., and Esteban, O. (2022). TemplateFlow: FAIR-sharing of multi-scale, multi-species brain models. *Nature Methods*, 19:1568–1571.

Corbetta, M. and Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews Neuroscience*, 3(3):201–215.

Cox, R. W. and Hyde, J. S. (1997). Software tools for analysis and visualization of fmri data. *NMR in Biomedicine*, 10(4-5):171–178.

Culham, J. C., Brandt, S. A., Cavanagh, P., Kanwisher, N. G., Dale, A. M., and Tootell, R. B. H. (1998). Cortical fMRI activation produced by attentive tracking of moving targets. *Journal of Neurophysiology*, 80(5). Publisher: American Physiological Society.

Dale, A. M., Fischl, B., and Sereno, M. I. (1999). Cortical surface-based analysis: I. segmentation and surface reconstruction. *NeuroImage*, 9(2):179–194.

Damm, W., Fränzle, M., Lüdtke, A., Rieger, J. W., Trende, A., and Unni, A. (2019). Integrating neurophysiological sensors and driver models for safe and performant automated vehicle control in mixed traffic. In *2019 IEEE Intelligent Vehicles Symposium (IV)*, pages 82–89. IEEE.

D'Arcy, R. C. N., Hamilton, A., Jarmasz, M., Sullivan, S., and Stroink, G. (2006). Exploratory data analysis reveals visuovisual interhemispheric transfer in functional magnetic resonance imaging. *Magnetic Resonance in Medicine*, 55(4):952–958. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/mrm.20839.

de Waard, D. (1996). *The measurement of drivers' mental workload*. PhD thesis, University of Groningen. date_submitted:2006 Rights: University of Groningen.

de Waard, D., Jessurun, M., Steyvers, F. J., Reggatt, P. T., and Brookhuis, K. A. (1995). Effect of road layout and road environment on driving performance, drivers' physiology and road appreciation. *Ergonomics*, 38(7).

de Winter, J. C. F., Happee, R., Martens, M. H., and Stanton, N. A. (2014). Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence. *Transportation Research Part F: Traffic Psychology and Behaviour*, 27:196–217.

Dijksterhuis, C., Brookhuis, K. A., and De Waard, D. (2011). Effects of steering demand on lane keeping behaviour, self-reports, and physiology. a simulator study. *Accident Analysis and Prevention*, 43(3).

Durantin, G., Dehais, F., and Delorme, A. (2015). Characterization of mind wandering using fnirs. *Frontiers in systems neuroscience*, 9:45.

Einhäuser, W. (2017). The Pupil as Marker of Cognitive Processes. In Zhao, Q., editor, *Computational and Cognitive Neuroscience of Vision*. Springer, Singapore.

Emmanouilidis, C., Pistofidis, P., Bertoncelj, L., Katsouros, V., Fournaris, A., Koulamas, C., and Ruiz-Carcel, C. (2019). Enabling the human in the loop: Linked data and knowledge in industrial cyber-physical systems. *Annual Reviews in Control*, 47. Publisher: Pergamon.

Endsley, M. (1988). Situation awareness global assessment technique (SAGAT). In *Proceedings of the IEEE 1988 National Aerospace and Electronics Conference*, pages 789–795 vol.3.

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human factors*, 37(1):32–64.

Endsley, M. R. (2020). The divergence of objective and subjective situation awareness: A meta-analysis. *Journal of Cognitive Engineering and Decision Making*, 14(1).

Engström, J., Johansson, E., and Östlund, J. (2005). Effects of visual and cognitive load in real and simulated motorway driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, 8(2).

Engström, J., Markkula, G., Victor, T., and Merat, N. (2017). Effects of cognitive load on driving performance: The cognitive control hypothesis. *Human Factors*, 59(5).

Esteban, O., Markiewicz, C. J., Blair, R. W., Moodie, C. A., Isik, A. I., Erramuzpe, A., Kent, J. D., Goncalves, M., DuPre, E., Snyder, M., Oya, H., Ghosh, S. S., Wright, J., Durnez, J., Poldrack, R. A., and Gorgolewski, K. J. (2019). fMRIPrep: a robust preprocessing pipeline for functional MRI. *Nature Methods*, 16(1). Publisher: Nature Publishing Group.

Evans, A., Janke, A., Collins, D., and Baillet, S. (2012). Brain templates and atlases. *NeuroImage*, 62(2):911–922.

Fernandez, S. A., Marinho, M. A. M., Vakilzadeh, M., and Vinel, A. (2021). Highway on-ramp merging for mixed traffic: Recent advances and future trends. In *2021 IEEE 29th International Conference on Network Protocols (ICNP)*, pages 1–6. ISSN: 2643-3303.

Fitch, G. M., Grove, K., Hanowski, R. J., and Perez, M. A. (2014). Compensatory behavior of drivers when conversing on a cell phone: Investigation with naturalistic driving data. *Transportation Research Record: Journal of the Transportation Research Board*, 2434(1).

Fonov, V., Evans, A., McKinstry, R., Almli, C., and Collins, D. (2009). Unbiased nonlinear average age-appropriate brain templates from birth to adulthood. *NeuroImage*, 47, Supplement 1:S102.

Foster, B. L., Koslov, S. R., Aponik-Gremillion, L., Monko, M. E., Hayden, B. Y., and Heilbronner, S. R. (2023). A tripartite view of the posterior cingulate cortex. *Nature Reviews Neuroscience*, 24(3). Publisher: Nature Publishing Group.

Fox, M. D., Snyder, A. Z., Vincent, J. L., Corbetta, M., Van Essen, D. C., and Raichle, M. E. (2005). The human brain is intrinsically organized into dynamic, anticorrelated functional networks. *Proceedings of the National Academy of Sciences*, 102(27):9673–9678. Publisher: Proceedings of the National Academy of Sciences.

Fraser, L. M., Stevens, M. T., Beyea, S. D., and D'Arcy, R. C. N. (2012). White versus gray matter: fMRI hemodynamic responses show similar characteristics, but differ in peak amplitude. *BMC Neuroscience*, 13(1):91.

Geng, J. J. and Vossel, S. (2013). Re-evaluating the role of TPJ in attentional control: Contextual updating? *Neuroscience & Biobehavioral Reviews*, 37(10).

Gharib, S., Zare-Sadeghi, A., Zakerian, S. A., and Haidari, M. R. (2020). The neural basis of hazard perception differences between novice and experienced drivers - an fMRI study. *EXCLI Journal*, 19.

Gigerenzer, G. and Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, 62(1).

Godley, S. T., Triggs, T. J., and Fildes, B. N. (2004). Perceptual lane width, wide perceptual road centre markings and driving speeds. *Ergonomics*, 47(3).

Greenshields, B. D. (1963). Driving behavior and related problems and discussion. *Highway Research Record*, (25).

Greve, D. N. and Fischl, B. (2009). Accurate and robust brain image alignment using boundary-based registration. *NeuroImage*, 48(1):63–72.

Gruberger, M., Ben-Simon, E., Levkovitz, Y., Zangen, A., and Hendler, T. (2011). Towards a neuroscience of mind-wandering. *Frontiers in human neuroscience*, 5:56.

Gunzelmann, G., Richard Moore, L., Salvucci, D. D., and Gluck, K. A. (2011). Sleep loss and driver performance: Quantitative predictions with zero free parameters. *Cognitive Systems Research*, 12(2). Publisher: Elsevier B.V.

Gusnard, D. A., Akbudak, E., Shulman, G. L., and Raichle, M. E. (2001). Medial prefrontal cortex and self-referential mental activity: Relation to a default mode of brain function. *Proceedings of the National Academy of Sciences*, 98(7):4259–4264. Publisher: Proceedings of the National Academy of Sciences.

Guériau, M. and Dusparic, I. (2020). Quantifying the impact of connected and autonomous vehicles on traffic efficiency and safety in mixed traffic. In *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–8.

Haghani, M., Bliemer, M. C., Farooq, B., Kim, I., Li, Z., Oh, C., Shahhoseini, Z., and MacDougall, H. (2021). Applications of brain imaging methods in driving behaviour research. *Accident Analysis & Prevention*, 154.

Hancock, P. A. (1989). A dynamic model of stress and sustained attention. *Human Factors*, 31(5). Publisher: SAGE Publications Inc.

Hancock, P. A., Jagacinski, R. J., Parasuraman, R., Wickens, C. D., Wilson, G. F., and Kaber, D. B. (2013). Human-automation interaction research: Past, present, and future. *Ergonomics in Design*, 21:9–14.

Hancock, P. A., Lesch, M., and Simmons, L. (2003). The distraction effects of phone use during a crucial driving maneuver. *Accident Analysis and Prevention*, 35(4).

Harding, J., Powell, G., Yoon, R., Fikentscher, J., Doyle, C., Sade, D., Lukuc, M., Simons, J., Wang, J., et al. (2014). Vehicle-to-vehicle communications: readiness of v2v technology for application. Technical report, United States. National Highway Traffic Safety Administration.

Hart, S. G. and Staveland, L. E. (1988). Development of NASA-TLX (task load index): Results of empirical and theoretical research. *Advances in Psychology*, 52.

He, J., Becic, E., Lee, Y.-C., and McCarley, J. S. (2011). Mind wandering behind the wheel: Performance and oculomotor correlates. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 53(1):13–21.

He, J. and McCarley, J. S. (2011). Effects of cognitive distraction on lane-keeping: Performance loss or improvement? *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 55(1):1894–1898.

He, J., McCarley, J. S., and Kramer, A. F. (2014). Lane keeping under cognitive load: Performance changes and mechanisms. *Human Factors*, 56(2). Publisher: SAGE PublicationsSage CA: Los Angeles, CA.

Heekeren, H. R., Marrett, S., and Ungerleider, L. G. (2008). The neural systems that mediate human perceptual decision making. *Nature Reviews Neuroscience*, 9(6).

Held, M., Minculescu, A., Rieger, J. W., and Borst, J. P. (2024a). Preventing mind-wandering during driving: Predictions on potential interventions using a cognitive model. *International Journal of Human-Computer Studies*, 181.

Held, M., Rieger, J. W., and Borst, J. P. (2024b). Multitasking while driving: Central bottleneck or problem state interference? *Human Factors*, 66(5):1564–1582. Publisher: SAGE Publications Inc.

Hicks, T. G. and Wierwille, W. W. (1979). Comparison of five mental workload assessment procedures in a moving-base driving simulator. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 21(2). Publisher: SAGE PublicationsSage CA: Los Angeles, CA.

Highway Traffic Safety Administration, N. and Department of Transportation, U. (2016). Technical report.

Hiser, J. and Koenigs, M. (2018). The multifaceted role of the ventromedial prefrontal cortex in emotion, decision making, social cognition, and psychopathology. *Biological Psychiatry*, 83(8).

Horberry, T., Anderson, J., Regan, M. A., Triggs, T. J., and Brown, J. (2006). Driver distraction: The effects of concurrent in-vehicle tasks, road environment complexity and age on driving performance. *Accident Analysis and Prevention*, 38(1).

Ito, H., Atsumi, B., Uno, H., and Akamatsu, M. (2001). Visual distraction while driving. *IATSS Research*, 25(2).

Jenkinson, M., Bannister, P., Brady, M., and Smith, S. (2002). Improved optimization for the robust and accurate linear registration and motion correction of brain images. *NeuroImage*, 17(2):825–841.

Jenness, J. W., Lattanzio, R. J., O'Toole, M., Taylor, N., and Pax, C. (2002). Effects of manual versus voice-activated dialing during simulated driving. *Perceptual and motor skills*, 94(2). Publisher: Dr. C.H. Ammons.

Jia, L., Huang, C., and Du, N. (2024). Drivers' situational awareness of surrounding vehicles during takeovers: Evidence from a driving simulator study. *Transportation Research Part F: Traffic Psychology and Behaviour*, 106.

Jin, C. Y., Borst, J. P., and van Vugt, M. K. (2019). Predicting task-general mind-wandering with EEG. *Cognitive, Affective, & Behavioral Neuroscience*, 19(4).

Jin, C. Y., Borst, J. P., and Vugt, M. K. (2020). Distinguishing vigilance decrement and low task demands from mind□wandering: A machine learning analysis of EEG. *European Journal of Neuroscience*, 52(9):4147–4164.

Kahneman, D. (1973). *Attention and effort*, volume 1063. Citeseer.

Kahneman, D. and Beatty, J. (1966). Pupil diameter and load on memory. *Science*, 154(3756).

Kass, S. J., Cole, K. S., and Stanny, C. J. (2007). Effects of distraction and experience on situation awareness and simulated driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, 10(4). Publisher: Pergamon.

Katidioti, I., Borst, J. P., Bierens de Haan, D. J., Pepping, T., van Vugt, M. K., and Taatgen, N. A. (2016). Interrupted by your pupil: An interruption management system based on pupil dilation. *International Journal of Human–Computer Interaction*, 32(10).

Khosroshahi, E. B., Salvucci, D. D., Veksler, B. Z., and Gunzelmann, G. (2016). Capturing the effects of moderate fatigue on driver performance. In *Proceedings of ICCM 2016 - 14th International Conference on Cognitive Modeling*.

Klaproth, O. W., Halbrügge, M., Krol, L. R., Vernaleken, C., Zander, T. O., and Russwinkel, N. (2020). A neuroadaptive cognitive model for dealing with uncertainty in tracing pilots' cognitive state. *Topics in Cognitive Science*, 12(3).

Klein, A., Ghosh, S. S., Bao, F. S., Giard, J., Häme, Y., Stavsky, E., Lee, N., Rossa, B., Reuter, M., Neto, E. C., and Keshavan, A. (2017). Mindboggling morphometry of human brains. *PLOS Computational Biology*, 13(2):e1005350.

Kriegeskorte, N. and Douglas, P. K. (2018). Cognitive computational neuroscience. *Nature Neuroscience*, 21(9). Publisher: Nature Publishing Group.

Kriegeskorte, N. and Douglas, P. K. (2019). Interpreting encoding and decoding models. *Current opinion in neurobiology*, 55. Publisher: NIH Public Access.

Kujala, T. and Salvucci, D. D. (2015). Modeling visual sampling on in-car displays: The challenge of predicting safety-critical lapses of control. *International Journal of Human Computer Studies*, 79. Publisher: Academic Press.

Kutila, M. H., Jokela, M., Mäkinen, T., Viitanen, J., Markkula, G., and Victor, T. W. (2007). Driver cognitive distraction detection: Feature estimation and implementation. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, 221(9).

Lanczos, C. (1964). Evaluation of noisy data. *Journal of the Society for Industrial and Applied Mathematics Series B Numerical Analysis*, 1(1):76–85.

Langenfeld, V., Westphal, B., and Podelski, A. (2019). On formal verification of ACT-r architectures and models. In *CogSci*, pages 618–624.

Lebiere, C. (1999). The dynamics of cognition: An ACT-r model of cognitive arithmetic. *Kognitionswissenschaft*, 8(1).

Lee, Y. C., Lee, J. D., and Boyle, L. N. (2007). Visual attention in driving: The effects of cognitive load and visual disruption. *Human Factors*, 49(4). Publisher: SAGE PublicationsSage CA: Los Angeles, CA.

Levy, J., Pashler, H., and Boer, E. (2006). Central interference in driving: Is there any stopping the psychological refractory period? *Psychological Science*, 17(3).

Lewis, R. L., Vasishth, S., and Van Dyke, J. A. (2006). Computational principles of working memory in sentence comprehension. *Trends in cognitive sciences*, 10(10).

Li, Z., Bao, S., Kolmanovsky, I. V., and Yin, X. (2018). Visual-manual distraction detection using driving performance indicators with naturalistic driving data. *IEEE Transactions on Intelligent Transportation Systems*, 19(8).

Lin, C., Zhang, H., Gong, B., and Wu, D. (2021). Factors identification and prediction for mind wandering driving using machine learning. *Journal of Advanced Transportation*, 2021. Publisher: Hindawi.

Lin, C.-T., Chuang, C.-H., Kerick, S., Mullen, T., Jung, T.-P., Ko, L.-W., Chen, S.-A., King, J.-T., and McDowell, K. (2016). Mind-wandering tends to occur under low perceptual demands during driving. *Scientific Reports*, 6(1). Number: 1 Publisher: Nature Publishing Group.

Liu, R., Reimer, B., Song, S., Mehler, B., and Solovey, E. (2021a). Unsupervised fNIRS feature extraction with CAE and ESN autoencoder for driver cognitive load classification. *Journal of Neural Engineering*, 18(3):036002.

Liu, R., Walker, E., Friedman, L., Arrington, C. M., and Solovey, E. T. (2021b). fNIRS-based classification of mind-wandering with personalized window selection for multimodal learning interfaces. *Journal on Multimodal User Interfaces*, 15(3).

Liu, Z. and Wang, J. (2020). Human-cyber-physical systems: concepts, challenges, and research opportunities. *Frontiers of Information Technology & Electronic Engineering*, 21(11).

Lohani, M., Payne, B. R., and Strayer, D. L. (2019). A review of psychophysiological measures to assess cognitive states in real-world driving. *Frontiers in human neuroscience*, 13:57.

Lyu, D., Pappas, I., Menon, D. K., and Stamatakis, E. A. (2021). A precuneal causal loop mediates external and internal information integration in the human brain. *The Journal of Neuroscience*, 41(48):9944–9956.

Macdonald, W. A. and Hoffmann, E. R. (1977). A secondary task measure of driving demands: test track evaluation. Technical report, No. ARR Report No. 70.

Macdonald, W. A. and Hoffmann, E. R. (1980). Review of relationships between steering wheel reversal rate and driving task demand. *Human Factors*, 22(6).

Malouin, F., Richards, C. L., Jackson, P. L., Dumas, F., and Doyon, J. (2003). Brain activations during motor imagery of locomotor-related tasks: A PET study. *Human Brain Mapping*, 19(1). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hbm.10103.

Markkula, G. and Engström, J. (2006). A steering wheel reversal rate metric for assessing effects of visual and cognitive secondary task load. In *Proceedings of the 13th ITS World Congress*. Leeds.

Marquart, G., Cabrall, C., and de Winter, J. (2015a). Review of Eye-related Measures of Drivers' Mental Workload. *Procedia Manufacturing*, 3.

Marquart, G., Cabrall, C., and de Winter, J. (2015b). Review of eye-related measures of drivers' mental workload. *Procedia Manufacturing*, 3. Publisher: Elsevier B.V.

Martens, M. H. and Brouwer, R. F. (2013). Measuring being lost in thought: An exploratory driving simulator study. *Transportation Research Part F: Traffic Psychology and Behaviour*, 20. Publisher: Elsevier Ltd.

Mason, M. F., Norton, M. I., Van Horn, J. D., Wegner, D. M., Grafton, S. T., and Macrae, C. N. (2007). Wandering minds: The default network and stimulus-independent thought. *Science*, 315(5810):393–395. Publisher: American Association for the Advancement of Science.

Mathôt, S., Aarts, E., Verhage, M., Veenvliet, J. V., Dolan, C. V., and van der Sluis, S. (2013a). A simple way to reconstruct pupil size during eye blinks. *Figshare*, 17. ISBN: 1546-1726 (Electronic)\n1097-6256 (Linking).

Mathôt, S., Fabius, J., Van Heusden, E., and Van der Stigchel, S. (2018). Safe and sensible preprocessing and baseline correction of pupil-size data. *Behavior Research Methods*, 50(1). Publisher: Springer New York LLC.

Mathôt, S., Van Der Linden, L., Grainger, J., and Vitu, F. (2013b). The Pupillary Light Response Reveals the Focus of Covert Visual Attention. *PLoS ONE*, 8(10):e78168.

Matthews, S. C., Simmons, A. N., Lane, S. D., and Paulus, M. P. (2004). Selective activation of the nucleus accumbens during risk-taking decision making. *NeuroReport*, 15(13).

Mclean, J. R. and Hoffmann, E. R. (1973). The effects of restricted preview on driver steering control and performance. *Human Factors: The Journal of Human Factors and Ergonomics Society*, 15(4).

McLean, J. R. and Hoffmann, E. R. (1975). Steering reversals as a measure of driver performance and steering task difficulty. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 17(3). Publisher: SAGE PublicationsSage CA: Los Angeles, CA.

McVay, J. C. and Kane, M. J. (2009). Conducting the train of thought: Working memory capacity, goal neglect, and mind wandering in an executive-control task. *Journal of experimental psychology. Learning, memory, and cognition*, 35(1).

Medeiros-Ward, N., Cooper, J. M., and Strayer, D. L. (2014). Hierarchical control and driving. *Journal of Experimental Psychology: General*, 143(3).

Mishler, S. and Chen, J. (2023). Boring but demanding: Using secondary tasks to counter the driver vigilance decrement for partially automated driving. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, page 001872082311686.

Moye, A. J. and van Vugt, M. K. (2021). A computational model of focused attention meditation and its transfer to a sustained attention task. *IEEE Transactions on Affective Computing*, 12(2):329–339. Conference Name: IEEE Transactions on Affective Computing.

Newell, A. (2012). You can't play 20 questions with nature and win: Projective comments on the papers of this symposium. In *Machine intelligence*, pages 121–146. Routledge.

Nijboer, M., Borst, J., van Rijn, H., and Taatgen, N. (2014). Single-task fMRI overlap predicts concurrent multitasking interference. *NeuroImage*, 100. Publisher: Elsevier Inc.

Nijboer, M., Borst, J., van Rijn, H., and Taatgen, N. (2016a). Contrasting single and multi-component working-memory systems in dual tasking. *Cognitive Psychology*, 86. Publisher: Elsevier Inc.

Nijboer, M., Borst, J. P., van Rijn, H., and Taatgen, N. A. (2016b). Driving and multitasking: The good, the bad, and the dangerous. *Frontiers in Psychology*, 7.

Northoff, G. and Bermpohl, F. (2004). Cortical midline structures and the self. *Trends in Cognitive Sciences*, 8(3).

Oliveira, L., Burns, C., Luton, J., Iyer, S., and Birrell, S. (2020). The influence of system transparency on trust: Evaluating interfaces in a highly automated vehicle. *Transportation Research Part F: Traffic Psychology and Behaviour*, 72. Publisher: Elsevier Ltd.

Papantoniou, P., Papadimitriou, E., and Yannis, G. (2017). Review of driving performance parameters critical for distracted driving research. In *Transportation Research Procedia*, volume 25. Elsevier. ISSN: 23521465.

Park, S., Jeong, S., and Myung, R. (2018). Modeling of multiple sources of workload and time pressure effect with ACT-r. *International Journal of Industrial Ergonomics*, 63.

Park, S., Xing, Y., Akash, K., Misu, T., and Boyle, L. N. (2022). The impact of environmental complexity on drivers' situation awareness. In *Proceedings of the 14th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, pages 131–138. ACM.

Pashler, H. (1994). Dual-task interference in simple tasks: Data and theory. *Psychological Bulletin*, 116(2):220. Publisher: US: American Psychological Association.

Patriat, R., Reynolds, R. C., and Birn, R. M. (2017). An improved model of motion-related signal changes in fMRI. *NeuroImage*, 144, Part A.

Pepin, G., Fort, A., Jallais, C., Moreau, F., Ndiaye, D., Navarro, J., and Gabaude, C. (2021). Impact of mind□wandering on visual information processing while driving: An electrophysiological study. *Applied Cognitive Psychology*, 35(2).

Pillai, P., Balasingam, B., Jaekel, A., and Biondi, F. (2021). Kalman filtering to track changes in pupil size for automated driving systems. In *2021 IEEE 94th*

Vehicular Technology Conference (VTC2021-Fall), pages 1–6. ISSN: 2577-2465.

Power, J. D., Mitra, A., Laumann, T. O., Snyder, A. Z., Schlaggar, B. L., and Petersen, S. E. (2014). Methods to detect, characterize, and remove motion artifact in resting state fmri. *NeuroImage*, 84(Supplement C):320–341.

Pujara, M. S., Wolf, R. C., Baskaya, M. K., and Koenigs, M. (2015). Ventromedial prefrontal cortex damage alters relative risk tolerance for prospective gains and losses. *Neuropsychologia*, 79.

Raichle, M. E., MacLeod, A. M., Snyder, A. Z., Powers, W. J., Gusnard, D. A., and Shulman, G. L. (2001). A default mode of brain function. *Proceedings of the National Academy of Sciences*, 98(2):676–682. Publisher: Proceedings of the National Academy of Sciences.

Rajkumar, R., Lee, I., Sha, L., and Stankovic, J. (2010). Cyber-physical systems: The next computing revolution. In *Proceedings - Design Automation Conference*. ISSN: 0738100X.

Ratcliff, R. and Vanunu, Y. (2022). The effect of aging on decision making while driving: A diffusion model analysis. *Psychology and aging*, 37(4).

Ruff, C. C. and Fehr, E. (2014). The neurobiology of rewards and values in social decision making. *Nature Reviews Neuroscience*, 15(8). Publisher: Nature Publishing Group.

Ruijten, P. A., Terken, J. M., and Chandramouli, S. N. (2018). Enhancing trust in autonomous vehicles through intelligent user interfaces that mimic human behavior. *Multimodal Technologies and Interaction*, 2(4). Publisher: MDPI AG.

Sakagami, M., Pan, X., and Uttl, B. (2006). Behavioral inhibition and prefrontal cortex in decision-making. *Neural Networks*, 19(8).

Salmon, P. M., Stanton, N. A., Walker, G. H., Baber, C., Jenkins, D. P., McMaster, R., and Young, M. S. (2008). What really is going on? review of situation awareness models for individuals and teams. *Theoretical Issues in Ergonomics Science*, 9(4):297–323.

Salvucci, D., Taatgen, N. A., and Kushleyeva, Y. (2006). Learning when to switch tasks in a dynamic multitasking environment. *Proceedings of the seventh international conference on cognitive modeling*.

Salvucci, D. D. (2006). Modeling driver behavior in a cognitive architecture. *Human Factors*, 48(2).

Salvucci, D. D. and Beltowska, J. (2008). Effects of memory rehearsal on driver performance: Experiment and theoretical account. *Human Factors*, 50(5).

Salvucci, D. D. and Gray, R. (2004). A two-point visual control model of steering. *Perception*, 33(10). Publisher: SAGE PublicationsSage UK: London, England.

Salvucci, D. D. and Macuga, K. L. (2002). Predicting the effects of cellular-phone dialing on driver performance. *Cognitive Systems Research*, 3(1). Publisher: Elsevier.

Salvucci, D. D. and Taatgen, N. A. (2008). Threaded cognition: An integrated theory of concurrent multitasking. *Psychological Review*, 115(1).

Salvucci, D. D. and Taatgen, N. A. (2010). *The multitasking mind*. Oxford University Press.

Satterthwaite, T. D., Elliott, M. A., Gerraty, R. T., Ruparel, K., Loughead, J., Calkins, M. E., Eickhoff, S. B., Hakonarson, H., Gur, R. C., Gur, R. E., and Wolf, D. H. (2013). An improved framework for confound regression and filtering for control of motion artifact in the preprocessing of resting-state functional connectivity data. *NeuroImage*, 64(1):240–256.

Saxby, D. J., Matthews, G., Warm, J. S., Hitchcock, E. M., and Neubauer, C. (2013). Active and passive fatigue in simulated driving: Discriminating styles of workload regulation and their safety impacts. *Journal of Experimental Psychology: Applied*, 19(4).

Saxe, R. and Kanwisher, N. (2003). People thinking about thinking peopleThe role of the temporo-parietal junction in “theory of mind”. *NeuroImage*, 19(4).

Scerbo, M. W., Freeman, F. G., and Mikulka, P. J. (2003). A brain-based system for adaptive automation. *Theoretical Issues in Ergonomics Science*, 4(1). ISBN: 1463922021000.

Scharfe, M. and Russwinkel, N. (2020). Towards a cognitive model of the takeover in highly automated driving for the improvement of human machine interaction. *Proceedings of ICCM 2019 - 17th International Conference on Cognitive Modeling*. ISBN: 9780998508238.

Scheunemann, J., Unni, A., Ihme, K., Jipp, M., and Rieger, J. W. (2019). Demonstrating brain-level interactions between visuospatial attentional demands and working memory load while driving using functional near-infrared spectroscopy. *Frontiers in Human Neuroscience*, 12:542. ISBN: 1662-5161.

Schirner, G., Erdogmus, D., Chowdhury, K., and Padir, T. (2013). The future of human-in-the-loop cyber-physical systems. *Computer*, 46(1).

Schweizer, T. A., Kan, K., Hung, Y., Tam, F., Naglie, G., and Graham, S. J. (2013). Brain activity during driving with distraction: an immersive fmri study. *Frontiers in human neuroscience*, 7:53.

Schwerd, S. and Schulte, A. (2021). Operator state estimation to enable adaptive assistance in manned-unmanned-teaming. *Cognitive Systems Research*, 67:73–83.

Sharma, P. K. and Chakraborty, P. (2024). A review of driver gaze estimation and application in gaze behavior understanding. *Engineering Applications of Artificial Intelligence*, 133.

Simpson, H. M. and Molloy, F. M. (1971). Effects of Audience Anxiety on Pupil Size. *Psychophysiology*, 8(4). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1469-8986.1971.tb00481.x.

Smallwood, J. (2011). Mind-wandering while reading: Attentional decoupling, mindless reading and the cascade model of inattention. *Language and Linguistics Compass*, 5(2). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1749-818X.2010.00263.x.

Smallwood, J., Fishman, D. J., and Schooler, J. W. (2007). Counting the cost of an absent mind: Mind wandering as an underrecognized influence on educational performance. *Psychonomic Bulletin & Review*, 14(2):230–236.

Smallwood, J. and Schooler, J. W. (2015). The science of mind wandering: Empirically navigating the stream of consciousness. *Annual Review of Psychology*, 66(1). _eprint: https://doi.org/10.1146/annurev-psych-010814-015331.

Stolte, M., Gollan, B., and Ansorge, U. (2020). Tracking visual search demands and memory load through pupil dilation. *Journal of Vision*, 20(6).

Strayer, D. L., Drews, F. A., and Johnston, W. A. (2003). Cell phone-induced failures of visual attention during simulated driving. *Journal of Experimental*

Psychology: Applied, 9(1). Publisher: American Psychological Association Inc.

Strayer, D. L., Turrill, J., Cooper, J. M., Coleman, J. R., Medeiros-Ward, N., and Biondi, F. (2015). Assessing cognitive distraction in the automobile. *Human Factors*, 57(8). Publisher: SAGE Publications Inc.

Szpunar, K. K., Moulton, S. T., and Schacter, D. L. (2013). Mind wandering and education: From the classroom to online learning. *Frontiers in psychology*, 4:495.

Taatgen, N. A., Juvina, I., Schipper, M., Borst, J. P., and Martens, S. (2009). Too much control can hurt: A threaded cognition model of the attentional blink. *Cognitive Psychology*, 59(1). Publisher: Elsevier Inc.

Taatgen, N. A., van Vugt, M. K., Daamen, J., Katidioti, I., Huijser, S., and Borst, J. P. (2021). The resource-availability model of distraction and mind-wandering. *Cognitive Systems Research*, 68.

Tang, S., Liang, Y., and Li, Z. (2023). Mind wandering state detection during video-based learning via EEG. *Frontiers in Human Neuroscience*, 17.

Teasdale, J. D., Dritschel, B. H., Taylor, M. J., Proctor, L., Lloyd, C. A., Nimmo-Smith, I., and Baddeley, A. D. (1995). Stimulus-independent thought depends on central executive resources. *Memory & Cognition*, 23(5).

THC Staff (2017). Trivia signs set up along australian highway to keep drivers awake. Section: Lifestyle.

Transport for NSW (2019). ROAD TRAFFIC CASUALTY CRASHES IN NEW SOUTH WALES.

Trende, A., Unni, A., Jablonski, M., Biebl, B., Lüdtke, A., Fränzle, M., and Rieger, J. W. (2022). Driver's turning intent recognition model based on brain activation and contextual information. *Frontiers in Neuroergonomics*, 3.

Tsimhoni, O., Smith, D., and Green, P. (2004). Address entry while driving: Speech recognition versus a touch-screen keyboard. *Human Factors*, 46(4).

Tustison, N. J., Avants, B. B., Cook, P. A., Zheng, Y., Egan, A., Yushkevich, P. A., and Gee, J. C. (2010). N4itk: Improved n3 bias correction. *IEEE Transactions on Medical Imaging*, 29(6):1310–1320.

Unni, A., Ihme, K., Jipp, M., and Rieger, J. W. (2017). Assessing the driver's current level of working memory load with high density functional near-infrared spectroscopy: A realistic driving simulator study. *Frontiers in Human Neuroscience*, 11:167. Publisher: Frontiers.

Van De Merwe, K., Mallam, S., Nazir, S., and Engelhardtsen, O. (2024). The influence of agent transparency and complexity on situation awareness, mental workload, and task performance. *Journal of Cognitive Engineering and Decision Making*, 18(2).

van der Velde, M. A. (2018). Modelling the effect of depression on working memory.

van Vugt, M., Taatgen, N., Sackur, J., and Bastian, M. (2015). Modeling mind-wandering: a tool to better understand distraction. In *Proceedings of the 13th International Conference on Cognitive Modeling*, page 252.

Vorobyev, V., Kwon, M. S., Moe, D., Parkkola, R., and Hämäläinen, H. (2015). Risk-taking behavior in a computerized driving task: Brain activation correlates of decision-making, outcome, and peer influence in male adolescents. *PLOS ONE*.

Walker, H. E. and Trick, L. M. (2018). Mind-wandering while driving: The impact of fatigue, task length, and sustained attention abilities. *Transportation Research Part F: Traffic Psychology and Behaviour*, 59.

Weaver, B. W. and DeLucia, P. R. (2022). A Systematic Review and Meta-Analysis of Takeover Performance During Conditionally Automated Driving. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 64(7):1227–1260.

Welford, A. T. (1952). The psychological refractory period and the timing of high-speed performance - a review and a theory. *British Journal of Psychology. General Section*, 43(1). Num Pages: 18 Place: London, etc., United Kingdom Publisher: Cambridge University Press.

Wheeler, E. Z. and Fellows, L. K. (2008). The human ventromedial frontal lobe is critical for learning from negative feedback. *Brain*, 131(5):1323–1331.

Wickens, C. D. (2002). Multiple resources and performance prediction. *Theoretical Issues in Ergonomics Science*, 3(2).

Wickens, C. D. (2008). Multiple resources and mental workload. *Human Factors*, 50(3):449–455. Publisher: SAGE PublicationsSage CA: Los Angeles, CA.

Wiese, S., Lotz, A., and Russwinkel, N. (2019). Seev-vm: Act-r visual module based on seev theory. In *Proceedings of the 17th International Conference on Cognitive Modeling (ICCM 2019)*.

Yanko, M. R. and Spalek, T. M. (2013). Route familiarity breeds inattention: A driving simulator study. *Accident Analysis & Prevention*, 57:80–86.

Yanko, M. R. and Spalek, T. M. (2014). Driving with the wandering mind: The effect that mind-wandering has on driving performance. *Human Factors*, 56(2):260–269. Publisher: SAGE Publications Inc.

Yi, H. G., Leonard, M. K., and Chang, E. F. (2019). The encoding of speech sounds in the superior temporal gyrus. *Neuron*, 102(6):1096–1110.

Yoshida, Y., Ohwada, H., Mizoguchi, F., and Iwasaki, H. (2014). Classifying cognitive load and driving situation with machine learning. *International Journal of Machine Learning and Computing*, 4(3):210–215.

Zgonnikov, A., Abbink, D., and Markkula, G. (2022). Should i stay or should i go? cognitive modeling of left-turn gap acceptance decisions in human drivers. *Human Factors*. Publisher: SAGE Publications Inc.

Zhang, T., Yang, J., Liang, N., Pitts, B. J., Prakah-Asante, K., Curry, R., Duerstock, B., Wachs, J. P., and Yu, D. (2023). Physiological measurements of situation awareness: A systematic review. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 65(5):737–758.

Zhang, Y., Brady, M., and Smith, S. (2001). Segmentation of brain MR images through a hidden markov random field model and the expectation-maximization algorithm. *IEEE Transactions on Medical Imaging*, 20(1):45–57.

Zhang, Y. and Kumada, T. (2017). Relationship between workload and mind-wandering in simulated driving. *PLOS ONE*, 12(5). Publisher: Public Library of Science.

Zhang, Y. and Kumada, T. (2018). Automatic detection of mind wandering in a simulated driving task with behavioral measures. *PLOS ONE*, 13(11). Publisher: Public Library of Science.

Acknowledgments

This thesis has been shaped by many people, to all of whom I owe my deepest gratitude. Completing this PhD has been a long and challenging journey, and it would not have been possible without the support, guidance, and encouragement of the remarkable individuals around me. I would like to take this opportunity to express my sincerest appreciation to everyone who contributed to this work, both academically and personally.

First, I would like to thank my supervisors Jelmer Borst and Jochem Rieger. You have both taught me more than I could ever adequately summarize here. Jelmer, I once compared you to a compass, and I still think that metaphor holds as you have always provided me with direction while letting me choose the destination. I am deeply grateful for your trust, your kindness, and your always approachable nature. Jochem, I greatly admire your curiosity and your determination to understand things at a depth where many others would long have stopped. Your commitment to true understanding in your professional and personal life has made you knowledgeable in ways that extend far beyond your own field. I feel fortunate to have learned from both of you.

I would also like to thank my assessment committee: Dario, Martin, Susanne & Dick as well as the additional members of my examination committee. Thank you for taking the time to read my thesis, providing valuable feedback and attending my defense.

Next, I would like to thank my two working groups for their feedback on presentations, projects and for all the fun times during lunch and coffee: The ANCP lab and the cognitive modeling group. So thanks to Anirudh, Arkan, Katharina, Jooris, Leo, Hayder, Aaron, Karel, Jessica, Sina and Alex. Also from the cognitive modeling group thanks to Corné, Abby, Joshua, Hermine, Gabriel, Marieke, Niels, Ivo, Katja, Hermine, Stefan, Maarten, Stephen, Jacolien, Lionel, Mi and Thomas.

Part of my PhD also involved acquiring data at the Neuroimaging Unit Oldenburg. Thank you to all other PhD students who let me observe their MRI acquisition and special thanks to Gülsen, Britta and Tina for teaching how to operate an MRI machine and trusting me to acquire the data. Also special thanks to Sude for tirelessly running MRI experiments to me at odd hours and making the whole process run so seamlessly and fun.

I also want to thank all the people in my personal life who helped me along the way. Hanjo without whom I would not have been able to attend university in the first place. Also thank you to my paranymphs Juan and Pauline as well as all the rest of my Oldenburg gang: Hatice, Tommaso, Izabel, Mina, Gustavo and Pushkar. I am so glad you are all in my life and you guys have brought so much joy during these years that all the stress and work of the PhD seemed only half as much.

Lastly, I want to thank Isabel for her unwavering emotional support and for always being there for me. Your presence, resilience to my frustration, and encouragement have meant more than I can put into words.