Challenges in Partially Automated Driving: A Human Factors Perspective

Ignacio Solís Marcos

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*Ahora digo —dijo a esta sazón don
Quijote— que el que lee mucho y anda
mucho, ve mucho y sabe mucho
(Don Quijote de la Mancha, Miguel
de Cervantes Saavedra, 1615)*

*Equipped with his five senses, man
explores the universe around him and calls the adventure
Science
(Edwin Hubble, 1929)*

ABSTRACT

The technological development in recent years is currently reflected in the implementation of more and more advanced driver assistance systems (ADAS). A clear example is found in the automated driving systems being marketed today. Some of these systems are capable of controlling crucial driving tasks such as keeping the vehicle within the lane or maintaining speed and the distance with the front vehicle constant. While this technology is still not mature enough to allow fully autonomous driving, current systems allow partially automated driving, or Level 2 (SAE, 2016). Level 2 automation enables feet-free, and for short periods hands-free driving, under specific situations. Yet, the driver is still expected to monitor the road and the system and be ready to intervene when required by the system. Regarding this, studies from the driving and other domains have warned about potential performance problems associated with placing operators in such monitoring role. Factors such as vigilance decrements or proneness to engage in other activities have been proposed to explain these problems; however, their role in the context of Level 2 automation remains to be further investigated.

In this context, the main aims of this thesis were to understand the attentional effects of monitoring a Level 2 automated system and to investigate drivers' strategies to integrate additional tasks while using such system. In particular, the following research questions were established: 1) Does monitoring a Level 2 system affect driver attention after short driving periods?; 2) Does Level 2 automation facilitate the performance of additional tasks?; 3) How do drivers integrate additional tasks into their monitoring responsibilities, and how is that influenced by automation trust and experience?. A complementary aim of this thesis was to explore the applicability of the event-related potentials (ERPs) technique to detect the effects of different types of ADAS, i.e. Level 2 automation and a visual in-vehicle information system (IVIS), on drivers' attention and on specific processing resources.

Three studies were conducted to address the aforementioned research questions. In Study I and III, the participants were asked to drive Level 2 automated and manually while performing an auditory oddball task (Study I) or a visuomotor task (Study III). In Study II, the participants were instructed to perform a computer tracking task with or without the support of an artificial visual IVIS while executing a secondary auditory oddball task. Measurements included performance indicators from the primary and secondary tasks, as well as subjective and psychophysiological measures. ERPs (N1 and P3 amplitude and latencies) elicited by the auditory oddball task were used to assess the participants' attentional resource allocation. Glance behaviour was also recorded to analyse drivers' visual monitoring strategies in Study III. In addition, subjective measures of mental workload, vigilance or automation trust were collected. Last, driving parameters such as speed, time spent on the left lane or number overtakings were used to account for driving

strategies to integrate an additional task while driving Level 2 automated or manually (Study III).

As hypothesized, monitoring a Level 2 automated system for short periods led to lower perceived demands and to reductions in the allocation of attentional resources to the auditory oddball task, as shown by lower amplitudes in the P3 component (Study I). In Study III, driving Level 2 automated led to worse performances on an additional visuomotor task, compared to when driving manually, which contradicted our expectations. Additionally, when the system was active, drivers tended to look less to the road and more to the dashboard; however, only drivers with automation experience or who perceived the system as more robust increased their visual attention to the additional task. Furthermore, the results from Study II showed that some specific ERPs parameters, namely N1 latency and P3 amplitude, were also sensitive to the demands of IVIS while performing the tracking task.

Based on previous studies (Young and Stanton, 2002), the lower attentional resource allocation observed in Study I could reflect a cognitive underload effect induced by the Level 2 automated driving. Cognitive underload is proposed as one of the explaining mechanisms for the observed worse performances in the additional visuomotor task during the automated conditions in Study III. However, other effects such as overload or task interferences could also explain this. Finally, the results revealed by the ERPs in Studies I and II suggest that this could be a useful technique to detect alterations in drivers' attention due to the excessive high or low demands placed by different ADAS. ERPs also showed a greater diagnosticity than other measures in the detection of specific task requirements of perceptual and cognitive resources. Thus, ERPs may be useful as a complementary tool to other mental workload measures.

Given that drivers need to remain attentive at all times while interacting with a Level 2 automated vehicle, the use of countermeasures to mitigate the negative attentional effects reported in this thesis is highly recommended. Specific training programs enhancing drivers' knowledge of the system or the implementation of systems that inform about the system reliability or detect inadequate driver states could be promising solutions.

LIST OF ABBREVIATIONS

ABS – Antilock Braking System
ACC – Adaptive Cruise Control
ADAS – Advanced Driver Automated Systems
ANOVA – Analysis of Variance
BASt – Federal Highway Research Institute
DiC – Driver in Control
EEG – Electroencephalogram
EOG – Electrooculography
ERH – Effort Regulation Hypothesis
ERPs – Event-Related Potentials
ESC – Electronic Stability Control
HMI – Human-Machine Interface
ICA – Independent Component Analysis
IVIS – In-vehicle Information Systems
LKA – Lane Keeping Assist
MART – Malleable Attentional Resource Theory
MiRA – Minimum Required Attention
MWL – Mental Workload
NHTSA –National Highway Traffic Safety Administration
OOL – Out of the loop
PA2 – Pilot Assist Generation 2
SAE – Society of Automotive Engineers
VRU – Vulnerable Road users
WHO – World Health Organization

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LIST OF PAPERS

For this thesis, three studies were conducted, and four papers were generated. The studies were performed in different experimental settings, from well-controlled laboratory conditions to more ecological contexts like driving in real traffic. Next, the list of papers included in this thesis is presented, as well as the authors' contribution to each of them.

LIST OF PAPERS

Paper I

Solís-Marcos, I., Galvao-Carmona, A., & Kircher, K. (2017). Reduced Attention Allocation during Short Periods of Partially Automated Driving: An Event-Related Potentials Study. *Frontiers in Human Neuroscience*, 11(November), 1–13. <http://doi.org/10.3389/fnhum.2017.00537>.

Paper II:

Solís-Marcos, I. & Kircher, K. (2018). Event-Related Potentials As Indices of Mental Workload While Using an In-Vehicle Information System. *Cognition, Technology and Work*, 1-13. <https://doi.org/10.1007/s10111-018-0485-z>

Paper III:

Solís-Marcos, I., Ahlström, C. & Kircher, K. (in press). Performance of an additional task during Level 2 automated driving: An on-road study comparing drivers with and without experience with partial automation. *Human Factors: The Journal of Human Factors and Ergonomics Society*.

Paper IV:

Solís-Marcos, I., Eriksson, A., Strand, N., Ahlström, C. & Kircher, K. (under review). Can I look away now?. The role of trust and experience when engaging in non-driving related tasks in a partially automated vehicle. *Submitted to Human Factors: The Journal of Human Factors and Ergonomics Society*.

AUTHORS' CONTRIBUTION TO THE PAPERS

Paper I

I designed the study, collected and analyzed the data and wrote the paper. Katja Kircher and Alejandro Galvao Carmona supervised the conceptualization of the work and interpretation of results, respectively.

Paper II

I designed the study, collected and analyzed the data and wrote most part of the paper. Katja Kircher supervised the experimental design and wrote part of the paper.

Paper III

I designed the study and collected and analysed the data. I also interpreted the results and wrote most part of the paper. Christer Ahlström performed part of the glance analyses and contributed to the paper writing. Katja Kircher supervised the conceptualisation of the study and wrote part of the paper.

Paper IV

I conceptualised the work, collected and analysed the data, and interpreted the results. In addition, I wrote most part of the paper. Christer Ahlström performed part of the glance analyses. Katja Kircher supervised the conceptualisation of the work. Alexander Eriksson wrote some parts of the paper and, along with Niklas Strand, supervised the paper writing.

1. INTRODUCTION

1.1. TRAFFIC SAFETY

From 2007 to 2013, 7.5 million people died in a traffic accident, representing the leading cause of death among people aged 15 – 29 years. In addition, it is estimated that between 20 and 50 million people incur non-fatal accidents every year (World Health Organization, 2015), an intolerably high number that is expected to increase in the next decade. An important factor for such increase is the growing *monetization* of low- and middle-income countries, where 90% of the world fatalities occur. Despite the improvements in road safety in the last 10 years, different international initiatives are currently being undertaken to take coordinated and decisive actions to mitigate this global problem. A clear example is The Decade of Action for Road Safety (2011 - 2020), an initiative adopted by the United Nations General Assembly with the aim of halving the number of victims by 2020 (World Health Organization, 2011).

It is estimated that approximately 90% of all traffic accidents can be directly or indirectly attributed to human error (Singh, 2015). In many cases, these errors are attributed to states of inattention and/or distraction leading to poor performance in safety-critical tasks such as detecting hazards or reacting in a timely manner to potential events on the road. In other cases, human errors are directly linked to risky behaviours like driving under the influence of alcohol, driving over the speed limit or not using helmets, seat belts or child restraints (WHO, 2015).

To mitigate this global problem, one of the strategies adopted by the initiative The Decade of Action for Road Safety is to strengthen the legislation on road safety as a means to prevent drivers from developing risky behaviours. Another strategy is to take measures aimed at increasing the safety of vulnerable road users (VRUs) such as cyclists, motorcyclists and pedestrians in the transport system since they represent about 50% of the total victims. As an example, some initiatives consist of lowering the speed limits within urban areas to reach a more sustainable and integrative transportation system for all road users, including VRUs. Among other measures being taken by the Decade of Action for Road Safety, it is worth mentioning the development of more effective passive and active safety systems. Passive safety systems consist of solutions aimed at reducing the damages resulting from an accident as much as possible. Some examples are seatbelts, airbags or head restraints to protect the driver from whiplash injuries. On the other hand, active safety systems are mostly aimed at preventing or mitigating the occurrence of accidents and intervene when it is beyond the human capability to act (ERTRAC Task Force, 2015). Thus, active safety systems will not only be beneficial for the driver him/herself but for the other road users as well. Some examples of active safety systems include the antilock braking system (ABS), the blind spot detection system and the electronic stability control (ESC).

Within the group of active safety systems, there is a sub-group of systems known as the advanced driver assistance systems (ADAS). ADAS consist of a full range of different systems capable of assisting and even supplanting drivers in a wide variety of driving-related tasks. By means of cameras, radars and lidars, among other systems, ADAS obtain and analyse the information from the surrounding traffic situation. This information is then conveyed to the driver through displays (e.g. in-vehicle information systems or IVIS) or used by different automated systems to perform specific manoeuvres (e.g. Intelligent Parking Assist System) or to control certain vehicle dynamics for long periods of driving (e.g. adaptive cruise control or ACC). While some of these systems, like ACC, have been on the market for quite some time, great efforts are being invested today to develop and integrate new and more advanced ADAS. These efforts are becoming evident today with the commercialization of vehicles equipped with more advanced IVIS and automated systems capable of controlling and coordinating different simultaneous driving tasks. Some examples are the Volvo Pilot Assist Generation 2 system (henceforth referred to as “PA2 system”) or the Tesla Autopilot, both enabling feet-free and, for short periods, hands-free driving.

There exist some arguments for equipping vehicles with ADAS. As Parasuraman, Sheridan and Wickens (2000) pointed out, these systems do not only assist drivers in physical tasks but also in cognitive tasks like information acquisition and analysis, decision-making or action implementation. Expectedly, ADAS with such capabilities will outperform humans in safety-relevant tasks such as detecting obstacles or reacting in time to potential obstacles. In addition, the automated systems are expected to reduce the amount of physical and mental tasks to be performed by the drivers, giving them the opportunity to safely engage in other non-driving related tasks, thus increasing their comfort. Besides safety and comfort, automated systems are also expected to have a positive impact on other relevant aspects. For example, they are expected to optimize traffic flow by enhancing road capacity and reducing traffic jams. Likewise, fully automated vehicles may increase the mobility of non-drivers (e.g. children, the elderly, etc.), thus increasing their accessibility to the transport system and favouring social inclusion (ERTRAC Task Force, 2015).

1.2. ISSUES REGARDING HUMAN FACTORS IN AUTOMATED DRIVING

Despite the expected beneficial effects of automation on safety and comfort, research has shown that these systems may also negatively affect the driver abilities, behavior, and eventually, performance (Carsten and Nilsson, 2001; Saffarian, de Winter, Happee, 2012). For example, different studies have shown that some IVIS may increase the driver demands and the chances of distraction (Reyes and Lee, 2004). Likewise, automated systems enabling intermediate automation levels where the driver and the system have to cooperate, have also been shown to affect driving performance. Most of these issues have to do with the fact that the driver is still required to constantly supervise the system actions and/or intervene when the system or the situation requires it. As pointed out by Bainbridge

(1983), this represents an “irony of automation” as, despite the support provided by the system, the driver remains responsible for the most crucial aspects of driving.

Paradoxically, expected benefits of automation such as reducing the driver workload, have been found to hinder the optimal performance of his/her responsibilities, i.e. monitor and intervene when necessary. For example, different studies have shown that while the automation is active, drivers’ monitoring of the road and the system is reduced due to either, a lower ability to remain attentive or, to a greater proneness to engage in other tasks (e.g. Carsten, Lai, Barnard, Jamson and Merat, 2012; Körber, Cingel, Zimmermann and Bengler, 2015; Merat and Jamson, 2009; Young and Stanton, 2007). Consequently, drivers have a worse representation of the ongoing driving situation and a decreased capacity to react to critical situations (Eriksson and Stanton, 2017). In essence, these and other reported human factors concerns are thought to evidence poor driver-system interaction leading to unanticipated effects on drivers’ abilities and performance.

Likely, these issues will represent some of the most relevant safety challenges for the next generation of automated vehicles, and therefore, it is paramount to investigate them and provide effective countermeasures. With this aim, great efforts have been invested by different international industrial and academic partners all over the world in the last decade. One good example is the Human Factors of Automated Driving project (Human Factors of Automated Driving, 2013), funded by the European Commission through ITN-Marie Curie Actions, in which the present thesis is framed.

2. AIMS OF THE THESIS

Level 2 automated vehicles are a reality today, and despite their potential benefits for driver safety and comfort, a risk exists that they will affect drivers' abilities and behaviour with negative effects on safety. The literature on automation has highlighted vigilance decrements and distraction with other tasks as some of the main concerns in Level 2 automation. Despite this, very few studies have attempted to directly measure the driver attention while monitoring or to learn about the drivers' strategies to integrate additional tasks.

In this context, the primary aim of this thesis was to investigate the actual effects of Level 2 automation on the driver attention and on his/her monitoring strategies when engaged in additional tasks ("Main Goal 1" in Figure 1). Another complementary aim in this thesis was to explore the applicability of the event-related potentials (ERPs) technique to better account for the Level 2 automation effects on drivers' information processing capacity ("Main Goal 2" in Figure 1). This objective was also extended to analyse the applicability of ERPs to detect the attentional effects of an artificial visual IVIS.

Four different papers were developed, each of which addressed one or various of the aims aforementioned, as well as other more specific objectives. Below, the different papers included in the thesis are presented along with the main goals covered by them:

- Paper I. Reduced attention allocation during short periods of partially automated driving: an event-related potentials study.
 - Investigate the effects of monitoring a Level 2 automated system on drivers' attention, specifically, on the allocation of attentional resources.
 - Analyse the sensitivity of the ERPs technique to decrements in drivers' allocation of attentional resources derived from the potential cognitive underload effects induced by automation.
- Paper II. Event-related potentials as indicators of mental workload while using an in-vehicle information system.
 - Analyse the influence of the *number of concurrent tasks* to perform and the *time pressure* on drivers' mental workload, attention and performance.
 - Analyse the sensitivity of ERPs to the demands placed by the increasing number of concurrent tasks and time pressure. Explore the diagnostic capacity of ERPs to inform on the specific processing requirements of the different sources of demand.
- Paper III. Performance of an additional task during Level 2 automated driving: An on-road study comparing drivers with and without experience with partial automation.
 - Determine whether Level 2 automation facilitates the performance of additional visuomotor tasks.

- Investigate the strategies used by drivers with and without Level 2 experience while monitoring and performing an additional visuomotor task.
- Paper IV: Can I look away now? The role of trust and experience when engaging in non-driving related tasks in a partially automated vehicle.
 - Investigate the relationship between Level 2 automation experience and trust.
 - Analyse how trust in specific system properties (e.g. robustness, reliability, usefulness, etc.), influences drivers' monitoring strategies and interaction with the system and the additional task.

Figure 1. Outline representing the two main goals of this thesis and the corresponding studies and papers.

3. BACKGROUND

3.1. AUTOMATION LEVELS

Fully automated (or autonomous) vehicles, that is, vehicles that control all aspects of driving in all situations have received great attention in the last few years. However, realistic expectations might be that it will take a few decades until they become commonplace on public roads (IEEE, Read et al. 2012). For this reason, the path to full automation will be most probably gradual, with the progressive implementation of more and more advanced ADAS that will support drivers in various driving tasks, although not in all of them.

Attempts have been made to classify different levels of automation. However, apart from the manual and fully automated levels, where the driver role is well delimited, it is not easy to determine “how” automated a vehicle is, or “how much” support is being provided to the driver. While no taxonomy is perfect, their use may have some important advantages:

- Taxonomies have the practical ability to communicate to stakeholders (e.g. system operators and designers) that automation is not a unitary concept, but that there exist different intermediate levels of automation and, therefore, different design solutions (Endsley, 2017).
- They provide a common language for talking about automation and for highlighting relevant human performance concerns (Lee, 2017), like the out-of-the-loop (OOL) problem (Endsley and Kiris, 1995).
- Taxonomies provide guidance for the design of automated systems (Kaber, 2017).

Some of the most used taxonomies today are the ones provided by the National Highway Traffic Safety Administration (NHTSA, 2013), the Federal Highway Research Institute (BASt, Gasser and Westhoff, 2017), and the Society of Automotive Engineers (SAE, 2016). Basically, these taxonomies define *who*, the vehicle or the driver, does *what* at each level (*who does what* approach). Thus, each level represents a different allocation of the driving tasks between the driver and the system.

For this thesis, the SAE classification of automation levels will be used as a reference (SAE, 2016). This classification describes six levels of automation which in turn can be grouped into two global categories (see Figure 2): 1) Levels where the driver is responsible for monitoring traffic (e.g. hazards, traffic signs, etc.), and, 2) levels where the system monitors traffic. The first group includes the lowest levels of automation, that is, levels 0 (manual driving or no automation), 1 (driver-assisted) and 2 (partial automation). These levels basically differ in the number of vehicle actions that are controlled by the system, mainly steering and acceleration/deceleration. The second group includes levels 3 (conditional automation), 4 (high automation) and 5 (full automation). By contrast to levels 4 and 5, in level 3 the driver will be required as a

fallback when the system fails. In levels 4, as opposed to level 5, full automation is guaranteed but only on specific operational domains (e.g. highways).

Figure 2. SAE levels of automation (SAE, 2016)

While Level 1 automated vehicles have been commercially available for quite some time, Level 2 automated vehicles have only started to be deployed two or three years ago. Some examples are the Audi Traffic Jam Assist, the Mercedes Driver Assistance Systems, Tesla Autopilot or Volvo PA2. Nowadays, the number of drivers interacting with these vehicles is increasing, and expectations are that this trend will continue over the next years. Consequently, there is also a higher risk that some of the human factor issues associated with the interaction with Level 2 systems and reported by different studies on simulators or test tracks, will persist now on the real roads.

3.2. LEVEL 2 SYSTEM DESCRIPTION

A Level 2 or partially automated vehicle consists of different automated systems that work in unison to enable a feet-free and, for short periods, hands-free driving (SAE, 2016). An example of systems enabling Level 2 automation are the combination of ACC and the Lane Keeping Assist (LKA). The ACC system maintains speed and distance to the front vehicle constant. The LKA system detects the lane boundaries by means of different cameras and keeps the car within the lane. When both systems are active, drivers are relieved from using the pedals, and for specific periods of time, from using the steering wheel. Despite this, the working envelope of Level 2 systems remains limited to specific operational domains such as highways with good visibility and readable lane markings. Additionally, the system may even transfer control back to the driver with no warning in

advance. Consequently, drivers are required to actively monitor the system status and performance and remain ready to retake control when necessary.

Currently, car manufacturers are producing Level 2 automated vehicles equipped with different technical solutions aimed at ensuring driver attention to and awareness of the system status/performance and the traffic environment. One of the most common solutions among manufacturers is the limitation of the time that drivers are allowed to be hands-off. Such time budget, however, may widely vary depending on the car company, ranging from 15 seconds as is the case for the Volvo PA2 system to more than 5 minutes, as is the case for the Tesla latest Autopilot version in speeds below 70 km/h.

3.3. THE DRIVER ROLE

As stated by Lee (2017), automation taxonomies like that from SAE (SAE, 2016) can offer a somewhat simplistic view of the complexity of automated driving. On the one hand, these taxonomies may neglect the possibility that automation, besides reducing the driver tasks, may also place new demands on the driver. In addition, the dynamic interactions that can occur between the different concurrent tasks during automated driving are not adequately captured in such taxonomies. Lee (2017) also points out that taxonomies such as that from SAE might give the impression that drivers will only interact with a single level of automation when the reality is that drivers will interact with different levels during the same drive.

Given the limitations of such taxonomies to capture the complexity of the driving task, other models may be more appropriate to explain how the role of the driver is affected by the implementation of automated functions or another type of systems. The hierarchical Driver in Control model (henceforth referred to as DiC) proposed by Hollnagel, Nbo and Lau (2003) is one example. In this model, the driver and the vehicle are seen as part of the same system, rather than as separate agents, that closely cooperate to ensure an adequate and safe control of driving. Such control is comprised of multiple simultaneous sub-goals which can be classified into different functionally interconnected levels. The lowest level in the model is represented by the tracking control loop which involves feedback tasks such as keeping speed or headway distance constant. The immediate upper level is the regulatory level, which involves compensatory but also some anticipatory tasks like executing uncommon manoeuvres or maintaining lane position (Carsten et al. 2012). Next level up is the monitoring level which involves anticipatory and compensatory tasks aimed at evaluating the situation and the state of the vehicle with respect to the environment (e.g. do not exceed the speed limit). Finally, on the top level is the targeting level, which mainly involves anticipatory tasks mostly performed before the journey, like choosing the destination or arrival time.

The DiC model predicts that disturbances or changes at one control level may propagate to other levels. Thus, situations requiring a high tracking control (e.g. a slippery road) may affect the monitoring of the environment (e.g. reduced tracking of the traffic signs).

Thus, this model provides an appropriate framework for understanding how drivers are supported by different ADAS on specific control processes of the driving task, as well as how such support may influence the performance of other tasks at other control levels. Based on this model, it could be argued that in a Level 2 automated vehicle the driver is mostly supported at the tracking and regulating levels by the ACC and LKA systems, respectively. As explained earlier, under this level, drivers are relieved from most tasks that require feedback control (i.e. tracking and regulating levels). However, they will be responsible for the tasks at the monitoring level. As automation level increases, systems capabilities to monitor and react to the environment will free drivers from tasks falling into this level. The question remains whether such a change in the nature of driving will imply a lower effort from the driver, or in contrast, a greater demand.

3.4. ADAS EFFECTS ON MENTAL WORKLOAD, ATTENTION AND PERFORMANCE

3.4.1. Mental Workload: concept and relevance in the context of ADAS

One of the most used constructs in the field of the Human Factor is Mental Workload (MWL) (de Winter, Happee, Martens and Stanton, 2014). Generally, MWL is invoked when we wonder how busy an operator is or how much effort he/she is investing to perform a certain task. Then, it might be possible to make better predictions about the operator's comfort, performance and safety (Stanton and Young, 2000).

Despite MWL being an intuitive concept, there is not a unique definition of it, but rather multiple definitions that vary considerably (Carsten, 2014). However, a certain consensus exists in the literature regarding what MWL represents in terms of attentional capacity or what MWL levels are detrimental to performance. Next, some of these aspects are described and summarized to provide an idea of how MWL has been conceptualised in this thesis:

- 1) MWL is determined by the portion of resources mobilized by an operator with limited attentional capacity (O'Donnell and Eggemeier, 1986). When the amount of resources demanded exceeds the operator's capacity, overload occurs, increasing the chances of decrements in processing capacity and performance.
- 2) MWL is multidimensional (Wickens 1984; Young, Brookhuis, Wickens and Hancock. 2015). MWL cannot be defined by the complexity of a situation alone, but by the complex and dynamic interaction of different contextual and individual-related factors (e.g. age, experience, state, motivation, etc.). Thus, task complexity would represent the different computational processes demanded by the task (e.g. detection, identification, semantic processing, motor action, etc.) while task difficulty would refer to the amount of resources allocated by an operator (de Waard, 1996).

- 3) The MWL level generated by the concurrent performance of two or more tasks is not only defined by their intrinsic complexity of the tasks or by the number of tasks to time-share. Time-sharing performance is also influenced by the extent to which those tasks demand similar processing resources (Wickens, 1984). According to Wickens' (1984) Multiple Resource Theory (MRT), two or more tasks will conflict more when tapping into similar resources along three different dimensions, namely: stage of processing (perceptual/cognitive, response-related), modality (visual/auditory) and code (verbal/spatial).
- 4) The relationship between MWL and attention or performance is not linear, but rather U-inverted. Not only increases in demands impact negatively on attention and performance. Low demanding tasks may also give rise to conditions like passive fatigue, sleepiness, boredom or cognitive underload, which may also affect operators' processing ability and performance (Körber et al., 2015; May and Baldwin, 2009; Saxby, Matthews, Warm, Hitchcock and Neubauer, 2013; Young and Stanton, 2002).

Nowadays, with the development of new and more advanced ADAS, standard vehicles are expected to be equipped with a wide variety of systems, some of which will directly interface the driver. As shown in multiple studies, such systems have the potential of substantially increase or decrease the driver demands, eventually affecting drivers' processing ability and performance. This explains the relevance of measuring drivers' MWL as a way to determine the ADAS impact on their performance. Some examples will be presented next, specifically in the context of IVIS and automated systems.

3.4.2. IVIS and mental workload

A full range of different IVIS is available today. Besides the well-known navigation and route guidance systems (e.g. GPS), new ones are being developed and implemented to provide drivers with more advanced information about the environment, the driving situation or the vehicle. Within this group, the infotainment systems could be categorized as a type of IVIS. These systems, which are becoming commonplace nowadays, are designed to provide drivers with entertaining information/activities (e.g. internet access, audio, videos, USB connectivity, etc.) rather than directly support driving. Although the IVIS and infotainment systems are aimed at improving the safety and comfort of the driver, there is a risk that they can also place new demands and interfere with the driver's performance (Blanco et al. 2006; Verwey, 2000). For example, Reyes and Lee (2004), observed that a system presenting auditory information of the location of restaurants can increase drivers' breaking reaction times. Similarly, the visual presentation of decision-making elements may increase drivers' MWL and affect performance (Blanco et al., 2006). In addition, drivers' visual attention towards the road has been shown to be 'narrowed' as a result of the demands imposed by either visual or non-visual IVIS (Recarte and Nunes 2000; Strayer and Johnston 2001). In support of this, studies have reported that the processing and execution of secondary tasks decreases when drivers interact with

other in-vehicle activities or IVIS (Harms and Patten, 2003; Merat and Jamson, 2008; Patten, Kicker, Östlund and Nilsson, 2004; Strayer et al. 2015).

While this thesis is mostly aimed at investigating the implications of Level 2 automation, the effects of the IVIS system were also explored in one of the studies (Paper II) as part of “Main goal 2” (see Figure 1).

3.4.3. Automation and mental workload

Automated vehicles, when operating within their working envelope, have been shown to reduce the driver’s MWL. In relation to this, a meta-analysis conducted by de Winter et al. (2014) based on 32 studies showed that being supported by Level 1 automation (only ACC) or Level 3 automation (ACC + LKA + monitoring systems) reduces subjective MWL by 5% and 20%, respectively, compared to manual driving. Studies using secondary tasks as a measure of MWL also corroborated this in the same meta-analysis. It was estimated that drivers can perform 1.1 times more tasks when assisted by the ACC compared to manual driving. Such proportion increased to 2.6 more tasks in the case of highly automated driving or Level 3.

From a resource model perspective (Kahneman, 1973; Norman and Bobrow, 1975), this evidence would indicate that, as more tasks are automated, more attentional resources become available for the performance of other tasks, like monitoring the traffic and the system. However, such relationship is not well-established as other important effects affecting performance and safety have been reported in automated driving. Some of the most relevant issues observed in the literature are slower reactions to critical events (Eriksson and Stanton, 2017; Merat and Jamson, 2009; Strand, Nilsson, Karlsson, and Nilsson, 2014), a worse vehicle control after taking over when a potential collision was presented (Louw, Kountouriotis, Carsten and Merat, 2015) and a reduced situational awareness (SA) (for a review see, de Winter et al. 2014). Additionally, other problems affecting performance such as inadequate mental models or behavioural adaptations have also been reported (Hoedemaeker and Brookhuis, 1998; Saffarian et al. 2012).

To summarize, automated systems tend to reduce drivers’ MWL, but that does not necessarily guarantee a better performance and a greater safety. Rather, other unanticipated negative effects may occur. This represents a real safety problem in Level 2 vehicles today where drivers’ attention and readiness to react is required at all times.

3.4.4. Automation and attention

The above introduced performance problems indicate that reducing the driver demands may inadvertently affect his/her ability to efficiently select and process the relevant information from the traffic environment and the system. Attentional problems such as inattention or distraction, well-studied in the realm of manual driving, are some potential

mechanisms leading to a poorer monitoring ability in partial automation. Therefore, these conditions need to be assessed and counteracted in the context of Level 2 automated driving.

However, defining inattention or distraction in driving research has always been as challenging as defining “attention” itself. A variety of operational definitions exists today for inattention and distraction leading to different criteria to categorize drivers as attentive or inattentive. One good example is Regan, Hallett and Gordon’s taxonomy (2011), who described five different types of inattention, defined as “insufficient, or no attention, to activities critical for safe driving” (p. 1775). Despite this, as indicated by Regan et al. (2011) and by other authors (e.g. Kircher and Ahlström, 2016), these and other existing definitions suffer from hindsight bias, meaning that it is only after the traffic incident has occurred when it can be determined whether the driver was inattentive or not. However, inattentive states do not always lead to accidents. This is especially the case for Levels 2 and 3 of automated driving where inattentive states may start long before any performance decrement occurs. This highlights the need for using other criteria to determine when a driver is inattentive or not.

Different authors have suggested starting by defining what an attentive driver is rather than what inattention or distraction is (Hancock, Senders and Mouloua, 2009; Kircher and Ahlström, 2016). An illustrative example of this effort is the Minimum Required Attention (MiRA, Kircher and Ahlström, 2016), according to which, a driver is attentive when he/she has acquired the minimum information necessary to have a good-enough internal representation of the situation. As long as this requirement is fulfilled, the driver could be considered attentive. Based on MiRA, it would be possible to specify, a priori, the minimum requirements to be sampled by the driver. Such requirements would, however, change depending on the driving situation and other factors like the automation level. Thus, we could argue that, in Level 2 automation, an attentive driver is expected to check the system status and performance more often than if driving a Level 3 automated vehicle. If the specific requirements for each automation level are not fulfilled, it could indicate that drivers are inattentive and likely out-of-the-loop (OOL; Endsley and Kiris 1995), which means that drivers are unaware of the driving situation and the system operations.

Endsley and Kiris (1995) pointed out two different mechanisms by which drivers may go OOL. One of them is vigilance decrement, that is, an inability to sustain attention and detect critical events. The second mechanism is complacency, whereby drivers overtrust the system capabilities and, consequently, reduce their monitoring of the system. While vigilance decrements would occur as a result of using the system, complacency effects would rather reflect a misuse of the system (Parasuraman and Riley, 1997). These two issues are especially important when drivers use a Level 2 automated vehicle in real traffic, as they may affect drivers’ ability to sample the minimum required information to have an adequate representation of the ongoing situation.

Different studies have shown that these two mechanisms may occur when monitoring a Level 2 automated vehicle or other similar systems. In the next sections, some of these

studies, as well as some proposed mechanisms for these effects will be described in more detail.

3.4.4.1. Vigilance decrements associated with monitoring automated systems

Most evidence coming from the driving and aviation realms, as well as from experimental psychology, indicates that humans' ability to monitor a situation for a certain time is rather limited (e.g. Martel, Dähne and Blankertz, 2014; Molloy and Parasuraman, 1996; Schmidt et al. 2009). Such monitoring declines seems to be specially aggravated when the operator is not actively involved in the operations of the system, like when driving automated. Empirical studies as well official reports from real accidents in driving or aviation have already warned about the occurrence of poor monitoring performance when interacting with automated systems. Despite this, the underlying mechanisms proposed to explain this vary across authors.

For example, some authors have emphasized the influence of performing a low demanding task for prolonged periods of time (or time on task effect) as the main cause of vigilance decrements and task disengagement. This problem has been reported in studies on manual driving (e.g. Larue, Rakotonirainy and Pettitt, 2011; Schmidt et al. 2009), but evidence indicate that it might be exacerbated under partially or higher levels of automation (Greenlee, DeLucia and Newton, 2018; Körber et al. 2015; Saxby et al. 2013). Commonly, this phenomenon has been attributed to an effect of passive fatigue (Desmond and Hancock, 2001), a type of task-induced fatigue that arises when drivers are placed in a supervisory role for a prolonged time and that leads to task disengagement. Task-induced passive fatigue should be differentiated from active fatigue, which arises under constant high demanding conditions (Desmond and Hancock, 2001), and from sleep-related fatigue which is influenced by sleep deprivation, time of the day or extended durations of wakefulness (May and Baldwin, 2009). Different mechanisms have been proposed to explain why operators' ability to allocate and sustain attention is reduced under passive fatigue. One well-accepted explanation is that arousal reductions take place when demands are low, eventually affecting specific brain systems involved in the maintenance of an adequate tonic alertness (Oken, Salinsky, Elsas, 2006). Thus, vigilance decrements would occur due to progressive reductions in the activation level of the operator. Contrary to this view, other authors claim that monitoring an understimulating situation for some time, rather than reducing the driver's activation state, it increases MWL and stress (de Waard, 1996; Greenlee et al. 2018; Warm, Parasuraman and Matthews, 2008). From this perspective, vigilance decrements would be the result of a progressive depletion of resources that cannot be replenished in time (Warm et al. 2008). Part of these resources would be aimed at compensating the degraded driver state when exposed to lasting tasks (de Waard, 1996).

Complementary to the above explanations, other authors have proposed that, regardless of the time on task, attentional impairments can also occur due to the effects of the low demands. For example, Young and Stanton (2002) proposed the Malleable Attentional

Resource Theory (MART), according to which, low demanding tasks could lead to cognitive underload as a result of a shrinkage in attentional capacity to adapt to the lower demands. Cognitive underload would be independent of arousal or effort and may arise in relatively short periods (Young and Stanton, 2002; Young et al. 2015). Empirical support for MART was also provided by the authors who observed that as the automation level increased in a simulated driving, the drivers needed longer glances to a visuomotor secondary task to make a correct response (“attention ratio”). This was interpreted as a lower attention allocation efficiency associated with increases in automation level. Given the short duration of the driving conditions, the authors attributed these findings to a cognitive underload effect rather than to vigilance decrements associated with the time on task. Other theories like the Effort-Regulation Hypothesis (ERH, Hancock and Warm, 1989), suggest that such cognitive underload effect would rather be the result of an underestimation of the amount of resources necessary to allocate when demands are low, leading to an insufficient investment of effort (or resource allocation).

To date, few studies have attempted to assess reductions in attention allocation during Level 2 automated driving. For example, Körber et al. (2015) observed that over the course of a 42-minute long partially automated drive, drivers exhibited greater blink durations and blink frequencies and lower pupil diameters, which is compatible with lower vigilance levels. More recently, Greenlee et al. (2018), observed that the drivers presented a lower hazard detection rate and slower reaction times over prolonged periods of partially automated driving. These results would confirm that passive fatigue occurs during Level 2 automation, leading to vigilance decrements. However, as shown above, other authors have warned about the possibility that the low demands alone, regardless of the time on task, may also reduce drivers’ attentional capacity due to a cognitive underload effect (Young and Stanton, 2002). Both, passive fatigue and cognitive underload remain poorly studied in the context of Level 2 automation. Given that at this level, an adequate attentional level of the driver is crucial at all times, the role of these potential mechanisms need to be understood.

3.4.4.2. Performance of additional tasks while driving automated

As explained earlier, complacency has been proposed as another factor that makes drivers become OOL (Endsley and Kiris, 1995). Complacency occurs when drivers are confident that the system will handle every, or almost every, traffic situation. In such conditions, drivers may feel tempted to engage in other non-driving related tasks (Merat and Lee, 2012). By contrast to vigilance decrements or cognitive underload in which drivers’ ability to allocate and sustain attention is affected, complacency would reflect a change in drivers’ allocation policy (Parasuraman and Manzey, 2010).

Different studies have reported a greater proneness of drivers to engage in other non-driving related tasks while driving automated (Banks, Eriksson, O’Donoghue and Stanton, 2017; Carsten et al. 2012; Llaneras, Salinger, & Green, 2013). Such proneness could be explained by at least two factors. The first one relates to the lower demands of

automated driving, which gives drivers a greater capacity to perform other tasks (de Winter et al. 2014). The second one relates to the extent to which the system is perceived as trustworthy. Recent studies have shown that higher levels of trust lead to a lower monitoring of the road and to a greater engagement level in other tasks while driving highly or fully automated (Hergeth, Lorenz, Vilimek & Krems, 2016; Körber, Baseler and Bengler, 2018).

As Naujoks et al. (2016) indicated, the literature on drivers' engagement in additional tasks during Level 2 automation is very limited. Despite this, the few existing studies seem to corroborate the observations from higher automation levels. As some examples, Llaneras et al. (2013) and Banks et al. (2018) observed that drivers tended to engage more in other tasks while driving Level 2 automated in a test track or a real road, respectively. Similar observations were reported by Naujoks et al. (2016), but only in drivers with prior experience with Level 1 (only ACC). Naujoks' results (2016) may reflect that besides trust, prior experience with automation is another factor influencing drivers' willingness to engage in other tasks. This could be explained by these drivers having a more precise mental model of the system capabilities, as reported by Larsson (2012) and Larsson, Kircher and Hultgren (2014) in drivers with Level 1 experience. Drivers can then integrate this model into the performance of specific tactical manoeuvres (Kircher, Larsson and Hultgren, 2014) or when engaging in other tasks.

While more studies are needed, the studies presented above indicate that drivers' proneness to engage in other tasks will likely increase in the recently launched Level 2 automated vehicles. An important aspect that remains to be investigated is how drivers will integrate other tasks into their monitoring responsibilities and their implications on driving performance and safety.

3.5. MEASUREMENT OF MENTAL WORKLOAD IN THE ADAS CONTEXT

3.5.1. Main techniques for MWL assessment: sensitivity and diagnosticity

Despite the disagreement about its definition and nature, MWL remains today as a practically relevant construct to assess how much effort an operator is investing in an operational environment. Since its inception, a wide range of different techniques have been used. O'Donnell and Eggemeier (1986) grouped these techniques into three major categories, namely, behavioural, subjective and physiological measures. A debate remains today as to which method is the most suitable to measure MWL; however, no consensus exists on this, as every method has been shown to have pros and cons. Next, some of the most common MWL measures in human factors research will be shortly presented along with their main advantages and drawbacks:

- *Subjective measures.* Subjective MWL measures indicate the amount of information in working memory and have been considered as the easiest and most flexible method to use (Yeh and Wickens, 1988). These measures do not

necessarily interfere with the primary task if administered at the right time (e.g. between conditions or at the end of the experiment). The diagnosticity of these measures is higher for the multidimensional scales (e.g. NASA-TLX, Hart and Staveland, 1988) than for the unidimensional scales (e.g. Rating scale mental effort or RSME, Zijlstra and van Doorn, 1985). Thus, asking an operator to rate specific dimensions (e.g. mental demand, physical demand or temporal demand) provides a more detailed information about the main sources of MWL. However, one downside of subjective scales is their dependence on operators' memory, meaning that they should be administered shortly after the execution of the task (de Waard, 1996). Another problem worth mentioning is that they do not inform about transient changes in MWL levels over time (e.g. overload peaks), but rather provide an estimation of the overall MWL perceived over a period of time (Yeh and Wickens, 1988).

- *Primary task measures.* Decrements in primary task performance indicate overall decrements in the operator-system efficiency (O'Donnell and Eggemeier, 1986). Primary task performances are a direct and non-intrusive measure (Sirevaag, Kramer and Wickens, 1993). However, they are not sensitive to effort investments to protect performance ("task-related effort") or compensate for inadequate driver states ("state-related effort", de Waard, 1996). Thus, two operators with similar performances but investing a different amount of effort may not be discriminated. Finally, performances decline may be diagnostic of demands placed on response-related resources (Duncan-Johnson and Kopell, 1981); however, they could just reflect the outcome due to overloads in previous stages of information processing (e.g. perceptual or cognitive resources).
- *Secondary task measures.* Secondary tasks have been widely used to detect spare capacity not consumed by the primary task demands (Siveraag et al. 1993). Therefore, they are an indirect indicator of the primary task demands. However, their sensitivity depends on the extent to which they compete for the same processing resources as the primary task (Wickens, 1984). One drawback, as indicated by O'Donnell and Eggemeier (1986) is that these tasks may inadvertently disrupt the performance of the primary task.
- *Physiological measures.* A wide range of physiological parameters has been used to detect the physical reactions to variations in MWL (e.g. cardiac activity, skin conductance, respiration, etc.). Some of their main advantages are that they provide continuous monitoring of MWL and, generally, do not require a direct response from the operator. However, some downsides should be noted. For example, most of these techniques are also affected by physical activity and emotional changes, thus limiting their diagnosticity. It is possible however to find physiological techniques with a very high level of diagnosticity like the event-related potential (ERPs), which will be described later. Another drawback of these techniques is that they require special equipment and a certain level of expertise to record, analyse and interpret the signals (de Waard, 1996).

Despite the proven sensitivity of these techniques to variations in MWL, the literature has shown that they do not always correlate and even dissociations can be found between them (Matthews, Reinerman-Jones, Barber and Abich, 2015). One possible reason for such uncorrelations/dissociations could be related to differences in their sensitivity to different levels of demands. For example, de Waard (1996) described a model where dissociations between performance and different MWL levels were highlighted. In this model, performance remains insensitive to low-moderate levels or “regions” of demands. Additionally, performance measures are also unaffected when efforts are invested to protect performance when task demands increase (“task-related effort”) or to compensate deteriorated operator states due to the low demands (“state-related effort”). Thus, performance measures may not be able to discriminate operators with different MWL levels. In these cases, other types of measures, like subjective or physiological, may be more informative. Still, dissociations between these two types of measurements may occur. For example, it has been observed that a greater complexity of the task can increase the subjective perception of MWL but not the “objective” MWL measured through different physiological measures, such as heart activity measures (e.g. Brookhuis, Van Driel, Hof, Van Arem and Hoedemaeker, 2008; Dijksterhuis, Brookhuis and de Waard, 2011; de Waard, 2009).

The lack of associations between MWL indices may also respond to differences in their diagnosticity, that is, in their sensitivity to demands on specific resource pools (i.e. perceptual, cognitive, response-related). For example, some studies have shown that interference tasks like the Stroop task (Stroop, 1935) or the Eriksen flanker task (Eriksen and Eriksen, 1974), mostly affect response-related processes as observed by lower reaction times or accuracy (Duncan-Johnson and Kopell, 1981). However, perceptual and cognitive processes indexed by specific ERP components remained unaffected. A similar effect was observed by Baldwin, Freeman and Coyne (2004) in a simulated driving task under different levels of traffic density. Increments in traffic density led to decrements in performance measures but did not affect specific perceptual/cognitive resources, as measured through ERPs. However, when the driving difficulty was manipulated by lowering the visibility of the road, the opposite pattern was observed.

While sensitivity and diagnosticity are important criteria for the assessment of MWL, MWL measures should also be able to inform when the demands are “too” high or low, preferably before performance decrements occur. As Brookhuis and de Waard (2010) pointed out, the relationship between MWL and performance decrement would be better understood by defining ‘when’ the MWL “redlines” for overload or underload are exceeded, that is when operators can no longer properly process the ongoing tasks. Although the measurements presented above are useful to detect variations in demands, they cannot inform on their own when demands are too high or low, that is, when operators’ processing ability is impaired. Thus, for example, decrements in heart rate, respiration rate or galvanic activity may reliably indicate decrements in MWL, but not whether the underload threshold has been exceeded such that operators’ processing ability is also affected. In that case, the use of specific measurements of information processing capacity could be a solution to complement other MWL measures.

3.5.2. ERPs in the ADAS context

For more than 50 years, one of the most used techniques to study human information processing is ERPs. This technique has been extensively used in the fields of medicine, psychophysiology and cognitive neuroscience. ERPs have greatly increased our understanding of how the brain selects and processes information at the sensory, perceptual and cognitive level. Moreover, ERPs has been one of the main diagnostic tools to evaluate the integrity of visual and auditory sensory neural pathways in patients with specific clinical conditions such as cortical blindness or deafness. Currently, the use of ERPs is being extended to the assessment of cognitive impairments associated with different brain pathologies, like attentional deficit hyperactivity disorder or ADHD (Barry, Johnstone and Clarke, 2003) or multiple sclerosis (Vázquez-Marrufo et al. 2014).

Since the 1980s, and especially in the last decade, there has been growing interest in investigating the applicability of ERPs as an indicator of MWL in dynamic and ecological contexts (e.g. driving, aviation, etc.) where simultaneous tasks are attended and/or executed. Moreover, the high diagnosticity of ERPs makes it a suitable technique to detect the processing requirements of complex tasks. Although research in this field is still emerging, an increasing number of studies are nowadays applying ERPs in the assessment of operators' MWL as will be shown in the next sections.

3.5.2.1. ERPs: Concept and physiological basis

ERPs represent specific brain electrical responses to sensory, cognitive and motor events. ERPs are computed by recording the brain electrical activity through an electroencephalogram (EEG) and averaging the activity that is time-locked to the occurrence of a certain event or response (Luck, 2005).

An ERP is comprised of a series of peaks, some of which are associated with specific neurocognitive processes. These specific peaks are known as “components”. Each component is defined by at least three parameters: (a) the polarity of the peak, positive (P) or negative (N); (b) its latency (usually measured in milliseconds), which shows “when” a specific brain process takes place (Kutas, McCarthy and Donchin, 1977); and (c) its amplitude (usually represented in microvolts), which indicates the “intensity” of the processing or the “amount” of neural resources allocated (Isreal, Wickens, Chesney and Donchin, 1980; Polich, 2007). Early components occurring shortly after the event onset are mostly modulated by the physical characteristics of the stimulus presented (e.g. frequency of the sound) and therefore are known as “exogenous” components. Exogenous components, like P1 or N1, are thought to reflect the neural activity associated with the sensory/perceptual processing of the event. Later components, however, are rather influenced by internal or “endogenous” factors. These components are thought to reflect the activity of different neural systems involved in the cognitive processing of the event (e.g. discrimination of the target, attention orientation). The sequence of the different

components, from exogenous (early) to endogenous (late), has been thought to reflect the mental chronometry of information processing (Kramer and Belopolsky, 2004)

3.5.2.2. ERPs as an index for resource allocation

A large body of research has emphasized the utility of ERPs as a reliable index for attentional resource allocation and information processing (Duncan-Johnson and Donchin, 1982; Isreal et al. 1980; Polich, 2007). In particular, one of the most studied components is P3b (henceforth referred to as P3). P3 is a positive deflection generated approximately 300 milliseconds after the identification of an infrequent target stimulus embedded in a sequence of frequent standard stimuli. Thus, this component has been linked to post-perceptual processes associated with the categorization of the stimulus. While the latency of P3 is thought to reflect the timing in which the target stimulus is identified (Kutas, et al. 1977), its amplitude has been used as an indicator of the amount of attentional resources mobilised for the categorization of the stimulus. Different studies have reported decrements in P3 amplitudes in conditions where the operator's activation level is decreased, such as when fatigued or sleepy (Gosselin, Koninck, Campbell et al., 2005; Koshino et al. 1993). In some cases, such decrements in resource allocation have been observed to precede attentional lapses in vigilance tasks, as shown by Martel et al. (2014). In driving research, P3 amplitude decrements have also been used to account for vigilance decrements after prolonged monotonous driving (Schmidt, et al. 2009; Zhao, Zhao, Liu and Zheng, 2012). On the other hand, P3 has also been used to detect reductions in operators' processing capacity due to high task demands. For example, many studies using dual-task paradigms have reported lower P3 amplitudes to a secondary task as a result of increments in the primary task demands, thus indicating a trade-off in the allocation of the limited attentional resources (Allison and Polich, 2008; Isreal et al. 1980; Kramer, Sirevaag and Braune, 1987; Miller, Rietschel, McDonald and Hatfield, 2011; Scheer, Bülthoff and Chuang, 2016; Ullsperger, Freude and Erdmann, 2001). Today, this body of evidence has led to an increased interest in using P3 as an indicator of MWL and operators' processing ability under very different operational environments, such as while performing tracking tasks (Scheer et al. 2018), interacting with brain-computer interfaces (Käthner, Wriessnegger, Müller-Putz, Kübler and Halder, 2014) or performing air traffic control tasks (Giraudet, Imbert, Bérenger, Trembla and Causse, 2016).

To a lesser extent, another component that has shown sensitivity to resource allocation is N1. N1 arises around 80-150 milliseconds after the presentation of an auditory or visual stimulus. Although N1 is modulated by exogenous factors (e.g., sound frequency), it is also influenced by endogenous factors like attention allocation (Näätänen, 1992). For example, Hillyard and Munte (1984) asked participants to selectively attend to stimuli presented on the left or right visual field and ignore those from the other visual field while gazing at a central fixation point. N1 amplitudes were larger for the stimuli presented on the prioritized visual field. Similar results have been observed in later studies (Hillyard and Mangun, 1987; Mangun and Hillyard, 1990). Given that N1 is an early component

linked to perceptual processes, these findings support the idea of N1 amplitude as an indicator of early attentional selective processes involved in the “sensory gain” of the relevant information (Kok, 1997). In complex tasks, reductions in N1 amplitudes to secondary tasks have been observed with increments in the primary task demands (Miller, et al. 2011; Ullsperger et al. 2001). While more research is needed, evidence shows that N1 can also be used as a measure of MWL. However, some authors have suggested that high demands are necessary for N1 to show sensitivity to variations in MWL (Kok, 1997; Kok, 2001; Parasuraman, 1985).

To summarize, N1 and P3 components probably represent the best ERPs parameters in the measurement of MWL in complex tasks. Given that N1 and P3 reflect different stages in information processing, the analysis of both components may be useful to detect the specific processing resources required by complex tasks such as driving while interacting with different support systems. In the next sections, the utility of ERPs to detect the effects of IVIS and automated systems on the driver attention and MWL will be introduced.

3.5.2.2.1. ERPs to detect IVIS demands

Different studies have shown the utility of ERPs to detect the demands of additional tasks/information presented to operators while performing a primary task (e.g. driving, piloting). For example, Strayer and Drews (2007) observed lower P3 amplitudes elicited by the onset of a pace cars’ brake light while driving and talking on a cell phone, compared to when just driving. Moreover, Strayer et al. (2015) analysed the cognitive load of seven different in-vehicle tasks. It was observed that those that required verbal and visual interaction (e.g. a speech-to-text e-mail system) significantly decreased P3 amplitude and performance on a secondary detection task. In another set of studies, Baldwin and Coyne (2005) used a similar setting in which a detection task (i.e. an auditory or a visual oddball task) that elicited the P3 component was used to detect changes in the primary task demands. The primary task consisted of a flight task to be performed while executing a single command (low demand condition) or multiple commands (high demand condition) presented via an information system in a visual or auditory modality. Overall, P3 amplitude discriminated when the participants were performing one (the detection task) or more tasks (the detection task and the flight task). P3 amplitude was reduced under the latter conditions. However, P3 did not discriminate between the single-command and multiple commands conditions.

Altogether, these results suggest that ERPs, and particularly the P3 component, could be a reliable indicator of the demands placed by other in-vehicle systems or activities. This relationship is graphically represented in Figure 3. While more research is needed on this, such information could then be used to design less resource-consuming and more ergonomic systems.

3.5.2.2.2. ERPs to detect automated systems demands

A relevant challenge in the field of automation is determining when the demands are “too low” before any performance problem occurs. As explained earlier, reducing demands too much, rather than improving drivers’ attention, may be detrimental to the drivers’ processing capacity and performance. However, determining when drivers’ attention is impaired during automated driving is difficult for different reasons. Firstly, as opposed to manual driving, attentional reductions in automated driving will rarely be reflected in any driving performance indicator (e.g., speed and lateral position variability; Campagne et al., 2004). Provided that the system keeps a constant speed and lateral position, there is a high risk that any decrement in attentional resources may go unnoticed until driver action is required, which may be too late. Secondly, as de Waard (1996) indicated, performance measures, such as the performance of secondary tasks, are not sensitive when demands are low. This could explain why in studies like that of Körber et al. (2015), vigilance decrements during a partially automated driving were only reported by specific blink parameters, whereas no effects were observed in the secondary task performance (an oddball task). In this sense, the use of ERPs may be a more suitable technique to detect covert vigilance decrements associated with automation-induced effects like cognitive underload or passive fatigue. This idea is represented on the left side of the curve in Figure 3.

Figure 3. A conceptual representation of the trade-off between the resource allocation to the primary and secondary tasks under different levels of demands placed by different type of ADAS. The effects on ERPs, exemplified by P3 amplitude, are also presented.

3.6. SUMMARY OF THE BACKGROUND AND MOTIVATION FOR THIS THESIS

The implementation of new ADAS on standard vehicles is one of the main steps adopted for The Decade of Action for Road Safety (2011-2020) to improve road users' safety. Despite this, research on ADAS effects has reported some relevant effects on drivers' performance while interacting with them (e.g. Eriksson and Stanton, 2017).

A clear example of current ADAS is the Level 2 automated vehicles (SAE, 2016), which have been recently launched on the market. Level 2 automated vehicles provide drivers with longitudinal and lateral support; however, the driver is expected to supervise the traffic and the system, and intervene when necessary. Different studies on Level 2 driving suggest that removing the driver from physical control of the vehicle can lead to poor monitoring, and therefore to decrements in safety. While different explanations have been proposed in the literature, these effects remain poorly investigated in the context of Level 2 automation. The available evidence points to two main types of problems leading to poor monitoring, namely, vigilance decrements and a greater proneness to engage in secondary tasks.

Based on this, it is crucial to better understand and detect these effects. The use of attention-specific measurements could be particularly useful and complement other measures in the detection of the effects of Level 2 systems and other ADAS like the IVIS.

On the other hand, given the reported greater proneness of the drivers to engage in secondary tasks during automated driving, it is necessary to shed light on how drivers will manage such situations and to what extent their monitoring responsibilities will be affected.

For better or for worse, these vehicles are already on the roads, and my personal perception is that there is still much to investigate about their effects on the drivers. While it is likely that Level 2 systems will improve safety in certain aspects of driving (e.g. keeping the car in the lane, keeping distance with the car ahead), it is also true that some of the safety issues detected in literature will likely become evident in the real world. It is therefore necessary to keep investing efforts to detect and mitigate such potential issues.

4. SUMMARY OF PAPERS

For this thesis, three empirical studies were conducted out of which four papers were generated. The studies were performed in different settings, from well-controlled laboratory conditions to more ecological contexts like real traffic.

- Study I was conducted on a fixed-base simulator. The main aim was to detect potential reductions in attention allocation in the drivers while driving Level 2 automated. Paper I is based on this study.
- Study II was based on a computer tracking task. The aim was to investigate the effect of the number of concurrent tasks and the time pressure on the participants' MWL, attention and performance. Paper II was based on this study.
- Study III was conducted on a highway with real traffic. A vehicle equipped with Level 2 automation was used as test vehicle. One aim was to investigate the effects of automation level, prior experience with Level 2 automation and type of additional task pacing (self- vs. system-paced) on drivers' monitoring strategies and performance of an additional task. This was covered in Paper III. Another aim was to understand the relationship between Level 2 experience and trust on drivers' monitoring strategies and use of the system. Paper IV addressed this objective.

4.1. OVERVIEW OF MATERIAL AND METHODS

In this section, the methodological aspects of each study will be presented. A summary table containing the most relevant information is also provided (Table 1).

Table 1. A summary table containing the most relevant information of each study.

	Study I	Study II	Study III	
			Experienced drivers	Novice drivers
Sample size	20	17	9	12
Gender (f/m)	9/11	10/7	0/9	2/10
Age (mean $\pm$ SD)	27.1 $\pm$ 3.8	23.2 $\pm$ 4.06	47 $\pm$ 10.7	40 $\pm$ 6.3
Experimental design	2 x 3 (within-subjects)	2 x 3 (within- subjects) plus a baseline condition	2 x 2 x 2 (mixed)	

Independent factors	<ul style="list-style-type: none"> • Speed • Automation level 	<ul style="list-style-type: none"> • Time pressure • Number of concurrent tasks 	<ul style="list-style-type: none"> • Automation level • Additional task pacing • Automation experience
Setting	Fixed-base simulator	Computer task	On-road
Scenario	Rural and slightly curvy road	Rural and curvy road	Straight highway
Measurements	NASA-TLX ("mental demand"). KSS Oddball task performance ERPs: N1 and P3 Driving speed (in the comfortable condition)	NASA-TLX ("mental demand"). Oddball task performance ERPs: N1 and P3 Tracking speed (in the adjustable condition). Lateral position	NASA-TLX SATI questionnaire Arrows task performance Glance parameters Driving behaviour Use of the PA2 system
Paper correspondence	Paper I	Paper II	Papers III and IV

4.1.1. Ethical considerations

All the studies were conducted in line with requirements established in the Helsinki Declaration.

An important ethical aspect that was addressed in the three studies was the preservation of the participants' identity. To do so, the participants were assigned codes only accessible by the researcher. Another important ethical aspect to be considered was the drivers' safety in Study III, where they were asked to drive in real traffic and perform a visuomotor task at the same time. To mitigate any risk as much as possible, drivers were informed they were free to engage or disengage the PA2 or the additional task whenever they deemed necessary. A research was seated in the back seat in all sessions to supervise the correct use of the system by the driver.

Ethical approvals for the Studies I (EPN Dnr: 2014/309-31) and III (EPN Dnr:2016/411-31) were obtained from the Regional Ethic Committee in Linköping. As for the Study II, ethical approval was received by the Ethics Review Board from the University of Loyola Andalucía (Seville, Spain). Informed consents were filled out by all of the participants.

4.1.2. Participants

Most of the participants were recruited through advertisements placed in the social media (e.g. Facebook, Twitter, etc.) or by asking colleagues from VTI and/or the University. In Study III, the automation-experienced drivers were recruited through a list of owners of one of the Volvo models launched in the Spring of 2016 and equipped with a PA2 system ("automation experienced" group). All participants were economically rewarded for their

participation (approximately 50 – 60 euros). The sample size, average age, and gender distributions varied across studies, see Table 1.

4.1.3. Design and procedure

A 3 x 2 within-subjects design was used in Studies I and II. The drivers were instructed to refrain from caffeine or tea intake for 4 h and alcohol for 24 h before the experiment day. Upon arrival, the participants were informed about the study and signed the informed consent form. The next step was to fit the electrodes for EEG measurements. In both studies, the participants reported a normal or corrected to normal visual acuity, and they did not report any history of neurological or psychiatric disease. The duration of the experiments was 1.5-2 hours, including a training period of approximately 15 minutes.

In Study I, a fixed-base simulator was used which was comprised of a car seat, steering wheel, automatic gearbox and dashboard (see Figure 4). The scenario consisted of a two-lane rural road (lane width 1.75 m) with mild curves. There were oncoming vehicles in the other lane, but no vehicles within the driver's lane. The same scenario was driven under three levels of speed (low, high and comfortable) and two automation levels (manually or Level 2 automated). Thus, each participant drove 6 times. Participants were asked to monitor the system performance and the road at all times in the automated conditions. Simultaneously, the drivers had to perform an auditory oddball task consisting of detecting infrequent target sounds (high pitch sound) embedded in a sequence of frequent standard sounds (low pitch sound) by pressing a button attached on the steering wheel (See Figure 4). They were told to do so as quickly as possible without making any error.

Study II was conducted on a computer screen in an electromagnetically isolated room. The participants were asked to perform an auditory oddball task alone (single-task) or in combination with a tracking task (dual-task) in which the participants had to keep a small car in a one-lane curvy road by using an Xbox 360 controller. In some conditions, a visual continuous display was presented on top of the tracking task (triple-task) showing drivers an extended view of the coming curves. Thus, this system intended to simulate a prototype of a visual IVIS. The participants were asked to perform the tracking task under different levels of time pressure, which was manipulated by using three different levels of speed (low, high and adjustable). In total, 7 conditions were presented to the participants: 1 baseline condition (single-task: only oddball), and 6 tracking task conditions (3 without the IVIS or dual-task and 3 with the IVIS or triple-task conditions).

Figure 4. The experimental setting in Study I. On the left, a pilot participant testing the scenario in manual mode. On the right, a representation of the concurrent auditory oddball task and the ERPs elicited. A similar setting was used in Study II, where a computer tracking task was used as a primary task instead.

Study III used a mixed factorial $2 \times 2 \times 2$ design, with 2 within- (automation level and additional task pacing) and 1 between-subjects factor (Level 2 automation experience). Prior to the experiment, the drivers were briefed about the study and instructed about the PA2 system. They also filled out a few questionnaires, gave informed consent and trained with an additional visuomotor task consisting of detecting an arrow pointing upwards in a 4×4 matrix of arrows. This task was based on the surrogate IVIS task used in Östlund et al. (2004). The target arrow was presented in 50% of the trials. An eye-tracker equipment was adjusted to the drivers and calibrated for glance behaviour recording. On the way to the test route, the drivers were asked to switch on/off the PA2 system several times while interacting with the additional task. Only when they reported to be confident with the PA2 system and the additional task, they were allowed to enter the highway. The drivers were asked to drive the same highway stretch four times, two automated and two manually. In half of the conditions, the task was system-paced and in the other half self-paced. The total duration of each session was approximately 2 hours.

4.1.4. Equipment

In Study I, a fixed-base simulator was used consisting of five screens that covered 190° of the field of view. Brain activity was continuously recorded from 30 scalp Ag-AgCl active electrodes distributed according to the 10–20 international system and referenced to the right and left earlobes. Horizontal and vertical ocular electrodes (HEOG and VEOG, respectively) were placed on the outer left and right canthi and above and below the left eye. Impedance levels were kept below 10 kOhms. A G.Tec amplifier was used for the brain signal recordings (G.Tec Medical Engineering).

In Study II, a tracking computer task was specifically designed for the purposes of the study. An Xbox 360 controller was used to perform the task. A button attached on the back side was used to respond to the concurrent auditory task. Electrical brain activity

was continuously recorded from 58 scalp electrodes. Horizontal and vertical ocular electrodes (HEOG and VEOG, respectively) were placed on the outer left and right canthi and above and below the left eye. Impedance levels were kept below 5 kOhms. The electrode signals were amplified with BrainAmp amplifiers and digitally stored using Brain Vision Recorder software (Brain Products GmbH, Germany)

As for Study III, the test vehicle (see Figure 5) was equipped with cameras filming the front view and the PA2 system symbol on the dashboard. Everything was recorded and stored in a data acquisition unit (Video VBox Pro, RaceLogic, Buckingham, UK). UTC time, vehicle speed and position were registered via an internal GPS at a sampling rate of 10 Hz. Glance behaviour was recorded through head-mounted eye trackers (SMI Eye Tracking Glasses 2.0., SensoMotoric Instruments, Teltow, Germany) at a sampling rate of 60 Hz

4.1.4.1. Pilot Assist Generation 2

A Volvo S90 model equipped with the PA2 system released in Spring 2016 was used for the Study III. The PA2 system provides steering support up to a speed of 80 mph (130 km/h, approximately). The system status is represented on the dashboard by a steering wheel indicating the LKA status along with 1-3 horizontal bars representing the selected headway distance with the car in front (See Figure 5). The set speed is shown on the speedometer. When the PA2 is functioning, the steering wheel is presented in green colour. However, if the detection of the lane markings is interrupted (e.g. poor lane markings), the system will enter a “stand-by” mode represented by a grey steering wheel symbol. During this time, only the longitudinal support would be available, until the steering support becomes active again. If the vehicle detects no hands on the steering wheel for more than the allowed 15 seconds, a visual icon will be displayed next the PA2 symbol prompting the driver to do so. In case the driver does not follow this warning, an auditory warning will be displayed around 3 – 5 seconds later and will fully disengage right afterwards. To take back full control of the car, the driver must touch the brake or select the manual driving mode via the keypad placed on the steering wheel.

Figure 5. On-road study (Study III). On the left, the position of the system symbol and system controls are indicated. As observed, the PA2 symbol is active. On the right, a picture of myself driving and performing the additional task with the eye trackers on.

4.1.5. Subjective measurements

The NASA-TLX (Hart and Staveland, 1988) was used to account for the drivers' perceived MWL after each condition in each study. In Studies I and II, only the "mental demand" sub-scale was used, whereas in Study III, the complete scale was used. Also, the Karolinska Sleepiness Scale or KSS (Åkerstedt and Gillberg, 1990) was used in Study I to account for subjective vigilance. The participants reported NASA-TLX and KSS once after each condition. Moreover, the drivers were administered the SHAPE Automation Trust Index (SATI; Dehn, 2008) to account for their trust in the PA2 system before and after the experiment. The trust effects on driver monitoring and interaction strategies are specifically covered in Paper IV.

4.1.6. Behavioural measurements

Performance measures of MWL were obtained from the different secondary tasks used. In Studies I and II, accuracy and reaction times to an auditory oddball task were registered (Segalowitz and Barnes, 1993). Moreover, from the visuomotor task used in Study III, different parameters were extracted, namely: % correct/missed/error responses, reaction times, % time with the additional task active and the number of switch-offs.

Drivers' visual behaviour was recorded via eye trackers in Study III. The system used was a head-mounted eye tracker (SMI Eye Tracking Glasses 2.0, SensoMotoric Instruments, Teltow, Germany). Therefore, parameters such as the percentage of time looking at specific areas of interest, number of glances or mean glance durations were calculated offline. The areas of interest comprised the front view, the dashboard (where the PA2 system was presented), the additional task and the rear mirrors (See Figure 6).

Figure 6. A representation of the areas of interest used in Study III to analyse drivers' glance behaviour.

4.1.7. Physiological measurements

In Studies I and II, drivers' brain activity was continuously recorded from 30 and 58 scalp electrodes, respectively. The amplitude and latency of N1 and P3 components were extracted offline for data analysis. Ocular activity was also recorded and used for data filtering and artefact rejection.

4.1.8. Analyses

ERPs data analysis from Studies I and II was performed in Matlab R2014b using EEGLab 13.4.4b, an open source toolbox developed at Swartz Center for Computational Neuroscience (Delorme and Makeig, 2004). N1 and P3 amplitudes and latencies were extracted by using the guidelines from Duncan et al. (2009). ICAs were used to detect and remove artefacts from muscle activity, blinks, and ocular movements. Moreover, trials where the amplitude exceeded $\pm 75 \mu V$ on HEOG were discarded.

The eye tracking data were coded manually using The Observer XT Version 13 software (Noldus Information Technology, Wageningen, The Netherlands), based on different predefined areas of interest (See Figure 6).

Overall, a parametric approach was used to statistically analyse the data. Repeated measures analysis of variance (ANOVA) were used to account for main and interaction effects from each study. The significance level was set at $\alpha = .05$. Violations of sphericity and corrections for multiple comparisons were applied when necessary by using Greenhouse-Geisser and Sidak' methods, respectively. Pearson's correlations and multiple linear regression models were performed for linear associations (e.g. in Paper I and Paper IV). In specific cases where the data was not normally distributed (e.g. Paper IV, analyses of warnings), non-parametric analyses were preferred (Mann-Whitney U test).

4.2. SPECIFIC RESEARCH QUESTIONS AND RESULTS

In this section, the main results will be presented and briefly discussed. Additionally, the research questions relevant to this thesis that were addressed in each paper are presented.

4.2.1. Paper I. Reduced Attention Allocation during Short Periods of Partially Automated Driving: An Event-Related Potentials Study

4.2.1.1. *Specific research questions*

- RQ1: Does the automation level (manual or Level 2 automated) and/or speed level (low, high and comfortable) affect drivers' subjective mental demand and vigilance, as well as their attentional resource allocation during short driving conditions?
- RQ2: Does the time on task (i.e., driving the different conditions) affect drivers' subjective mental demand and vigilance, and objective attention allocation?

4.2.1.2. *Results*

Statistical analyses revealed a main effect of “level of automation” on subjective mental demands ($F(1,38) = 4.61$, $P < 0.01$, $\eta^2_p = 0.2$) and P3 amplitudes ($F(1,38) = 5.181$, $P < 0.05$, $\eta^2_p = 0.25$, see Figure 7). When driving Level 2 automated, both measures were lower than when driving manually. Speed demands were detected by the subjective “mental demand” NASA-TLX sub-scale ($F(2,38) = 4.61$, $P < 0.01$, $\eta^2_p = 0.2$) with higher scores for the high (120 km/h) than in the low speed (70 km/h) condition ($p < .01$). Performance measures from the auditory oddball task and the KSS scores remained similar across the 6 conditions. Overall, the drivers performed well on the oddball task (accuracy > 98%) and reported intermediate scores in the KSS. Specific analyses of the time on task effect showed significant effects for P3 amplitude ($F(5,95) = 4.67$, $P < 0.05$, $\eta^2_p = 0.16$) and KSS ($F(5,95) = 5.12$, $P < 0.01$, $\eta^2_p = 0.28$). Trend analyses showed that, over time, KSS scores increased ($F(1,19) = 11.39$, $P < 0.01$, $\eta^2_p = 0.47$) and P3 amplitude declined ($F(1,19) = 6.94$, $P < 0.01$, $\eta^2_p = 0.3$, see Figure 8). A significant quadratic trend was observed for reaction times ($F(1,19) = 5.98$, $P < 0.05$, $\eta^2_p = 0.26$), with progressively shorter reaction times until the 4th condition and increments in the ensuing conditions.

Figure 7. Global P3 average waveforms (Pz electrode) for the manual and partially automated driving conditions. The topography of P3 in both conditions (on the right) shows where the maximum amplitudes of P3 were found (red colours).

Figure 8. Karolinska Sleepiness Scale (KSS) scores and P3 amplitudes over time (time on task effect). The x-axis represents the conditions performed in chronological order.

4.2.1.3. Brief discussion

Other studies have shown that reducing the primary task demands increase the amount of attentional resources allocated to a secondary task (e.g. Isreal et al. 1980; Ullsperger et al. 2001). In this study, however, the lower demands in the Level 2 automated conditions reduced the resources allocated to the secondary task. Given the conditions were short (5 minutes) and counterbalanced, and that the KSS scores were not affected (similar subjective vigilance levels), such effect may be reflecting a cognitive underload effect rather than to a passive fatigue effect developed over time. This would support the idea pointed out by Stanton and Young (2002; Malleable Attentional Resource Theory) or Hancock and Warm (1989; Effort-regulation hypothesis) that when demands are too low, attention may also be affected. Besides, specific analyses revealed a time on task effect

whereby vigilance decreased over time. Reductions in resource allocation due to cognitive underload and time on task effects were reported by the ERPs, while no worse secondary task performance was observed. Thus, ERPs may represent a sensitive tool to assess the attentional effects of automation and time on task.

4.2.2. Paper II. Event-Related Potentials As Indices of Mental Workload While Using an In-Vehicle Information System

4.2.2.1. Specific research questions

- RQ1: How does the *number of concurrent tasks* (single, dual and triple) and the *time pressure* (low, high and adjustable speeds) influence the participants' subjective MWL, attention, and performance?
- RQ2: Do ERPs inform about the task demands of perceptual and cognitive resources? Does such information complement other types of MWL measures (i.e. subjective, primary and secondary task performance)?

4.2.2.2. Results

As the number of concurrent tasks and/or the time pressure increased, MWL also did. However, the sensitivity of each measure to these effects varied. Most measurements discriminated between the performance of one (single-task, only the oddball task) or more tasks (dual- and triple-task), as well as between the low-speed conditions and the high or adjustable speed conditions. No differences between the latter two were observed for any dependent measure, probably because as observed, drivers selected similar speeds in the adjustable conditions as in the high-speed condition. Subjective ratings, tracking task performance and ERPs further discriminated between the dual (oddball task + tracking task) and triple task (oddball task+ tracking task + visual IVIS) conditions. In the case of ERPs, this only occurred under specific speed levels (interaction effect). Thus, only when speeds were high, N1 latency increased with the presence of the IVIS. Moreover, only when speeds were low, differences were found in P3 amplitude, with higher values in the dual (no IVIS) than in the triple task condition (with IVIS). Figure 9 shows the significant effects detected by the subjective and ERPs measures.

Figure 9. A) Scores in subjective mental demand for the three levels of “number of tasks” (single, dual and triple task conditions). B) N1 latencies and P3 amplitudes in the dual and triple task conditions at low and high speeds. The red dotted line represents the mean values observed in the single-task condition.

4.2.2.3. Brief Discussion

The findings of this study showed that incrementing the number of concurrent tasks to perform and/or the time pressure increase MWL and reduce primary task performance. However, not all measures were equally sensitive to different levels and sources of demands. When demands exceeded a certain level, secondary task performance was no longer sensitive, and other types of measures were necessary. ERPs were particularly informative to detect how different sources of demands affected specific processing resources (perceptual and cognitive). In accordance with Baldwin and Coyne (2005), these results would underscore the need of combining different methods to better account for all aspects of MWL. These results could be extrapolated to ecological situations such as driving while assisted by a visual continuous IVIS (e.g. route guidance systems). In such situations, specific demands may be placed not only by the number of concurrent tasks to coordinate but also by the time available to perform them, which will specifically demand perceptual-cognitive resources.

4.2.3. Paper III: Performance of an additional task during Level 2 automated driving: An on-road study comparing drivers with and without experience with partial automation

In this section, the results corresponding to Paper III will be presented. Additionally, an additional analysis was performed. This extra analysis is not included in Paper III, however, it was deemed useful to increase the comparability with the results from Paper I and Young and Stanton's study (2002), which will be discussed in the Discussion section.

4.2.3.1. Specific research question

- RQ1: Does Level 2 automation improve the performance of an additional visuomotor task?
- RQ2: What strategies do drivers use to integrate the additional task to their monitoring responsibilities? What is the role of prior experience with Level 2 automation on this?
- RQ3: Will drivers interrupt the additional task to compensate for increases in demands as much in manual as in Level 2 automated driving?

4.2.3.2. Results

Scores on the NASA-TLX revealed that the drivers perceived a lower mental demand when the task was self-paced compared to when it was system-paced ($F(1,19) = 4.1$, $P < 0.05$, $\eta^2_p = 0.17$), and a lower effort when driving automated compared to when driving manually ($F(1,19) = 11.94$, $P < 0.01$, $\eta^2_p = 0.4$). Moreover, automation-novice drivers scored higher in the frustration sub-scale than the experienced drivers in all conditions ($F(1,19) = 5.07$, $P < 0.05$, $\eta^2_p = 0.22$).

As for the additional task, drivers with Level 2 experience kept the task active for longer periods than the automation-novice group in the self-paced conditions ($F(1,19) = 9.23$, $P < 0.01$, $\eta^2_p = 0.33$). This was observed regardless the automation level. In addition, a lower percentage of correct responses and a greater percentage of missed responses were observed in the automated than in the manual conditions (Correct: $F(1,19) = 6.97$, $P < 0.05$, $\eta^2_p = 0.27$; Misses: $F(1,19) = 9.07$, $P < 0.01$, $\eta^2_p = 0.32$).

Regarding the driving variables, compared to the automation-novice drivers, the experienced drivers performed more overtakings ($F(1,19) = 6.13$, $P < 0.05$, $\eta^2_p = 0.24$), used the PA2 for a greater percentage of time ($F(1,19) = 5.1$, $P < 0.05$, $\eta^2_p = 0.18$) and spent more time in the left lane ($F(1,19) = 5.24$, $P < 0.05$, $\eta^2_p = 0.22$).

Furthermore, glance analyses showed that during the automated driving conditions the percentage of time looking to the front ($F(1,19) = 8.84$, $P < 0.01$, $\eta^2_p = 0.32$) and left

mirror ($F(1,19) = 4.56$, $P < 0.05$, $\eta^2_p = 0.19$) decreased, whereas the number of glances ($F(1,19) = 11.65$, $P < 0.01$, $\eta^2_p = 0.38$) and the percentage of time looking to the dashboard ($F(1,19) = 19.42$, $P < 0.01$, $\eta^2_p = 0.51$), where the PA2 system was presented, increased significantly. Moreover, some interaction effects were reported showing that the automation-experienced drivers directed more ($F(1,19) = 5.11$, $P < 0.05$, $\eta^2_p = 0.21$) and longer glances ($F(1,19) = 5.95$, $P < 0.01$, $\eta^2_p = 0.24$) to the tablet in the automated than in the manual conditions, while no differences were seen for the novice group. Regardless the level of automation, the automation-experienced group spent more time looking at the additional task ($F(1,19) = 4.77$, $P < 0.05$, $\eta^2_p = 0.2$) and looked less to the inside mirror ($F(1,19) = 11.37$, $P < 0.01$, $\eta^2_p = 0.37$). During the self-paced conditions, drivers looked more ($F(1,19) = 11.59$, $P < 0.01$, $\eta^2_p = 0.38$) and glanced more frequently ($F(1,19) = 6.4$, $P < 0.01$, $\eta^2_p = 0.25$) to the additional task than in the system-paced condition. Finally, when the task was self-paced, the automation-experienced drivers spent less time looking to the front than the novice drivers ($F(1,19) = 5.12$, $P < 0.05$, $\eta^2_p = 0.21$). Figure 10 displays the percentages of time spent looking at each of the different areas of interest by both groups of drivers under the different automation and additional task conditions.

Figure 10. Distribution of visual attention (percentages of time spent looking at each AOI) by the novice (N) and experienced (E) drivers during the manual/automated and the system/self-paced conditions. The figures represent the location of the different AOIs from the driver's perspective.

4.2.3.3. *Brief Discussion*

The findings presented above indicate that driving Level 2 automated does not necessarily improve the performance of other tasks, but even the opposite may occur. Thus, these results would contradict the trend observed in de Winter's meta-analysis (2014), where drivers are more capable of performing other tasks in Level 1, and particularly in Level 3. These findings also go against the general public expectations that automation will facilitate the performance of other tasks (Kyriakidis, Happee and de Winter, 2015). Moreover, experienced drivers also showed these effects, suggesting that prior experience with Level 2 automation does not help improve the performance of concurrent visuomotor tasks. This is striking considering that these drivers also looked more to the tablet and showed longer glances towards it compared to the novice drivers. It remains to be shown why Level 2 automation leads to worse performances on the additional task. This will be discussed in more detail in the discussion section of this thesis. To finalize, using self-paced additional tasks did not improve scores on the task, but decreased the perceived MWL, thus resembling the findings from other studies (Platten, Schwalm, Hülsmann and Krems, 2014).

4.2.3.4. *Additional analysis*

The attention ratio, as calculated by Young and Stanton (2002), was also analysed here. The number of correct responses obtained by each participant was divided by the total time spent looking to the tablet. Thus, an indication of attention allocation/efficiency was obtained. This would enable a better comparability with the results from Paper I and Young and Stanton's study (2002) were measures of attentional allocation or efficiency were used. A 2x2x2 mixed ANOVA was used with experience level (automation experienced or novice) as the between-subjects factor and automation level (manual or Level 2) and type of additional task (self- or system-paced) as the within-subjects factor. This brief analysis revealed a significantly higher ratio for the manual than automated conditions ($F(1, 20) = 6.48, p < .01, \eta^2_p = .28$). No significant effects were observed for level of experience ($F(1, 20) = 3.03, p = \text{n.s.}, \eta^2_p = .13$) or type of task ($F(1, 20) = 3.27, p = \text{n.s.}, \eta^2_p = .15$). Figure 11 shows the mean (and SEs) attention ratios obtained by each group of drivers under the different automation levels. These results indicate that drivers needed more time to obtain a correct answer when driving Level 2 automated. A brief discussion of these results will be presented in the Discussion section.

Figure 11. Attention ratios (Means and SEs) for each driver group in the automated and manual conditions.

4.2.4. Paper IV: Can I look away now? The role of trust and experience when engaging in non-driving related tasks in a partially automated vehicle

4.2.4.1. Specific research questions

- RQ1: Is there any relationship between prior experience with Level 2 automation and trust in Level 2 automation?
- RQ2: Does trust in the system, independently of experience level, influence driver monitoring behaviour and interaction strategies with the PA2 system and the additional task?. Which specific properties are most relevant when explaining drivers visual and behavioural strategies?

4.2.4.2. Results

Comparisons between groups of drivers showed similar levels of trust in automation in all SATI sub-scales before and after the experiment. After the experiment, the overall group rated significantly higher in the *understanding* ($F(1,19) = 4.81, P < .05, \eta^2_p = 0.2$), *utility* ($F(1,19) = 7.29, P < .01, \eta^2_p = 0.28$) and *robustness* ($F(1,19) = 9.37, P < .01, \eta^2_p = 0.33$), scores, leading to a significant increase of the global trust score ($F(1,19) = 8.34, P < .01, \eta^2_p = 0.31$). The different regression models showed that level of experience in combination with the *robustness* sub-scale helped to explain the total time looking to the front ($F(2,18) = 10.65, P < .01$), to the additional task ($F(2, 18) = 7.2, P < .05$), and the mean glance duration to the additional task ($F(2,18) = 5.4, P < .01$). The total time using the PA2 system was only influenced by the perception of *robustness* of the system (F

(1,19) = 7.2, $P < .02$). Finally, the total time the additional task was kept on was better explained by the level of experience ($F(1,19) = 8.1$, $P < .01$). Regarding the number of “hands-on” warnings issued to the drivers by the system, a greater number of auditory warnings were observed for the automation-experienced group (Mann-Whitney $U_z = -2.3$, $P < .05$). A specific analysis of the trust differences between drivers who got more warnings (3 or more) and fewer warnings (less than 3) showed that the latter perceived the system a significantly more robust (Mann-Whitney $U_z = -2.18$, $P < .05$).

4.2.4.3. Brief Discussion

The daily interaction with the PA2 system did not lead to a greater trust in the system. The monitoring requirements of the system continuously reminded by the warnings, along with the experience of some system failures or unexpected disengagements, may have prevented the experienced drivers from increasing their trust in the system. Despite this, experience with the system and trust in specific properties of the system did influence some specific behaviours, like the time with the PA2 and additional task engaged, or the time looking to the front and to the additional task. The perception of robustness, defined as the perception of the system as assisting, was the main explaining factor among all the SATI sub-scales. Drivers with a greater perception of robustness looked less to the road and more to the tablet; however, they also had the PA2 on for less time and received fewer warnings. While this remains to be further investigated, we hypothesize that perceiving a system as robust, also helps drivers to interact with it. Thus, these drivers integrated the system switch on/off strategy to better cope with the monitoring and the additional task.

5. DISCUSSION

Overall, the results of this thesis indicate that driving Level 2 automated affects drivers' attention and behaviour in different ways. It has been observed that while Level 2 automation reduces drivers' MWL, this does not translate into a greater attention allocation to other tasks, but rather the opposite. This could reveal a cognitive underload effect even after short periods of partially automated driving. Moreover, it was found that using the Level 2 system does not facilitate the execution of additional tasks, which contradicts previous studies and the popular belief (de Winter et al. 2014; Kyriakidis, et al. 2015). Finally, the applicability of ERPs in the detection of different levels and sources of demands placed by different ADAS seems promising in the light of the observed results. Despite this, certain methodological aspects and limitations need to be considered before this technique is applied. Next, each of these findings and their implications for safety will be discussed in more detail.

5.1. LOWER RESOURCE ALLOCATION WHILE MONITORING A LEVEL 2 SYSTEM

The findings in this thesis indicate that Level 2 automated driving reduces the driver demands as well as the drivers' mobilization of attentional resources, compared to manual driving. The lower attention allocation was only detected by decrements in P3 amplitudes to the secondary task and no performance decrements were detected in such task. Given the short and counterbalanced conditions (5 minutes), and the constant levels of subjective vigilance across conditions, these findings could be attributed to an effect of cognitive underload (Young and Stanton, 2002; Young et al., 2015), rather than to passive fatigue effects developed over time (Greenlee et al. 2018; Körber et al 2015; Saxby et al., 2013).

From a classic resource model perspective, these results are somewhat counterintuitive, as the lower demands in the automated conditions should have led to more available resources to process and execute the auditory oddball task. The effect has been observed by others using ERPs elicited by secondary tasks similar to the auditory oddball task used here (Allison and Polich, 2008; Kramer, Wickens and Donchin, 1983; Scheer et al., 2016; Strayer and Drews, 2007). Commonly, these studies have reported a trade-off between the primary task demands and the amount of resources allocated to a secondary task, usually indicated by P3 amplitude. Thus, as the primary task demands decrease, P3 amplitude to the secondary task increases, and vice versa. These results, however, were not replicated in Paper I, where lower primary task demands (i.e. when driving Level 2 automated) also led to decrements in P3 amplitudes.

According to MART (Young and Stanton, 2002), such effect could be explained by a shrinkage in drivers' attentional capacity due to the "excessively" low demands induced by the Level 2 system. In their study, Young and Stanton (2002) observed that the drivers needed more time looking at the additional task to obtain a correct response as the

automation level increased (i.e. a lower attention ratio), thus showing a cognitive underload effect reflected in a more inefficient allocation of resources. The lower P3 amplitudes observed in Paper I may represent a neurophysiological correlate of such lower attentional efficiency under low demanding conditions whereby fewer resources are allocated. However, it could also be argued that such reductions, rather than a consequence of the “excessive” low demands, were produced by the qualitative change in the driver role when the system was active, compared to when driving manually. As explained earlier, in Level 2 automated driving the driver is removed from the physical control of the vehicle and his/her main task is to passively monitor the traffic and the system. Endsley and Kiris (1995) warned that the loss of physical control could result in the drivers becoming out of the loop (OOL). The lower P3 amplitudes in Paper I could reflect a global decrease of drivers’ cognitive engagement in the ongoing tasks as a result of not being in physical control of the vehicle. Future studies dissociating the effects of driving demands and the driver role on attention should shed more light on this.

5.2. DECREASED PERFORMANCES ON ADDITIONAL VISUOMOTOR TASKS UNDER LEVEL 2 AUTOMATION

The results observed in this thesis, and particularly in Study III, do not support the literature showing better performances in secondary tasks with increments in automation level (de Winter et al., 2014). In fact, worse scores in the additional visuomotor task were observed when interacting with the Level 2 system. This also seems to go against the popular belief that it is easier to do other things while driving Level 2 automated (Kyriakidis, et al. 2015). Different possible accounts could be provided to such results.

One possible explanation is that Level 2 automation, despite supporting drivers at the tracking and regulating levels, also places new tasks on the monitoring control level associated with the need of supervising the system status/performance. This change might also cause an increase in the overall driving demands, thus affecting the performance of the additional visuomotor task in Study III. The analyses of the drivers’ glance behavior seem to support this. As observed, when the system was active, the drivers did not only monitor the road and the additional task but also increased their visual attention to the dashboard, where the PA2 symbol was presented. Despite this, the drivers reported having invested a significantly lower effort in the Level 2 automated than in the manual driving conditions, which is not in line with the overload hypothesis presented here.

An alternative explanation is that Level 2 automation led to cognitive underload. Based on this, the worse performances in the task would be explained by a shrinkage in the drivers’ attentional capacity (MART, Young and Stanton, 2002), or by decrements in the mobilization of effort (ERH, Hancock and Warm, 1989) due to an underestimation of the task demands. This explanation would be consistent with the lower self-reported effort in the automated conditions. In addition, this mechanism would be compatible with the lower attention allocation/efficiency reflected in the reduced P3 amplitudes in Paper I or in the lower attention ratios in Young and Stanton’s study (2002). To better compare the

observations from Study III with these two studies, the attention ratio was also calculated in an additional analysis in order to obtain an indicator of attention allocation/efficiency. This extra analysis is presented in section 4.2.3.4 (“Additional analysis”) and illustrated in Figure 11. As observed, the attention ratio was lower in the automated conditions, showing that drivers needed more time looking at the additional task to obtain a correct response. The observed results would support the findings from Paper I and those from Young and Stanton (2002) and would reinforce the cognitive underload hypothesis.

Furthermore, it could also be argued that, regardless of the overall level of demands, specific interferences occurred between the monitoring tasks in the Level 2 automated conditions and the additional task execution. Monitoring is primarily an anticipatory task which requires drivers to coordinate the sampling of different elements outside (e.g. other vehicles) and inside the vehicle (e.g. system status) (Hollnagel et al. 2003). Therefore, monitoring likely relies on cognitive processes like selective attention, planning or working memory. By contrast, driving manually on a straight highway with low-moderate traffic density may primarily depend on perceptual-motor skills falling into the tracking and regulating control levels in the DiC model (Hollnagel et al, 2003). As Hollnagel et al. (2003) indicated, these tasks may be effortlessly performed after some experience is gained. From our observations, it could be argued that the additional task itself and the task switching requirements contributed to extra cognitive demands. As a result, the monitoring task in the automated conditions was probably more disruptive to the additional task performance than the tracking task in the manual conditions. This explanation finds theoretical support in the Multiple Resource Theory (Wickens, 1984), and in the more recent Cognitive Control Hypothesis (Engström, Markkula, Victor, & Merat, 2017) which states that, "cognitive load selectively impairs driving subtasks that rely on cognitive control but leaves automatic performance unaffected" (p.3). Based on this last explanation, the result presented in Figure 11 could be reinterpreted. The greater attentional ratios in the automated conditions, rather than reflect cognitive underload, might evidence an inefficient ability to share cognitive resources between the monitoring and additional task. Thus, after glancing at the additional task, drivers might still need some extra time to cognitively disengage from the monitoring task, causing lower attention ratios.

Finally, a factor that was not analysed in Study III was the drivers' stress to the experimental situation. Stress has been shown to negatively impair working memory and other executive functions (Starcke, Wiesen, Trotzke and Brain, 2016). According to the attentional control theory (Eysenck, Derakshan, Santos, & Calvo, 2007), anxiety specifically affects inhibition and shifting functions, which are crucial for an efficient time-sharing performance. Stress also reduces task-directed effort, which could aggravate the automation effects (Funke, Matthews, Warm and Emo, 2007). It is possible that the experimental conditions did not only stress the novice drivers, who were presented with a Level 2 vehicle for the first time, but also the experienced drivers who possibly were not so familiar with having to perform an artificial visual task while driving automated for so long.

5.3. EXPERIENCE AND TRUST AFFECT DRIVER MONITORING STRATEGIES AND INTERACTION WITH THE PA2 SYSTEM AND THE ADDITIONAL TASK.

It has been shown that a greater knowledge of and trust in the automated system influences the way a driver interacts with it (Kircher, Larsson and Hultgren, 2014; Parasuraman & Riley, 1997) as well as the monitoring strategies used (Hergeth, Lorenz, Vilimek & Krems, 2016; Körber et al., 2018). The influence of these two factors was specifically analysed in the context of real-road driving under Level 2 automation while performing an additional task (Study III – Paper IV).

5.3.1. Experience

It was observed that previous experience with the PA2 system influenced the way drivers monitor and interact with the system and with the additional task. These drivers, compared to the automation-novices, directed more and longer glances to the additional task, kept the PA2 system and the additional task (in the self-paced conditions) active for a longer time and performed more overtakings. These results would be in line with the observations from Naujoks et al. (2016) where only drivers with prior Level 1 experience (ACC) engaged more in a secondary task while driving Level 2 automation. Possibly, the experienced drivers had a more precise mental model of the system which allowed them to better judge the behaviour of the system and to determine when it was safer to divert attention to the secondary task. In support of this, previous studies have observed that drivers with Level 1 experience (ACC) had a greater knowledge of the ACC system (Larsson, 2012), and used this knowledge when executing manoeuvres such as exiting the highway or avoiding a stopped car in the driver's lane (Kircher, Larsson, Hultgren, 2014). Despite this greater knowledge of the PA2 system, experienced drivers, as the novice drivers, performed worse in the additional task during the automated conditions than during the manual conditions. This could indicate that having a more developed mental model of the system may not help counteract the automation effects on the driver attention.

Experienced drivers also received more “hands-on the steering wheel” warnings than the novice drivers. One explanation might be that the experienced drivers were more familiar with the warnings sequence of the PA2 system (i.e. hands-off driving →^{15s} visual warning →^{5s} auditory warning →^{3s} system disengagement). Experienced drivers may have used this knowledge to maximize the total hands-off time to better engage in the additional task. Thus, these drivers might have waited until they received the first visual warning or even the second auditory warning to put their hands back on the steering wheel. However, this behaviour could also reflect an unanticipated behavioural adaptation developed by the drivers during their daily interaction with the system. In such case, the implications of this behaviour for driving performance and safety need to be considered in further research.

5.3.2. Trust

Contrary to expectations based on other studies (Lee and Moray, 1992, Muir 1994), the experienced drivers in this thesis did not trust the Level 2 system more than the novices. As Hoc (2000) stated, experience leads to trust when the system is predictable. However, trust may also decrease when the system fails (Manzey, Reichenbach & Onnasch, 2012). It is arguable that the limited development of trust in the experienced drivers may be partly due to the continuous monitoring requirements of the system, frequently reminded by the “hands-on the steering wheel” warnings. These drivers may have also experienced situations where the system failed, disconnected or did not behave as reliable as expected.

Furthermore, it was observed that trust in specific properties of the system, such as robustness, might explain some of the monitoring strategies used by the drivers when interacting with the additional task. Specifically, drivers who perceived the system as more robust looked less to the front and more to the additional task, which at first, could be indicative of overtrust in the system and complacency. However, it was observed that these drivers also activated the system for less time and received fewer “hands-on the steering wheel” warnings. It is possible that the drivers had a better "calibrated" trust level with the current system's capabilities and opted to switch it off when uncertain about the system performance in specific situations. It might also be that a greater robustness perception increases drivers' confidence to interact with the system by turning it on or off when deemed necessary. These drivers might have integrated this behaviour into their strategies when monitoring and performing the additional task. By contrast, the drivers who perceived the system as less robust probably preferred to interact with the system less and compensate by monitoring the road and the system performance more, as shown in our results.

5.4. ERPs APPLICABILITY TO DETECT ADAS DEMANDS

Another main objective of this thesis was to analyse the applicability of ERPs to estimate MWL in the context of ADAS. These efforts were carried out in two different contexts: during Level 2 automated driving (Study I), and during a tracking task supported by an artificial IVIS (Study II).

The cognitive underload effect of Level 2 automated driving was informed by the subjective measures and ERPs, particularly the P3 component. However, the performance indicators from the secondary task (i.e. accuracy and reaction times to the auditory oddball) were insensitive to variations in MWL. Given that P3 amplitudes can also decrease under high demands (e.g. Allison and Polich, 2008 or Strayer et al. 2015), subjective measures were necessary to conclude that a cognitive underload effect, rather than an overload effect, took place. The lack of differences in secondary task performance between conditions might be explained by the lower sensitivity of this type of measures when demands are low-moderate (de Waard, 1996). It is also possible that the low

difficulty of the oddball task and some learning effects allowed drivers to maintain performance even when fewer resources were allocated in the automated conditions.

ERPs were also useful to detect increments in demands associated with the use of an artificial IVIS and with higher time pressures. As shown in Study II, increments in MWL due to the increasing number of tasks and the tracking speed were detected in all MWL measures. All measures discriminated when the participants performed one (single-task condition = oddball task) or more tasks (i.e. dual-task = oddball + tracking task, triple-task = oddball + tracking task + IVIS). However, only the subjective measures and the ERPs detected the presence of IVIS (triple-task condition). Specifically, P3 amplitude discriminated the presence of the IVIS when speeds were low (i.e. P3 amplitude decreased). However, with higher speeds, P3 amplitude decreased to a “floor level” and no longer discriminated the presence of the IVIS. In relation to this, Gopher and Donchin (1996) suggested that once the performance is affected, the amplitude of P3 remains unaffected, which is compatible to what was observed in this study. In addition, N1 latency also detected the presence of the IVIS, but only when the tracking task was performed at high speeds. N1 latency was significantly longer if the IVIS was present. The need of high demands for the N1 component to be affected has been suggested elsewhere (Kok, 2001; Näätänen, 1992; Parasuraman, 1985).

As shown, one of the greatest advantages of ERPs with respect to other measures was its diagnosticity (Brookhuis and de Waard, 2010; de Waard, 1996). In this thesis, it has been observed that the allocation of cognitive resources, represented by the P3 component, was more sensitive to variations in demands than the allocation of perceptual resources, reflected by N1 component. P3 amplitude decreased in conditions of cognitive underload (Study I) and when demands increased to a certain level (Study II). However, N1 latency was only affected when demands were highest, which is in line with what other authors suggested (Kok, 1997; Kok, 2001; Parasuraman, 1985). As explained in the introduction of this thesis, N1 reflects perceptual processes influenced by exogenous factors but also by the voluntary allocation of resources (Kok, 2001; Mangun and Hylliard, 1990). These results could indicate that failures in the allocation of perceptual resources occurred after the cognitive resources were overloaded.

In short, these findings indicate that the use of ERPs could complement other MWL measures (i.e. self-reports, performance measures or other physiological measures) in three main aspects: a) to detect impairments in operators’ processing capacity when MWL is too high or too low, b) inform about such impairments before they become visible in performance decrements, or when performance measures are not available, and c) to inform on the specific processing resources tapped into by the task demands. However, ERPs cannot be used in isolation as they require other measures for a proper interpretation. As observed, P3 amplitudes may decrease in both, high and low demanding conditions; therefore, complementary measures such as subjective reports are necessary.

5.5. LEVEL 2 AUTOMATION: POTENTIAL IMPLICATIONS FOR SAFETY

In contrast to other studies in the literature, no safety-critical situations (e.g. sudden system failures or obstacles on the road) were included in any of the experiments contained in this thesis. Despite this, the findings observed here could be directly linked to the human factors issues reported in the literature on automation such as slower reactions to critical events (Eriksson and Stanton, 2017; Merat and Jamson, 2009; Strand, Nilsson, Karlsson, and Nilsson, 2014), worse vehicle control after taking over to potential collisions (Louw et al. 2015) or reduced situational awareness (SA) (de Winter et al. 2014).

Usually, these safety concerns in partial automation have been attributed to vigilance decrements over time due to passive fatigue effects induced by automation (Greenlee et al. 2018; Körber et al. 2015; Saxby et al. 2013). However, in this thesis, resource allocation reductions were also observed after short periods of automated driving, which points to the possibility that such performance issues could also take place after just a few minutes of automated driving. Future studies analyzing drivers' ability to respond to critical situations after different driving periods would help to shed more light on this.

Moreover, the observed worse performances in the additional visuomotor task in Study III could reveal other mechanisms through which Level 2 automation could affect safety. As suggested, specific tasks interferences may occur between the monitoring and additional visuomotor tasks, thus affecting drivers' ability to integrate them in an efficient manner. In this study, such lower time-sharing performance would have affected the performance of the additional task; however, they could have also reduced the drivers' ability to anticipate and react to critical traffic situations. Given that Study III was conducted in real traffic conditions, it was methodologically and ethically difficult to analyse drivers' performance under safety critical conditions.

Altogether, these findings would alert about the possibility that Level 2 vehicles, besides improving important aspects of manual driving, could also generate new problems associated with drivers' ability to remain attentive to the road events and the system performance. In real traffic, the implications of this safety issues for the driver could be fatal, as shown by some recent accidents involving Level 2 and Level 3 vehicles (National Transport Safety Board, 2016; National Transport Safety Board, 2018). Given that vehicles equipped with such systems are expected to become commonplace in the coming years, the number of this type of accidents will likely increase. It is therefore urgent to understand them and provide effective solutions.

5.6. COUNTERMEASURES

The main challenge in a Level 2 automated system is to keep the driver in the loop. Therefore, countermeasures should be aimed at solving or mitigating the main factors leading drivers to disengagement from the driving task, or in other words, become out of

the loop (OOL; Endsley, 1995). As observed in this thesis, such condition may occur due to reduced resource allocation induced by the low demands and/or the time on task, or due to a lower monitoring of the road/system when engaged in non-driving related tasks. Next, some possible countermeasures for these two conditions are presented:

- Specific education and training programs with a focus on Level 2 automation. These programs should not only aim at increasing the driver's knowledge of the system capabilities and limitations but also at raising awareness about their potential cognitive and behavioural effects and its consequences. Drivers may benefit from receiving specific training on how to monitor the system or how to detect situations that may exceed the system boundaries. The inclusion of practical sessions by means of videos, computer tasks or simulated driving, would be recommendable in the light of previous studies (Krampell, 2016; Payre, Cestac, Dang, Vienne and Delhomme, 2017). In short, these programs should guarantee that drivers acquire an adequate knowledge of the system and a well-calibrated level of trust in it.
- Driver state monitoring systems. Based on various parameters, these systems can detect different driver states. For example, some eye-based metrics such as glance pattern, eyes-off-the-road time, blink frequency or pupil diameter have been shown to be sensitive to different types of distraction (i.e. visual, auditory or cognitive; for a review, see Gonçalves and Bengler, 2015). Other metrics such as head position/direction detectors have shown good results in detecting distraction (Rauch, Kaussner and Krüger, 2009, Teyeb, Jemai, Zaied, and Amar, 2014). These systems may be particularly useful in detecting inappropriate driver states or monitoring behaviours while driving Level 2 automated.
- Human-machine interfaces (HMIs). HMIs should be able to keep the driver aware of what the system status is, and which tasks are being automated. This information should be conveyed to the drivers in an intuitive and effective way. In Level 2 systems, specific HMIs could be used to promote appropriate driver alertness levels for the ongoing traffic conditions. Previous studies have shown that this could be possible by providing drivers with updated information about the system reliability under specific conditions (Helldin, Falkman, Riveiro and Davidsson, 2013). Another potential solution is to dynamically adapt the time drivers are allowed to drive hands-off to the current reliability of the system. As an example, Tesla Autopilot system automatically adapts this time to factors such as speed or the presence of a vehicle in front. Hands-off time is reduced when speed exceeds 45mph and no vehicle in front is present. Other parameters, like the traffic conditions (e.g. visibility, traffic density, etc.) or even the current driver state could also be considered in future systems.

5.7. METHODOLOGICAL CONSIDERATIONS AND LIMITATIONS

Different methods, scenarios and techniques were used in the different studies, which should be mentioned as they may limit their comparability. Moreover, some limitations were encountered across the studies, which will also be highlighted here.

Throughout this discussion, an effort has been made to connect the findings from Studies I and III; however, some important differences should be mentioned. An obvious difference is that Study III was carried out in real traffic, where the risk of crashing was also real, while a simulator was used for Study I. Differences in risk perception may affect the extent to which drivers put effort to engage in the monitoring tasks. The lack of real risk in the simulator could have led to lower alertness levels in Study I, which could explain the cognitive underload effects observed. Another important difference is that in the simulator study no system symbol was presented to the driver in the dashboard. As shown in Study III, the system symbol is an important element that needs to be monitored while the Level 2 system is active. The absence of this symbol in Study I may have contributed to reducing the demands as fewer elements had to be monitored. This may have also favoured the occurrence of cognitive underload.

Another aspect to consider relates to the characteristics of the group of drivers in Study III. For example, the sample of drivers with Level 2 automation experience was quite small ($n = 9$). The main reason is that, at the time the study was planned, Level 2 vehicles had only been on the roads for 4-5 months and, therefore, few drivers with such level of experience were available. In addition, the two groups differed in their experience with Volvo vehicles, apart from their experience with Level 2 automation. Time and budget limitations led to recruiting drivers of different types of middle-class vehicles for the novice group. While it is theoretically possible that not being familiar with a Volvo had a confounding effect, it does not appear to be very likely, as the driving task on the freeway was very simple, not even requiring gear changes.

Moreover, it is necessary to consider that Level 2 systems available today offer different interfaces and technical solutions to maintain the drivers in the loop. In some cases, such differences are substantial. For example, the PA2 system only allows 15 seconds of hands-free driving, while the Tesla Autopilot can offer up to 5 minutes under certain speed conditions. While the role of the driver remains the same, i.e. monitor at all times, such differences may affect the driver in different ways. This could limit the generalizability of the results obtained with the Volvo PA2 system, to other Level 2 systems on the market.

Finally, some challenges encountered during the application of the ERPs should be noted. Firstly, the setting of the EEG equipment on the required participants between 30 minutes to 1 hour. This increased the feeling of drowsiness and fatigue, as verbally reported by some drivers. Secondly, despite the well-controlled environments chose for Studies I and II, artefacts were observed that contaminated the brain signals (e.g. blinks, head movements, etc.). This required the application of methods that partially, but not totally, removed such unwanted activity. Thirdly, as in other studies, a secondary task was used

to elicit the ERPs. However, this could have inadvertently affected the primary task performance, an effect that should be avoided (de Waard, 1996; O'Donnell and Eggemeier, 1986).

5.8. RECOMMENDATIONS FOR FUTURE RESEARCH

The different findings observed in this thesis also raised new questions that should be addressed in further research. In addition, some of the limitations encountered in this thesis could be mitigated in future studies. Regarding this, some recommendations will be provided for future studies.

To start with, an aspect that deserves to be further investigated is why Level 2 automated driving affects the performance of an additional visuomotor task. In this thesis, different mechanisms have been proposed (i.e. cognitive underload, overload, task interference). It would be interesting to see whether similar effects are found in tasks of different modalities, or when performing more ecological secondary tasks (e.g. texting on the phone).

In addition, future studies should account for the role of emotions while driving a Level 2 vehicle. As suggested here, the worse additional task performance may be also explained by the stress effects induced by the low reliability of the Level 2 systems. Different investigations have emphasized the impact of emotions in manual driving performance (Chan and Singhal, 2015; Jeon, Walker and Yim, 2014); however, little is known in relation to automated driving.

As mentioned, Level 2 automated vehicles differ between car manufacturers, each offering different warning systems and interfaces. Conducting similar studies on different Level 2 systems would help determine whether the results observed here are restricted to the PA2 system or, by contrast, can be generalized to any Level 2 system.

Finally, while the use of ERPs seems promising, some recommendations should be considered in future studies. For example, the time necessary to prepare the electrophysiological equipment could be reduced by only using the necessary electrodes to detect the component of interest (e.g. Pz electrode for detecting the P3 component). Additionally, the use of task-irrelevant stimuli to elicit the ERPs could help mitigate the primary-task intrusion generated by the use of secondary tasks like the auditory oddball task. Some studies have already shown that the presentation of sporadic environmental sounds elicits a type of P3 component (P3a) that is also sensitive to variations in the primary task demands (Dyke et al. 2015; Miller et al. 2011).

5.9. GLOBAL CONCLUSIONS

In the coming decades the society will witness the implementation of a wide range of advanced systems capable of taking control of more and more complex driving tasks. This constitutes a real challenge not only for the system designers or the entities responsible for regulating their safe implementation on the road, but also for the human factor researchers who must be able to anticipate possible problems in the driver-vehicle interaction and provide effective solutions.

Unfortunately, the pace of the market is usually faster than research, which means that some systems may be launched even when their safety is not empirically supported. Level 2 automated vehicles represent a clear example. Despite the little research on this level, and the warnings coming from other domains such as aviation or experimental psychology, Level 2 vehicles are now on the market and the number of users will increase exponentially in the coming years. While, expectedly, these vehicles will likely improve many aspects of manual driving, there are founded concerns that they could also generate new types of accidents derived from unanticipated effects of this technology on drivers' abilities and behaviour.

In this context, the objective of this thesis has been to increase the knowledge on the impact of Level 2 automated driving on drivers' attention and behaviour. Simplifying, the main contributions of this thesis could be summed up into three. Firstly, it has been shown that even short periods of Level 2 automated driving could lead to cognitive underload, and therefore, to lower attention allocation by the drivers. Secondly, it was found that driving Level 2 automated does not necessarily facilitate the execution of other tasks, but even the opposite, which contradicts a large body of research on this topic, as well as the public's expectations. Thirdly, the ERPs technique has been explored to better detect the attentional effects of automation and other ADAS, showing promising results. While the results of the different studies have shed more light on the Level 2 automation effects, there remain many open questions to be investigated. Hopefully, this thesis will contribute to raising awareness and motivate future researchers on the importance of devoting efforts on investigating this problem.

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7. REFERENCES

- Åkerstedt, T. & Gillberg, M. (1990). Subjective and objective sleepiness in the active individual. *Int J Neurosci*, 52, 29–37. doi: 10.3109/00207459008994241
- Allison, B.Z. & Polich, J. (2008). Workload assessment of computer gaming using a single-stimulus event-related potential paradigm. *Biol Psychol*, 77, 277–283. doi: 10.1016/j.biopsycho.2007.10.014
- Bainbridge, L. (1983). Ironies of automation. *Automatica*, 19(6), 775–779. [http://doi.org/10.1016/0005-1098\(83\)90046-8](http://doi.org/10.1016/0005-1098(83)90046-8)
- Baldwin, C. L., & Coyne, J. T. (2005). Dissociable aspects of mental workload: examinations of the P300 ERP component and performance assessments. *Psychologia*, 48, 102–119. <http://doi.org/10.2117/psysoc.2005.102>
- Baldwin, C. L., Freeman, F. G., & Coyne, J. T. (2004). Mental Workload as a Function of Road Type and Visibility: Comparison of Neurophysiological, Behavioral, and Subjective Indices. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 48(19), 2309–2313. <http://doi.org/10.1177/154193120404801922>
- Banks, V.A., Eriksson, A., O'Donoghue J. & Stanton, N.A. (2018). Is partially automated driving a bad idea? Observations from an on-road study. *Appl Ergon* , 68, 138–145. doi: 10.1016/j.apergo.2017.11.010
- Barnard, Y., & Lai, F. (2010). Spotting sheep in Yorkshire: Using eye-tracking for studying situation awareness in a driving simulator. In D. de Waard, A. Axelsson, M. Berglund, B. Peters, & C. Weikert (Eds.), *Human Factors: A system view of human, technology, and organisation*, 249–261. Maastricht, The Netherlands: Shaker Publishing.
- Barry, R. J., Clarke, A. R., & Johnstone, S. J. (2003). A review of electrophysiology in attention-deficit/hyperactivity disorder: I. Qualitative and quantitative electroencephalography. *Clinical Neurophysiology*, 114, 184–198. [http://doi.org/10.1016/S1388-2457\(02\)00362-0](http://doi.org/10.1016/S1388-2457(02)00362-0)
- Blanco, M., Biever, W. J., Gallagher, J. P., & Dingus, T. A. (2006). The impact of secondary task cognitive processing demand on driving performance. *Accident Analysis and Prevention*, 38(5), 895–906. <http://doi.org/10.1016/j.aap.2006.02.015>
- Brookhuis, K. A., & de Waard, D. (2010). Monitoring drivers' mental workload in driving simulators using physiological measures. *Accident; Analysis and Prevention*, 42(3), 898–903. <http://doi.org/10.1016/j.aap.2009.06.001>

- Brookhuis, K. A., Van Driel, C. J., Hof, T., Van Arem, B., & Hoedemaeker, M. (2009). Driving with a congestion assistant; mental workload and acceptance. *Applied Ergonomics*, 40, 1019–1025. <http://dx.doi.org/10.1016/j.apergo.2008.06.010>.
- Campagne, A., Pebayle, T. & Muzet, A. (2004). Correlation between driving errors and vigilance level: influence of the driver's age. *Physiol Behav*, 80, 515–524. doi: 10.1016/j.physbeh.2003.10.004
- Carsten, O. (2014). Introduction to the special section: Can workload take the strain? *Cognition, Technology & Work*, 16(3), 285–287. <http://doi.org/10.1007/s10111-014-0280-4>
- Carsten, O., Lai, F. C. H., Barnard, Y., Jamson, A. H., & Merat, N. (2012). Control Task Substitution in Semiautomated Driving: Does It Matter What Aspects Are Automated? *Human Factors*, 54(5), 747–761. <http://doi.org/10.1177/0018720812460246>
- Carsten, O. & Nilsson, L. (2001). Safety Assessment of Driver Assistance Systems. *European Journal of Transport and Infrastructure Research*, 1, 225–244. doi: 10.1016/S1366-5545(02)00012-1
- Chan, M. & Singhal, A. (2015). Emotion matters: Implications for distracted driving. *Safety Science*, 72, 302–309. doi: 10.1016/j.ssci.2014.10.002
- De Waard, D. (1996). *The Measurement of Drivers' Mental Workload*. *Dissertationsubrugnl* (Vol. 39). <http://doi.org/10.1016/j.apergo.2003.11.009>
- De Winter, J. C. F., Happee, R., Martens, M. H., & 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. <http://doi.org/10.1016/j.trf.2014.06.016>
- Dehn, D. M. (2008). Assessing the Impact of Automation on the Air Traffic Controller: The SHAPE Questionnaires. *Air Traffic Control Quarterly*, 16 (2), 127-146.
- Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1), 9–21. <http://doi.org/10.1016/j.jneumeth.2003.10.009>
- Desmond, P. A., & Hancock, P. A. (2001). “Active and passive fatigue states,” in *Stress, Workload, and Fatigue*, eds P. A. Hancock and P. A. Desmond (Mahwah, NJ: Lawrence Erlbaum), 455–465.

- Dijksterhuis C., Brookhuis K. A. & De Waard, D. (2011). Effects of steering demand on lane-keeping behaviour, self-reports, and physiology. A simulator study. *Accid Anal Prev*, 43, 1074–1081. doi: 10.1016/j.aap.2010.12.014
- Duncan, C. C., Barry, R. J., Connolly, J. F., Fischer, C., Michie, P. T., Näätänen, R. & Van Petten, C. (2009). Event-related potentials in clinical research: Guidelines for eliciting, recording, and quantifying mismatch negativity, P300, and N400. *Clinical Neurophysiology*, 120(11), 1883–1908. <http://doi.org/10.1016/j.clinph.2009.07.045>
- Duncan-Johnson, C. C., & Donchin, E. (1982). The P300 component of the event-related brain potential as an index of information processing. *Biological Psychology*, 14(1–2), 1–52. [http://doi.org/10.1016/0301-0511\(82\)90016-3](http://doi.org/10.1016/0301-0511(82)90016-3)
- Duncan-Johnson, C. C., & Kopell, B. S.(1981). The Stroop effect: Brain potentials localize the source of interference. *Science*, 214, 938–940.
- Dyke, F.B., Leiker, A.M., Grand, K.F., et al (2015). The efficacy of auditory probes in indexing cognitive workload is dependent on stimulus complexity. *Int J Psychophysiol*, 95, 56–62. doi: 10.1016/j.ijpsycho.2014.12.008
- Endsley, M. R., & Kiris, E. O. (1995). The Out-of-the-Loop Performance Problem and Level of Control in Automation. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 37(3), 381–394. <http://doi.org/10.1518/001872095779064555>
- Endsley, M.R. (2018). Level of Automation Forms a Key Aspect of Autonomy Design. *J Cogn Eng Decis Mak* 12:29–34. doi: 10.1177/1555343417723432
- Engström J, Markkula G, Victor T, Merat N (2017). Effects of Cognitive Load on Driving Performance. *The Journal of the Human Factors and Ergonomics Society*, 59 (5), 734-764. doi: 10.1177/0018720817690639
- Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception and Psychophysics*, 16, 143–149.
- Eriksson, A., & Stanton, N. A. (2017). Takeover Time in Highly Automated Vehicles: Noncritical Transitions to and From Manual Control. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 59(4), 689–705. <http://doi.org/10.1177/0018720816685832>
- ERTRAC Task Force (2015). Automated Driving Roadmap (Retrieved from) http://www.ertrac.org/uploads/documentsearch/id38/ERTRAC_Automated-Driving-2015.pdf.

- Eysenck, M. W., Derakshan, N., Santos, R., & Calvo, M. G. (2007). Anxiety and cognitive performance: attentional control theory. *Emotion*, 7(2), 336–53. <http://doi.org/10.1037/1528-3542.7.2.336>
- Funke, G., Matthews, G., Warm, J. S., & Emo, A. K. (2007). Vehicle automation: a remedy for driver stress? *Ergonomics*, 50(8), 1302–23. <http://doi.org/10.1080/00140130701318830>
- Gasser, T., & Westhoff, D. (2012). BAST-study: Definitions of automation and legal issues in Germany. In TRB Road Vehicle Automation Workshop, Irvine, CA, USA.
- Giraudet L, Imbert JP, Bérenger M, et al (2015). The neuroergonomic evaluation of human machine interface design in air traffic control using behavioral and EGG/ERP measures. *Behav Brain Res*, 294, 246–253. doi: 10.1016/j.bbr.2015.07.041
- Gonçalves, J., & Bengler, K. (2015). Driver State Monitoring Systems– Transferable Knowledge Manual Driving to HAD. *Procedia Manufacturing*, 3, 3011–3016. <http://doi.org/10.1016/j.promfg.2015.07.845>
- Gopher, D., & Donchin, E. (1986). Workload-An examination of the concept. In K. R. Boff, L. Kaufman & J. P. Thomas (Eds.), *Handbook of Perception and Human Performance*. Vol. II: Cognitive Processes and Performance (pp. 41-41–41-49). New York: John Wiley & Sons.
- Gosselin A., De Koninck J. & Campbell K.B. (2005). Total sleep deprivation and novelty processing: Implications for frontal lobe functioning. *Clin Neurophysiol*. 116, 211–222. doi: 10.1016/j.clinph.2004.07.033
- Greenlee, E.T., DeLucia, P.R. & Newton, D.C. (2018). Driver Vigilance in Automated Vehicles: Hazard Detection Failures Are a Matter of Time. *Hum Factors*. doi: 10.1177/0018720818761711
- Hancock, P.A., & Warm, J.S. (1989). A dynamic model of stress and sustained attention. *Hum. Factors*, 31, 519–537. doi: 10.1177/001872088903100503
- Hancock, P.A., Mouloua, M., & Senders, J.W. (2009). On the philosophical foundations of the distracted driver and driving distraction. In M. A. Regan, J. D. Lee, & K. L. Young (Eds.), *Driver distraction. Theory, effects and mitigation* (pp. 11–30). Boca Raton, FL: CRC Press
- Harms, L., & Patten, C. (2003). Peripheral detection as a measure of driver distraction. A study of memory-based versus system-based navigation in a built-up area. *Transportation Research Part F: Traffic Psychology and Behaviour*, 6(1), 23–36. [http://doi.org/10.1016/S1369-8478\(02\)00044-X](http://doi.org/10.1016/S1369-8478(02)00044-X)

- Hart, S.G. & Staveland, L.E. (1988). Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. *Adv Psychol*, 52, 139–183. doi: 10.1016/S0166-4115(08)62386-9
- Helldin, T., Falkman, G., Riveiro, M., & Davidsson, S. (2013). Presenting system uncertainty in automotive UIs for supporting trust calibration in autonomous driving. Proceedings of the 5th International Conference on Automotive User Interfaces and Interactive Vehicular Applications - AutomotiveUI '13, 210–217. <http://doi.org/10.1145/2516540.2516554>
- Hergeth, S., Lorenz, L., Vilimek, R., & Krems, J. F. (2015). Keep Your Scanners Peeled: Gaze Behavior as a Measure of Automation Trust during Highly Automated Driving. *Human Factors*, 58(3), 509–519. <http://doi.org/10.1177/0018720815625744>
- Hillyard, S.A. & Munte, T.F. (1984). Selective attention to color and location: an analysis with event-related brain potentials. *Percept Psychophys*, 36, 185–198.
- Hillyard, S.A. & Mangun, G.R. (1987). Sensory gating as a physiological mechanism for visual selective attention. *Electroencephalogr. Clin. Neurophysiol. Suppl*, 40, 61–67
- Hoc, J. M. (2000). From human-machine interaction to human-machine cooperation. *Ergonomics*, 43(7), 833–843. <http://doi.org/10.1080/001401300409044>
- Hoedemaeker, M., & Brookhuis, K. A. (1998). Behavioural adaptation to driving with an adaptive cruise control (ACC). *Transportation Research Part F: Traffic Psychology and Behaviour*, 1(2), 95–106. [http://doi.org/10.1016/S1369-8478\(98\)00008-4](http://doi.org/10.1016/S1369-8478(98)00008-4)
- Hollnagel, E., Năbo, A., & Lau, I. V. (2003). A systemic model for driver-in-control. *Proceedings of the Second International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*, 86–91. <http://doi.org/ExportDate14October2011>
- Human Factors of Automated Driving (HF-Auto) (2013). <http://hf-auto.eu/>
- Isreal, J.B., Wickens, C.D., Chesney, G.L. & Donchin, E. (1980). The event-related brain potential as an index of display-monitoring workload. *Hum Factors*, 22, 211–224. doi: 10.1177/001872088002200210
- Jeon, M., Walker, B.N., Yim & J. Bin (2014). Effects of specific emotions on subjective judgment, driving performance, and perceived workload. *Transp Res Part F Traffic Psychol Behav*, 24, 197–209. doi: 10.1016/j.trf.2014.04.003

- Kaber, D.B. (2017). Issues in Human–Automation Interaction Modeling: Presumptive Aspects of Frameworks of Types and Levels of Automation. *J Cogn Eng Decis Mak*, 12(8), 7–24. doi: 10.1177/1555343417737203
- Kahneman, D. (1973). Attention and effort. Englewood Cliffs, NJ: Prentice Hall
- Käthner, I., Wriessnegger, S.C., Müller-Putz, G.R., et al. (2014). Effects of mental workload and fatigue on the P300, alpha and theta band power during operation of an ERP (P300) brain-computer interface. *Biological Psychology*, 102, 118–129. doi: 10.1016/j.biopsycho.2014.07.014
- Kircher, K., & Ahlstrom, C. (2016). Minimum Required Attention: A Human Centered Approach to Driver Inattention. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 59(3), 471–484. <http://doi.org/10.1177/0018720816672756>
- Kircher, K., Larsson, A., & Hultgren, J.A. (2014). Tactical Driving Behavior With Different Levels of Automation. *IEEE Transactions on Intelligent Transportation Systems*, 15(1), 158–167. <http://doi.org/10.1109/TITS.2013.2277725>
- Kok, A. (1997). Event-related-potential (ERP) reflections of mental resources: A review and synthesis. *Biol Psychol*, 45, 19–56. doi: 10.1016/S0301-0511(96)05221-0
- Kok, A. (2001). On the utility of P3 amplitude as a measure of processing capacity. *Psychophysiology*, 38(3), 557–577. [http://doi.org/10.1016/S0167-8760\(98\)90168-4](http://doi.org/10.1016/S0167-8760(98)90168-4)
- Körber, M., Baseler, E., & Bengler, K. (2018). Introduction matters: Manipulating trust in automation and reliance in automated driving. *Applied Ergonomics*, 66, 18–31. <http://doi.org/10.1016/j.apergo.2017.07.006>
- Körber, M., Cingel, A., Zimmermann, M. & Bengler, K. (2015). Vigilance Decrement and Passive Fatigue Caused by Monotony in Automated Driving. *Procedia Manuf*, 3, 2403–2409. doi: 10.1016/j.promfg.2015.07.499
- Koshino, Y., Nishio, M., Murata, T., Omori, M., Murata, I., Sakamoto, M. & Isaki, K. (1993). The Influence of Light Drowsiness on the Latency and Amplitude of P300. *Clin EEG Neurosci*, 24, 110–113. doi: 10.1177/155005949302400307
- Kramer A.F., Sirevaag E.J. & Braune R. (1987). A Psychophysiological Assessment of Operator Workload During Simulated Flight Missions. *Human Factors*, 29, 145–160. doi: 10.1177/001872088702900203
- Kramer, A.F., Wickens, C.D. & Donchin, E. (1983). An analysis of the processing requirements of a complex perceptual- motor task. *Human Factors*, 25, 597–621.

- Kramer, A.F. & Belopolsky, A. (2004). Assessing brain function and mental chronometry with event-related potentials (ERP). In: Stanton, N., Hedge, A., Hendrick, H.W., Brookhuis, K.A., Salas, E. (Eds.), *Handbook of Ergonomics and Human Factors Methods*. Taylor & Francis, London
- Krampell, M. (2016). Accelerated Behavioural Adaptation through Targeted Training Programs : the Case of Highly Automated Driving (Dissertation). Retrieved from <http://urn.kb.se/resolve?urn=urn:nbn:se:liu:diva-129626>
- Kutas, M., McCarthy, G. & Donchin, E. (1977). Augmenting mental chronometry: the P300 as a measure of stimulus evaluation time. *Science*, 197, 792–795. doi: 10.1126/science.887923
- Kyriakidis, M., Happee, R. & De Winter, J.C.F. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transp Res Part F Traffic Psychol Behav*, 32, 127–140. doi: 10.1016/j.trf.2015.04.014
- Larsson, A. F. L. (2012). Driver usage and understanding of adaptive cruise control. *Applied Ergonomics*, 43(3), 501–6. <http://doi.org/10.1016/j.apergo.2011.08.005>
- Larsson, A.F.L., Kircher, K. & Hultgren, J.A. (2014). Learning from experience: Familiarity with ACC and responding to a cut-in situation in automated driving. *Transport. Res. Part F: Traffic Psychol. Behav.* 27, 229–237, <http://dx.doi.org/10.1016/j.trf.2014.05.008>
- Larue, G. S., Rakotonirainy, A., & Pettitt, A. N. (2011). Driving performance impairments due to hypovigilance on monotonous roads. *Accident Analysis and Prevention*, 43(6), 2037–2046. <http://doi.org/10.1016/j.aap.2011.05.023>
- Lee, J. D. (2017). Perspectives on Automotive Automation and Autonomy. *Journal of Cognitive Engineering and Decision Making*, 155534341772647. <http://doi.org/10.1177/1555343417726476>
- Lee, J. D., & Moray, N. (1994). Trust, self-confidence, and operators' adaptation to automation. *International Journal of Human - Computer Studies*, 40(1), 153–184. <http://doi.org/10.1006/ijhc.1994.1007>
- Llaneras, R., Salinger, J. & Green, C. (2013). Human factors issues associated with limited ability autonomous driving systems: drivers' allocation of visual attention to the forward roadway. In: *Proceedings of the 7th International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design*. The University of Iowa, Public Policy Center, Iowa City, Iowa, pp. 92e98.

- Louw, T., Kountouriotis, G., Carsten, O., & Merat, N. (2015). 'Driver inattention during vehicle automation: how does driver engagement affect resumption of control?' in Proceedings of the 4th International Conference on Driver Distraction and Inattention (Sydney, Australia), doi: 10.13140/RG.2.1.2017.0089
- Luck, S. J. (2005). An introduction to the event-related potential technique. Cambridge, MA: MIT Press
- Mangun, G. R., & Hillyard, S. A. (1990). Allocation of visual attention to spatial locations: Trade off functions for event-related brain potentials and detection performance. *Perception & Psychophysics*, 47(6), 532–550.
<http://doi.org/10.3758/BF03203106>
- Manzey, D., Reichenbach, J., & Onnasch, L. (2012). Human Performance Consequences of Automated Decision Aids: The Impact of Degree of Automation and System Experience. *Journal of Cognitive Engineering and Decision Making*, 6(1), 57–87. <http://doi.org/10.1177/1555343411433844>
- Martel, A., Dähne, S., & Blankertz, B. (2014). EEG predictors of covert vigilant attention. *Journal of Neural Engineering*, 11(3), 35009.
<http://doi.org/10.1088/1741-2560/11/3/035009>
- Matthews, G., Reinerman-Jones, L. E., Barber, D. J., & Abich, J. (2015). The Psychometrics of Mental Workload. *Human Factors*, 57(1), 125–143.
<http://doi.org/10.1177/0018720814539505>
- May, J. F., & Baldwin, C. L. (2009). Driver fatigue: The importance of identifying causal factors of fatigue when considering detection and countermeasure technologies. *Transportation Research Part F: Traffic Psychology and Behaviour*, 12(3), 218–224. <http://doi.org/10.1016/j.trf.2008.11.005>
- Merat, N., & Jamson, A. H. (2008). The effect of stimulus modality on signal detection: implications for assessing the safety of in-vehicle technology. *Human Factors*, 50(1), 145–158. <http://doi.org/10.1518/001872008X250656>
- Merat, N., & Jamson, A. H. (2009). How do drivers behave in a highly automated car? *Proceedings of the 5th International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design HOW*, 514–521.
- Merat, N., & Lee, J. D. (2012). Preface to the Special Section on Human Factors and Automation in Vehicles: Designing Highly Automated Vehicles With the Driver in Mind. *Human Factors*, 54(5), 681–686.
<http://doi.org/10.1177/0018720812461374>

- Miller, M.W., Rietschel, J.C., McDonald, C.G. & Hatfield, B.D. (2011). A novel approach to the physiological measurement of mental workload. *Int J Psychophysiol*, 80, 75–78. doi: 10.1016/j.ijpsycho.2011.02.003
- Molloy, R., & Parasuraman, R. (1996). Monitoring an automated system for a single failure: Vigilance and task complexity effects. *Human Factors*, 38, 311–322
- Muir, B.M. (1994). “Trust in Automation: Part I. Theoretical Issues in the Study of Trust and Human Intervention in Automated Systems.” *Ergonomics*, 37 (11), 1905-1922. doi:10.1080/ 00140139408964957
- Naätänen, R., (1992). Attention and brain function. Erlbaum, Hillsdale, NJ
- National Transportation Safety Board (2016). Preliminary Report, Highway HWY16FH018. Retrieved from: <https://www.nts.gov/investigations/AccidentReports/Pages/HWY16FH018-preliminary.aspx>
- National Transportation Safety Board (2018). Car with automated vehicle controls crashes into pedestrian. Retrieved from <https://www.nts.gov/investigations/Pages/HWY18FH010.aspx>
- Naujoks F., Purucker C. & Neukum A. (2016). Secondary task engagement and vehicle automation – Comparing the effects of different automation levels in an on-road experiment. *Transp Res Part F Traffic Psychol Behav* 38:67–82. doi: 10.1016/j.trf.2016.01.011
- NHTSA. (2013). National Highway Traffic Safety Administration Preliminary Statement of Policy Concerning Automated Vehicles. *National Highway Traffic Safety Administration*, 14.
- Norman, D. A., & Bobrow, D. G. (1975). On data-limited and resource-limited processes. *Cognitive Psychology*, 7(1), 44–64. [http://doi.org/10.1016/0010-0285\(75\)90004-3](http://doi.org/10.1016/0010-0285(75)90004-3)
- O'Donnell, R. D. & Eggemeier, F. T. (1986). Workload assessment methodology. In K. R. Boff, L. Kaufman & J. P. Thomas (Eds.), *Handbook of Perception and Human Performance - Cognitive Processes and Performance* (pp. 1-49). New York, N. Y.: Wiley.
- Oken, B.S., Salinsky, M.C. & Elsas, S.M. (2006). Vigilance, alertness, or sustained attention: physiological basis and measurement. *Clin. Neurophysiol*, 117, 1885–1901.

- Östlund, J., Nilsson, L., Carsten, O., Merat, N., Jamson, H., Jamson, S., Mouta, S.,
Carvalhois, J., Santos, J., Anttila, V. et al. (2004). Haste. Deliverable 2. HMI and
Safety-Related Driver Performance.
- Parasuraman R., Sheridan T.B. & Wickens C.D. (2000). A model for types and levels
of human interaction with automation. *IEEE Trans Syst Man Cybern A Syst Hum*
,30, 286–297. doi: 10.1109/3468.844354
- Parasuraman, R. (1985). Event-related brain potentials and intermodal divided
attention. *Proceedings of the Human Factors Society*, 29, 971–975.
- Parasuraman, R., & Manzey, D. H. (2010). Complacency and Bias in Human Use of
Automation: An Attentional Integration. *Human Factors*, 52(3), 381–410.
<http://doi.org/10.1177/0018720810376055>
- Parasuraman, R., & Riley, V. (1997). Humans and Automation : Use, Misuse, Disuse,
Abuse. *Human Factors*39(2), 230–253.
<http://doi.org/10.1518/001872097778543886>
- Patten, C. J. D., Kircher, A., Östlund, J., & Nilsson, L. (2004). Using mobile
telephones: Cognitive workload and attention resource allocation. *Accident*
Analysis and Prevention, 36(3), 341–350. [http://doi.org/10.1016/S0001-](http://doi.org/10.1016/S0001-4575(03)00014-9)
[4575\(03\)00014-9](http://doi.org/10.1016/S0001-4575(03)00014-9)
- Payre, W., Cestac, J., & Delhomme, P. (2016). Fully Automated Driving: Impact of
Trust and Practice on Manual Control Recovery. *Human Factors*, 58(2), 229–241.
<http://doi.org/10.1177/0018720815612319>
- Platten, F., Schwalm, M., Hülsmann, J. & Krems, J. (2014). Analysis of compensative
behavior in demanding driving situations. *Transp Res Part F Traffic Psychol*
Behav 26, 38–48. doi: 10.1016/j.trf.2014.06.006
- Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clin*
Neurophysiol, 118, 2128–2148. doi: 10.1016/j.clinph.2007.04.019
- Rauch, N., Kaussner, A., & Krüger, H. (2009). The importance of driver state
assessment within highly automated vehicles. *16th World Congress and*
Exhibition on Intelligent Transport Systems and Services, 1–8.
- Read, R. (2012). IEEE says that 75% of vehicles will be autonomous by 2040.
Available online at [http://www.thecarconnection.com/news/1079261_ieee-says-](http://www.thecarconnection.com/news/1079261_ieee-says-that-75-of-vehicles-will-be-autonomous-by-2040)
[that-75-of-vehicles-will-be-autonomous-by-2040.](http://www.thecarconnection.com/news/1079261_ieee-says-that-75-of-vehicles-will-be-autonomous-by-2040)
- Recarte, M. A., & Nunes, L. M. (2000). Effects of verbal and spatial-imagery tasks on
eye fixations while driving. *Journal of Experimental Psychology: Applied*, 6(1),
31–43. <http://doi.org/10.1037/1076-898X.6.1.31>

- Regan, M. A, Hallett, C., & Gordon, C. P. (2011). Driver distraction and driver inattention: definition, relationship and taxonomy. *Accident; Analysis and Prevention*, 43(5), 1771–81. <http://doi.org/10.1016/j.aap.2011.04.008>
- Reyes, M. L., & Lee, J. D. (2004). The Influence of IVIS Distractions on Tactical and Control Levels of Driving Performance. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 48, 2369–2373. <http://doi.org/10.1177/154193120404801935>
- SAE International. (2016). U.S. Department of Transportation’s New Policy on Automated Vehicles Adopts SAE International’s Levels of Automation for Defining Driving Automation in On-Road Motor Vehicles. *SAE International*. <http://doi.org/P141661>
- Saffarian, M., de Winter, J.C.F., & Happee, R. (2012). Automated Driving: Human-Factors Issues and Design Solutions. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 56(1), 2296–2300. <http://doi.org/10.1177/1071181312561483>
- Saxby, D. J., Matthews, G., Warm, J. S., Hitchcock, E. M., & 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), 287–300. <http://doi.org/10.1037/a0034386>
- Scheer, M., Bülthoff, H.H. & Chuang, L.L. (2016). Steering Demands Diminish the Early-P3, Late-P3 and RON Components of the Event-Related Potential of Task-Irrelevant Environmental Sounds. *Front Hum Neurosci*, 10, 73. doi: 10.3389/fnhum.2016.00073
- Schmidt, E.A., Schrauf, M., Simon, M., et al (2009). Drivers’ misjudgement of vigilance state during prolonged monotonous daytime driving. *Accid Anal Prev*, 41, 1087–93. doi: 10.1016/j.aap.2009.06.007
- Segalowitz, S.J. & Barnes, K.L., (1993). The reliability of ERP components in the auditory oddball paradigm. *Psychophysiology*, 30(5), 451–459
- Singh S (2015) Critical reasons for crashes investigated in the National Motor Vehicle Crash Causation Survey. *Natl Highw Traffic Saf Adm* 1–2.
- Sirevaag, E. J., Kramer, A.F., Wickens, C. D., Reisweber, M., Strayer, D. L., & Grenell, J. F. (1993). Assessment of pilot performance and mental workload in rotary wing aircraft. *Ergonomics*, 36(9), 1121–1140.
- Stanton, N.A., & Young, M.S. (2000). A proposed psychological model of driving automation. *Theoretical Issues in Ergonomics Science*, 1, 315–331.

- Starcke, K., Wiesen, C., Trotzke, P., & Brand, M. (2016). Effects of acute laboratory stress on executive functions. *Frontiers in Psychology*, 7(461) <http://doi.org/10.3389/fpsyg.2016.00461>
- Strand, N., Nilsson, J., Karlsson, I. C. M., & Nilsson, L. (2014). Semi-automated versus highly automated driving in critical situations caused by automation failures. *Transportation Research Part F: Traffic Psychology and Behaviour*. <http://doi.org/10.1016/j.trf.2014.04.005>
- Strayer, D.L., & Johnston, W.A. (2001). Driven to distraction: Dual-task studies of simulated driving and conversing on a cellular telephone. *Psychological Science*, 12(6), 462–466. <http://doi.org/10.1111/1467-9280.00386>
- Strayer, D.L. & Drews, F.A. (2007). Cell-Phone? Induced Driver Distraction. *Curr Dir Psychol Sci*, 16:128–131. doi: 10.1111/j.1467-8721.2007.00489.x
- Strayer, D.L., Turrill, J., Cooper, J. M., Coleman, J. R., Medeiros-Ward, N., & Biondi, F. (2015). Assessing Cognitive Distraction in the Automobile. *Human Factors*, 57(8), 1300–24. <http://doi.org/10.1177/0018720815575149>
- Stroop, J.R. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*, 18(6), 643–662. <http://doi.org/10.1037/h0054651>
- Teyeb, I., Jemai, O., Zaid, M., & Ben Amar, C. (2014). A drowsy driver detection system based on a new method of head posture estimation. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 362–369. http://doi.org/10.1007/978-3-319-10840-7_44
- Ullsperger, P., Freude, G., & Erdmann, U. (2001). Auditory probe sensitivity to mental workload changes – an event-related potential study. *International Journal of Psychophysiology*, 40(3), 201–209. [http://doi.org/10.1016/S0167-8760\(00\)00188-4](http://doi.org/10.1016/S0167-8760(00)00188-4)
- Vázquez-Marrufo M, Galvao-Carmona A, González-Rosa J.J., et al (2014). Neural correlates of alerting and orienting impairment in multiple sclerosis patients. *PLoS ONE* 9(5): e97226. doi:10.1371/journal.pone.0097226
- Verwey, W. B. (2000). [Traffic] On-line driver workload estimation. Effects of road situation and age on secondary task measures. *Ergonomics*, 43(2), 187–209. <http://doi.org/10.1080/001401300184558>
- Warm, J. S., Parasuraman, R., & Matthews, G. (2008). Vigilance Requires Hard Mental Work and Is Stressful. *Human Factors*, 50(3), 433–441. <http://doi.org/10.1518/001872008X312152>

- WHO (2011). Decade of Action for Road Safety 2011-2020: Global Launch.
- WHO (2015). Global status report on road safety. Geneva: World Health Organisation.
- Wickens, C. D. (1984). Processing resources in attention. In R. Parasuraman, & R. Davies (Eds.), *Varieties of attention* (pp. 63–102). London: Academic Press
- Yeh, Y. Yu, & Wickens, C.D. (1988). Dissociation of Performance and Subjective Measures of Workload. *Human Factors*, 30(1), 111–120.
<http://doi.org/10.1177/001872088803000110>
- Young, M. S., & Stanton, N. A. (2002). Malleable Attentional Resources Theory: A New Explanation for the Effects of Mental Underload on Performance. *Human Factors*, 44(3), 365–375. <http://doi.org/10.1518/0018720024497709>
- Young, M. S., & Stanton, N.A. (2007). Back to the future: brake reaction times for manual and automated vehicles. *Ergonomics*, 50(January 2015), 46–58.
<http://doi.org/10.1080/00140130600980789>
- Young, M.S., Brookhuis, K.A., Wickens, C.D. & Hancock, P.A. (2015). State of science: mental workload in ergonomics. *Ergonomics*, 139,1–17. doi: 10.1080/00140139.2014.956151
- Zhao, C., Zhao, M., Liu, J. & Zheng, C. (2012). Electroencephalogram and electrocardiograph assessment of mental fatigue in a driving simulator. *Accid Anal Prev*, 45, 83–90. doi: 10.1016/j.aap.2011.11.019
- Zijlstra, F.R.H., & van Doorn, L. (1985). The construction of a scale to measure perceived effort. Delft, The Netherlands: Department of Philosophy and Social Sciences, Delft University of Technology.

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