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Mediating between human driver and automation

state-of-the art and knowledge gaps : D1.1 of the H2020 project MEDIATOR

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Mediating between human driver and automation: state-of-the art and knowledge gaps

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Mediating between human driver and automation: state-of-the art and knowledge gaps

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Table of contents

Executive summary	1
1. Introduction.....	6
1.1. Outline of the Mediator concept.....	6
1.2. The a priori functional requirements	7
1.3. Aim and structure of this deliverable	8
2. Existing Mediator-like systems	9
2.1. Cognitive Systems Engineering.....	9
2.2. Designing cognitive automation	11
2.3. Mediator-like systems	14
2.4. Conclusion	20
2.5. References	20
2.6. Webpages.....	23
3. Assessment of human fitness.....	25
3.1. Driving experience, age and gender	25
3.2. Mental workload	29
3.3. Distraction by non-driving related tasks (NDRTs)	34
3.4. Sleep-related and task-related fatigue.....	39
3.5. Driving comfort, emotions, trust in automation	44
3.6. Hazard awareness	47
3.7. Conclusions	49
3.8. References	51
4. Assessment of automation fitness	66
4.1. Introduction.....	66
4.2. Background knowledge	67
4.3. Required output of the automated system	71
4.4. Driving Automation Systems as a source of information	76
4.5. Conclusions	79
4.6. References	80
5. The Human Machine Interface (HMI).....	83
5.1. Introduction.....	83
5.2. Challenges	84
5.3. Design Space	91

5.4.	Recommendations	97
5.5.	Learning from aerospace and maritime	101
5.6.	Conclusions	105
5.7.	References	106
6.	The decision making component.....	110
6.1.	Introduction.....	110
6.2.	Solutions in other fields.....	112
6.3.	Decision Logic	114
6.4.	State space.....	116
6.5.	Action Space.....	119
6.6.	Conclusion	125
6.7.	References	126
7.	Use cases and their functional requirements	128
7.1.	Introduction.....	128
7.2.	Preliminary use cases	128
7.3.	Related functional requirements.....	130
7.4.	Non-functional requirements	132
7.5.	Sub-use cases	133
8.	Overall conclusions and next steps	138
8.1.	The (non)-functional requirements	138
8.2.	The human state component.....	138
8.3.	The automation state component	139
8.4.	The HMI component	140
8.5.	The decision logic component.....	140
8.6.	Next steps	141
	Appendix: Driver measurements based on inward-facing cameras	142

Foreword

We are proud to present this first main deliverable of the MEDIATOR project. This deliverable shows the result of working together for about half a year, with people from different backgrounds, different organisations and different countries, people with different areas of expertise, different use of terminologies and different ideas. Together we have been further shaping the MEDIATOR concept and we've made major steps in aligning our thinking; we've set out the functional requirements of the mediator system, we've described the state of the art knowledge to build upon for building the mediator system, we've defined the use cases and identified the knowledge gaps.

This document gives a good introduction to the MEDIATOR concept and a comprehensive overview of the state of the art knowledge on vehicle automation. For us, this deliverable serves as a foundation for the project, it gives focus to our further research (in WP1) and is a starting point for the development of the mediator system (WP2). At the same time, it is important to be aware that it is impossible to be exhausting and that this is snapshot of the current situation. New information will become available and new insights will be gained to build upon.

Many people have contributed to this work. This is reflected by the extensive list of authors, and even more people have contributed on the background. I want to thank everybody for their contribution to this result!

A special thanks to the reviewers, Prof. Dr. Josef F. Krems (TU Chemnitz, Germany) and Prof. Dr. David Shinar (Ben-Gurion University of the Negev, Israel) for their constructive and useful comments. And a big complement to Michiel Christoph, Diane Cleij and Ingrid van Schagen for managing the process, the editorial work and putting it all nicely together.

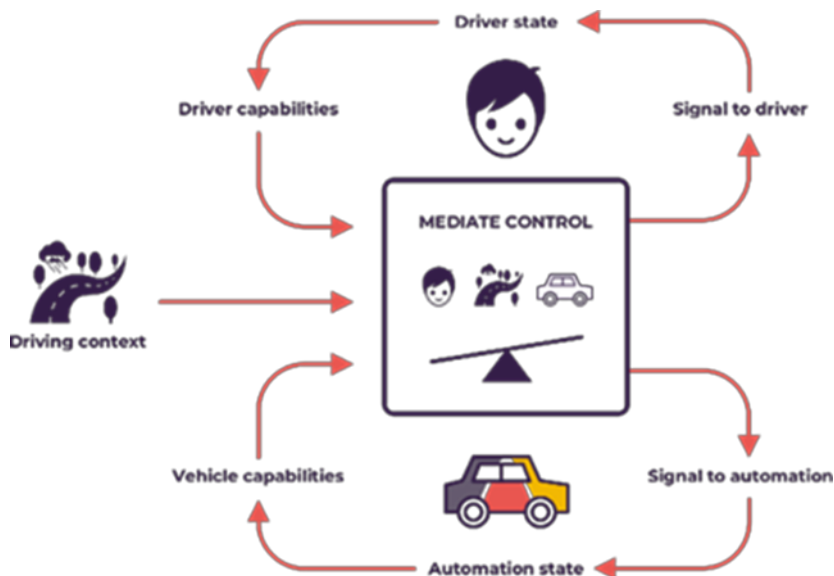
Nicole van Nes
Project Coordinator

About MEDIATOR

MEDIATOR is a 4-year project led by SWOV. It started in May 2019. MEDIATOR will develop a mediating system for drivers in semi-automated and highly automated vehicles, resulting in safe, real-time switching between the human driver and automated system based on who is most fit to drive. MEDIATOR pursues a paradigm shift away from a view that prioritises either the driver or the automation, instead integrating the best of both.

Vision

Automated transport technology is developing rapidly for all transport modes, with huge safety potential. The transition to full automation, however, brings new risks, such as mode confusion, overreliance, reduced situational awareness and misuse. The driving task changes to a more supervisory role, reducing the task load and potentially leading to degraded human performance. Similarly, the automated system may not (yet) function in all situations. The objective of the Mediator system is to intelligently assess the strengths and weaknesses of both the driver and the automation and mediate between them, while also taking into account the driving context:



The MEDIATOR system will continuously weigh driving context, driver state and vehicle automation status, while personalising its technology to the drivers' general competence, characteristics, and preferences

MEDIATOR will optimise the safety potential of vehicle automation during the transition to full (level 5) automation. It will reduce risks, such as those caused by driver fatigue or inattention, or on the automation side imperfect automated driving technology in the presence of adverse environments. MEDIATOR will facilitate market exploitation by actively involving the automotive industry during the development process.

To accomplish the development of this support system MEDIATOR will integrate and enhance existing knowledge of human factors and HMI, taking advantage of the expertise in other transport modes (aviation, rail and maritime). It will develop and adapt available technologies for real-time data collection, storage and analysis and incorporate the latest artificial intelligence techniques, such as deep learning.

Partners

MEDIATOR will be carried out by a consortium of highly qualified research and industry experts, representing a balanced mix of top universities and research organisations as well as several OEMs and suppliers. The consortium, supported by an international Industrial Advisory Board and a Scientific Advisory Board, will also represent all transport modes, maximising input from, and transferring results to, aviation, maritime and rail (with mode-specific adaptations).

Executive summary

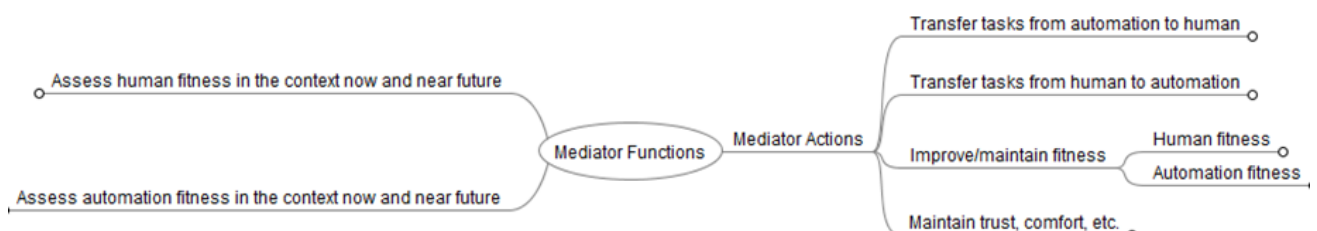
The MEDIATOR project and the Mediator system

The MEDIATOR project is working towards a system that mediates, in real time, between the automated functions of a vehicle and the driver/operator ensuring that the one that is most fit for the task at hand is in control. The Mediator system aims to reduce the risks related to the transition towards full automation, a phase that still relies on the human driver for taking over when the automation does not yet function at a sufficiently reliable level or in a limited number of situations.

The aim of the project is to develop a Mediator prototype for SAE levels 2 - 4 and have them tested in a number of relevant traffic scenarios. Each of these levels of automation provide different requirements to the system. Whereas SAE level 2 automation requires drivers to be 'in-the-loop' all the time, the higher SAE levels allows them to be 'out-the-loop' for shorter or longer periods of time.

In order to decide whether it is safer to have the driver or the automated system in control, the Mediator system must be able to assess the fitness of the driver and the fitness of the automation, as well as the requirements of the driving context. This not only includes an assessment of the situation right now, but also a prediction of the situation in the next few seconds up to minutes. Based on the assessment and prediction, the system has to apply the correct logic to decide if a transfer of control from vehicle to driver or vice versa is needed, whether such a transfer would require specific actions to improve the fitness of the driver or of the automation, while also taking account of driving comfort and driver preferences. In case of a transfer of control it has to be ensured that the human machine interface (HMI) conveys a message (the Mediator action) that is trustworthy and transparent for the driver in order to guarantee acceptance of the system and prevent unintended negative effects such as mode confusion and overreliance.

At the most basic level, this means that the Mediator system has to fulfil the following functional requirements:



Aims and scope of this deliverable

The current report is the first Deliverable of the project. It aims to define what we need to know to assess the fitness of the human driver and the automation, what we already know based on the available literature, and what are the research gaps that need to be bridged in order to develop the Mediator system. Information and approaches of existing Mediator-like systems in road and in other transport domains were also considered. In a more or less iterative process the review of

needed and available knowledge helped to further elaborate a set of feasible functional requirements for three use cases. The results form the basis for the concrete design and work plan for the technical development of the various components of the Mediator system and their interaction. The results also form the basis for the definition of a series of targeted experiments to fill the most prominent research gaps in the area of human fitness, automation fitness, and HMI, in order to make the best possible decision for a transfer of control, and define the best means of communication to the driver.

In separate chapters, this deliverable discusses the assessment of human fitness, the assessment of the fitness of the automation, the HMI requirements, the decision making logic, and the functional requirements in relation to the identified use cases.

Existing Mediator-like systems

A brief, non-exhaustive literature overview of early systems for assisting humans and of more recent driver monitoring systems was performed. This review showed that in the aviation and military domain, research and applications of systems that mediate between the human and automation date back several decades. However, in the automotive industry it is a relatively new concept. Even though there are obvious differences between these domains, the research in the other transport domains is in many aspects also applicable to the car domain. For instance, both domains benefit from understanding human information processing and decision making. Also monitoring and prediction of human states, such as workload and situation awareness, are integral to human-automation cooperative designs in all domains. In the automotive domain, research and development of driver monitoring systems has recently increased with the advancements in vehicle automation, and several ongoing or recently finished projects have been identified that can provide very useful input for the development of our Mediator system.

Assessment of human fitness

In the area of assessing the human fitness to drive, several potentially relevant factors were considered: personal factors related to, in particular, age, experience and gender, as well as feelings of comfort, emotions and trust in automation, and the more information-processing aspects related to mental workload, distraction, fatigue, and hazard perception. An overview is provided of factors affecting drivers' performance in the context of automated driving. Based on these findings we identified key human-related variables that should be monitored by our Mediator system in order to determine the driver state (e.g., fatigued, distracted, bad mood). The exact factors, and the way they impact fitness to drive depend on the level of automation.

Assessment of automation fitness

Analogous to assessing the human fitness, the fitness of the automation has to be assessed. In other words, what has to be measured (and how) to decide whether the automated system is sufficiently fit to take over or continue the driving task? To better understand vehicle automation systems, a generalized functional architecture of driving automation systems is provided, accompanied with engineering concepts for analysing the driver task. For assessing the automation fitness and defining the corresponding appropriate actions, the Mediator system requires detailed information on the automation functioning now and in the next few seconds to minutes. The assessment would need to include reliability measures and reasons for degraded performance. Furthermore, context related information gathered by the vehicle automation should also be sent to the Mediator system, as it could be a source for improving human fitness in terms

of, for example, situation awareness. Based on what the Mediator system requires, an initial overview of possible information sources within existing vehicle automation systems is provided.

HMI requirements

The Human Machine Interface (HMI) of a vehicle can be defined as set of all interfaces that allow the user of a vehicle to interact with the vehicle and/or devices connected to it. It is a fundamental aspect to ensure that the driver and the automated vehicle have a safe and acceptable exchange of roles. The HMI should take into consideration several demands that need to be evaluated and balanced: driver needs, available technology, applicable regulations, and the costs. Related challenges include trust, mode awareness, fatigue and distraction, information load, user acceptance, industry acceptance, as well as learning and unlearning. Quite a few studies have been identified dealing with each these challenges, both in the road transport section as in maritime and aviation. Nevertheless, some challenges were identified that were not yet or only partly solved. Moreover, whereas studies generally focus on individual challenges, knowledge on dealing with multiple challenges simultaneously is largely missing. This is specifically relevant because a solution for one challenge may have negative side-effects with regard to dealing with other challenges, requiring evidence-based trade-offs.

Decision making logic

Central to the Mediator system is what we called the Mediate Control component, i.e., the decision making component. The basic goal of the decision making component is making the decisions whether the human driver or the automation is most fit to control the vehicle, based on information about the driving context, the human driver state and capabilities, and the automation state and capabilities.

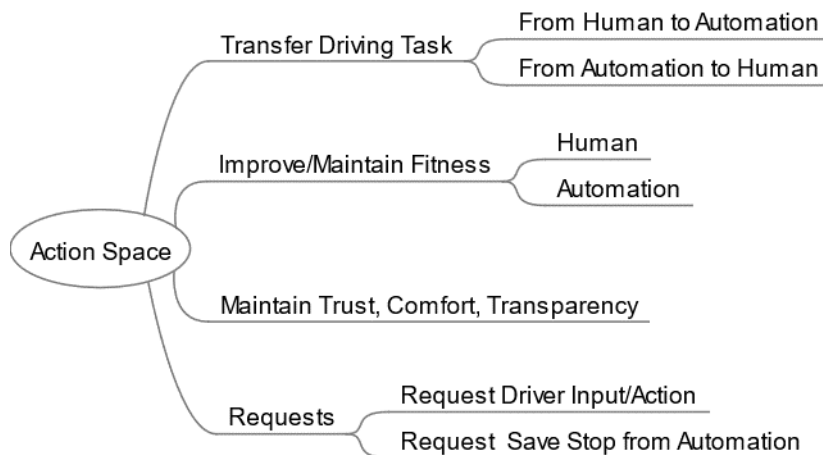
The core of the decision logic process will most likely be based on Markov Decision Processes (MDP). In the terminology of the MDP, this requires a description of the state space and the action space. The state space consists of the driving context, the current human driver state and capabilities, and the current automation state and capabilities. The action space refers to the set of actions the system can perform. At this stage, four main classes of actions were identified (see Figure on next page).

The main action of the Mediator system is to mediate the transfer of a driving task between automation and human. The other three actions can be seen as sub actions. These include

- actions that ensure the human or the automation remains fit/becomes fitter, e.g., instructing the driver to put hands on the steering wheel again;
- actions that optimise trust, comfort and transparency, e.g. by providing information about the automation state in order to reduce overreliance or mode confusion; and
- actions requesting the driver for additional input in case of incomplete or uncertain information, e.g., indicating how fatigued he/she is, or requesting the automation to initiate a save-stop procedure.

Once an action has been decided, this action must be 'negotiated' or 'managed' with and by the interface to the human driver (HMI) and the automated driving system, leading to a safe and comfortable transfer.

Whereas the basic principles of the MDP seem to suitable for our Mediator system, it most likely requires several adaptations and related additional research. A list of key knowledge and development gaps were identified.



Use cases and functional requirements

In order to limit the scope of the development of the Mediator system during the project three use cases were identified which reflect the intended functioning of the Mediator system. Within the project an operational prototype of the Mediator system will be developed for these use cases.

- The 'continuous mediation' use case focuses at a lower level of automation which requires the driver to be involved in the driving task continuously. While the automation performs certain parts of the driving task, the driver performs other parts. Continuous mediation is needed between the automation and the driver. Maintaining adequate situational awareness, avoiding mode confusion, and underload are the main challenges here.
- The 'driver stand-by' use case focuses on a higher level of automation in which the driver can hand over full control to the automation and be "out of the loop" for some period of time. This is only possible for situations where the automation is confident it can function for the next moments. Hence, the driver should be prepared to resume control on short notice at any time. The main challenges here are determining how long it takes to regain driver fitness, how long automation is fit to drive, and how these times should be balanced.
- The time-to-sleep use case focuses at a level of automation that allows the driver to be completely out of the loop for prolonged periods, and do completely things unrelated to driving and monitoring, including sleeping. The main challenges in this use case are predicting the moment the take-over should take place with sufficient confidence, and bringing the driver back into the loop after a period of full absence.

For each of the above-mentioned use cases, an initial list of higher-level functional requirements was made, related to the assessment of the human fitness, the automation fitness and the Mediator actions, as well as more general description of the required properties of the system. In the next stage of the project, a limited number of specific sub-use cases or test scenarios will be defined, in order to test the functionalities of the Mediator system.

Overall conclusions and next steps

The main goal of the Mediator system is to determine who is fittest to drive, human or automation, and consequently define preferred actions to be sent to the HMI or automation in order to ensure safety and comfort of the human driver. To this end, four components of the system were defined:

human state, automation state, HMI and decision logic. This deliverable described the state of the art knowledge and corresponding knowledge and development gaps related to these four components as well as a description of the high level (non) functional requirements and relevant use cases for the MEDIATOR project. The identified knowledge and development gaps will be further investigated in the next steps in the project. More detailed requirements will be defined as well as a clear structure for the integration of all components into one Mediator system. Detailed use cases will be defined to test the Mediator system throughout the project and help with the prioritization of investigations into the identified knowledge gaps.

1. Introduction

This deliverable describes the scientific knowledge that is needed for the development of a Mediator system, the knowledge that is already available from previous studies and, hence, the knowledge that is still missing. The deliverable serves two goals: first it results in a description of the functional requirements, as a first step towards the exact technical specifications for building the Mediator system; second it identifies the knowledge that is needed for building the Mediator system, what we already know, what we do not yet know, and which knowledge gaps absolutely need to be bridged for developing the intended prototype and that will be studied in a series of targeted experimental studies in the next phase of the project.

1.1. Outline of the Mediator concept

The MEDIATOR project is working towards a system that mediates, in real time, between the automated functions of a vehicle and the driver/operator ensuring that the one that is most fit for the task at hand is in control. Hereto the system will assess the current situation as well as predict the situation in the next few seconds to minutes. The Mediator system aims to reduce the risks related to the transition towards full automation, a phase that still relies on the human driver for taking over when the automation does not yet function at a sufficiently reliable level or in a limited number of traffic situations.

Mediating between vehicle and driver requires the mediating system to intelligently assess and weigh the strengths and weaknesses (i.e., the fitness) of both the driver and the automation, taking account of their general and temporary capabilities and of the requirements for the actual driving context (see Figure 1.1).

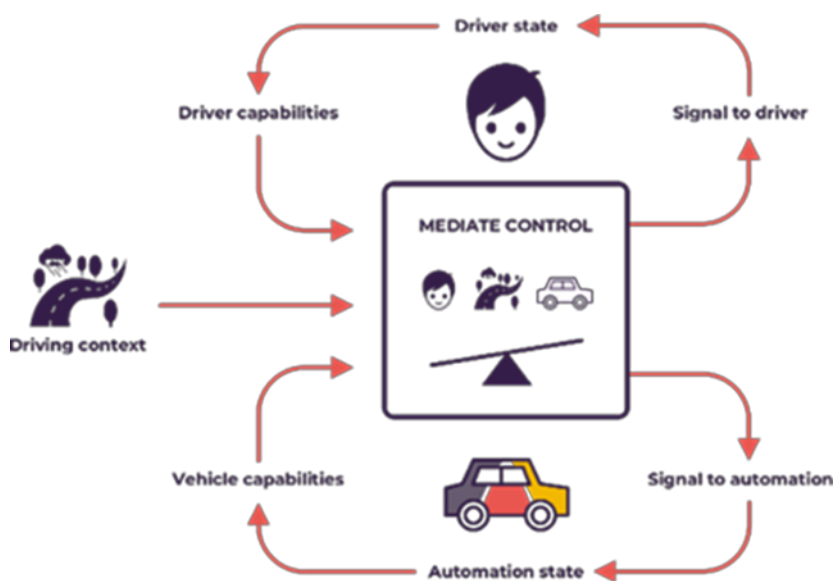


Figure 1.1 The MEDIATOR system constantly weighs driving context, driver state and vehicle automation status, while taking account of the general capabilities of the driver and the vehicle.

This Mediator concept builds on the Fuller model¹, which states that driving errors occur when driver capabilities are insufficient to deal with the demands of the driving task. These task demands are largely determined by driving contexts such as weather condition, traffic volumes, other road users and more. Whether a driver is capable to deal with the task demands depends on both the more stable competencies of the driver (e.g. related to age and experience) and the temporary state of the driver (e.g. related to fatigue or distraction). As indicated, for the Mediator system this model is extended to include the capabilities and state of the automated system.

1.2. The a priori functional requirements

In order to decide whether it is safest to have the driver or the automated system in control, the Mediator system must be able to assess not only the current state of automation, driver and driving context, but also predict their state in the (near) future. Based on that, the system has to apply the correct logic to decide if a transfer of control from vehicle to driver or vice versa is needed. In case of a transfer of control it has to be ensured that the human machine interface (HMI) conveys a message that is trustworthy, comfortable and transparent for the human user in order to guarantee acceptance of the system and prevent unintended negative effects such as mode confusion and overreliance. In its most basic way these functional requirements can be summarised by means of an input-output relationship (see Figure 1.2).

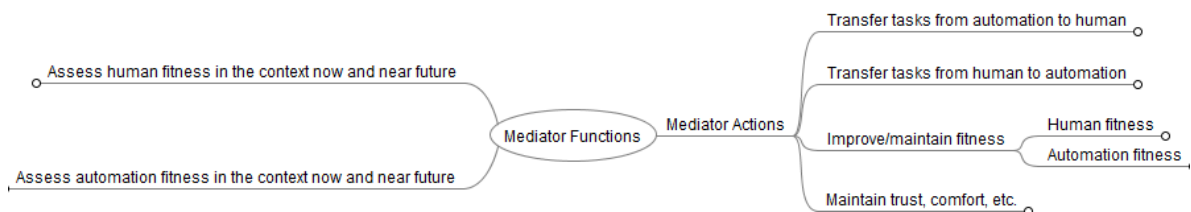


Figure 1.2 The basic a priori functional requirement of the Mediator system

Input to the system is the assessed fitness of the driver and the assessed fitness of the automated system now, and in the next couple of seconds to minutes, set-off against the current and oncoming driving context. Output of the system is the decision whether it is safer to have the automation or the driver in control. This decision might require a transfer of control from one to the other. If it is safer to have the driver in control, even though he is not completely fit, an additional output of the Mediator system is the decision to take actions to improve his fitness or at least make sure it does not deteriorate.

In order to fulfil these basic functional requirements, it has to be defined when a driver can be considered fit enough, when the automated system can be considered fit enough, and which one is fitter. This requires an exact description of the variables that determine fitness of both the driver and the automated system as well as the thresholds for defining fitness or unfitness. Obviously, the answers depend to a large extent on the level of vehicle automation and the characteristics of the situation. Within MEDIATOR a system prototype will be developed and tested for different levels of automation, i.e., with different requirements for driver involvement: for the lower levels drivers have to be 'in-the-loop' all the time; at higher levels driver can be 'out-the-loop' for shorter or longer periods of time.

¹ Fuller, R. (2005) Towards a general theory of driver behaviour. Accident Analysis and Prevention, 37, 461-472.

1.3. Aim and structure of this deliverable

The current Deliverable is the first step towards the Mediator system. It lists what we already know and what needs to be studied in more detail in order to develop the Mediator system. This results in an overview of research gaps that need to be filled in order to develop the intended Mediator system, as well as an initial set of feasible functional requirements for some specified use cases and traffic scenarios.

In order to set the scene, the next Chapter (**Chapter 2**) provides a brief overview of Mediator-like systems, discussing available prototypes and systems that resemble (part of) the Mediator system. The next four Chapters provide an overview of the relevant literature showing what we would need to know, what we already know and, hence, what we need to find out. **Chapters 3 and 4** are about assessing driver state and automation state respectively. The basic questions here are:

- Which single valid and reliable measure can we use to estimate the overall driver/automation fitness now and in the next seconds to minutes?
- How do we determine which driver/automation state(s) determine(s) the overall fitness (important for identifying measures to improve the overall fitness)?
- Which measurements/data do we need for the fitness estimate?
- What are the major remaining research questions that need to be answered for the development of the Mediator prototype?

Chapter 5 deals with the HMI-related aspects of the Mediator system and answers questions like how to convey transfer-of-control messages, how to avoid mode confusion and overreliance, how to create trust and acceptability, how to personalise the HMI solutions, and again what are the major remaining research questions for realising the best possible HMI solution?

Chapter 6 is about the decision logic and describes how the assessment of the current and near future driver state and automation state can be combined to determine the safest action of the Mediator system and how to deal with the unpreventable uncertainties in these assessments.

Chapter 7 elaborates the use cases for the Mediator system prototypes and describes a series of relevant traffic scenarios in which they can be tested, as well as the functional requirements for these use cases, based on the results from each of the previous chapters. Chapter 7 will be the main input for the design and technical specifications for building the Mediator system. The chapter also summarises the main conclusions with respect to the functional requirements and the remaining research needs for the different components of the Mediator system and the identified use cases and traffic scenarios.

2. Existing Mediator-like systems

This chapter provides a brief, non-exhaustive, overview of design methods for Mediator-like systems and discusses existing research, prototypes and systems that resemble (part of) the Mediator system. The aim of this chapter is to provide a basis for the design of our Mediator system as a whole, as compared to the design of its sub systems.

2.1. Cognitive Systems Engineering

As described by Smith and Hoffman (2017), cognitive systems engineering is a discipline that deals with the analysis, modelling, design, and evaluation of complex sociotechnical systems in a way that workers can do their work and carry out tasks more safely, and with greater efficiency. In these socio-technical systems the human is involved in decision making, planning, collaborating and managing. As our Mediator system is such a system, it can be useful to look at established design principles of cognitive systems engineering.

Cognitive systems engineering finds its basis in the work of Rasmussen (1983, 1985). Two frameworks based on this work in particular are of interest for further investigation within the MEDIATOR project: Cognitive Work Analysis (CWA) and Ecological Interface Design (EID).

Stanton and Jenkins (2017) describe CWA as a framework that provides a systematic approach to analysing systems, by explicitly identifying the purposes and constraints. The main novelty of this approach is the focus on constraints instead of on particular ways of working. By clearly defining the boundaries of acceptable performance, the approach promotes designs that support the worker in adapting to new and changing work conditions. CWA is therefore particularly useful when designing work systems that need to deal with unanticipated events (Stanton, & Jenkins, 2017). Sanderson, Naikar, Lintern and Goss (2016) and Elm et al. (2008) have compared work domain analysis to more widely used approaches in systems engineering. They argue that the contribution of CWA is to support the development of revolutionary systems unconstrained by previous solutions, rather than of just evolutionary systems. As the Mediator system is such a new, i.e., revolutionary system that needs to perform in a variety of situations, including unanticipated events, during the next design steps, it might be interesting to further look into some of the methods of CWA.

Two of these methods, the Abstraction Hierarchy (AH), which is part of the Work Domain Analysis (WDA), and the Skill, Rule and Knowledge (SDK) framework, are also the basis of Ecological Interface Design (EID). EID is a theoretical framework that supports the fundamental properties of human cognition (Rasmussen, & Vicente, 1989; Vicente, & Rasmussen, 1988). This is achieved by relating the results of a Work Domain Analysis, i.e., the AH, to the SDK framework. The resulting EID design principles are described as (Vicente, 2002, p. 64):

- **Skill-based behaviour:** Workers should be able to act directly on the interface.
- **Rule-based behaviour:** There should be a consistent one-to-one mapping between the work domain constraints and the perceptual information in the interface.
- **Knowledge-based behaviour:** The interface should represent the work domain in the form of an abstraction hierarchy to serve as an externalized mental model for problem solving.

While CWA originates from the nuclear power plant domain, many transport related studies have also adopted its methods. Borst, Mulder and Van Paassen (2010) discuss the application of CWA to flight deck automation and in Lundberg et al. (2018) present the first steps of CWA for the design of an unmanned urban air traffic management system. Millen et al. (2011) compare the CWA for air traffic management to that for rail signalling. Van Paassen et al. (2018) apply WDA for an EID-based flight control display that shows both the work domain constraints and affordances. They argue that such interface can then function as a cognition/decision support system, rather than solely a data source. A nice overview of CWA, describing the influence and potential of this method, emphasized by a case study on the application of CWA to the military domain is given in Naikar (2017).

In the road transport domain CWA and EID have been applied extensively as well. CWA has been used for road design (Stevens, & Salmon, 2015) and the evaluation of such designs (Cornelissen, Salmon, Stanton, & McClure, 2015). Also for driver assistance systems, a domain more closely related to the Mediator system, CWA and EID have been applied. Lane change support displays were designed using CWA and EID by Lee, Nam and Myung (2008) and by Lee et al. (2006). The latter study showed that the EID-based displays were more robust and could outperform the more conventional display in a driving simulator study. Mendoza, Lindgren and Angelelli (2011) combined the AH with usability testing to design and evaluate an EID-based HMI. A simulator experiment showed a significantly higher time to collision when driving with compared to without HMI. Stanton and Allison (2019) used CWA to analyse fuel-efficient driving, leading to recommendations for in-vehicle displays promoting eco-friendly driving. In Stoner, Wiese and Lee (2003) the results of an AH are presented, leading to recommendations for EID-based driver support systems. They propose that false alarms in driver support systems could be reduced by taking into account intentional constraints that guide other drivers, and that the system's sensitivity could be improved using traffic flow stability measures. Seppelt and Lee (2007) developed an EID display to create a visual representation of ACC behaviour. Results from a driving simulator experiment showed that the EID display promoted appropriate reliance and improved take-over performance. They argue that providing continuous information in the form of EID displays, even though it increases the information flow to the human driver, can be preferred over a display-by-exception approach. This trade-off between informing the driver on the automation and information overload is also mentioned as one of the main challenges for human-automation system design by Parasuraman (2000).

Throughout the literature presented in this section, two key notions that differentiate cognitive systems engineering methods from more conventional methods are described. The first notion, relates to the differences between conventional control system design and cognitive system design. The former is usually designed to look for an optimal solution. What is "optimal" is then defined by the designer of that system and implemented in the objective function of some optimization algorithm. For cognitive systems applied to complex work domains, such optimal solution is often not evident. Rather, the system should be designed to cope with a wide range of potential situations, and the focus shifts from optimal to robust control (Borst, Flach, & Ellerbroek, 2015).

The second notion relates to how coping with different situations can be implemented. The literature presented in this section described the importance of determining work domain constraints and affordances, and conveying this information to the human, so that he/she can apply novel ways of working rather than being guided along a predefined "optimal" path. This notion takes advantage of the well-developed human ability to apply knowledge-based behaviour in novel

situations. As the Mediator system will have to deal with a large range of different situations, which cannot all be conceived and tested during the design phase, these two notions are particularly important to take into account during the design process.

2.2. Designing cognitive automation

While Cognitive Systems Engineering deals with a very wide range of socio-technical systems, the subfield of cognitive automation focusses specifically on systems in which the human interacts or co-operates with a certain type of automation, such as the Mediator system. Onken and Schulte (2010, p. 92) summarise cognitive automation as standing for artificial capabilities

- to understand the situation in case of unforeseen events and to independently interpret it in the light of the known motivational contexts as drivers for voluntary actions;
- to develop an understanding of the necessary sequence of actions best- suited to accomplish the desired result according to the assignment, thereby distinguishing between important and unimportant information, urgent and less urgently needed actions;
- to perform those actions which are authorised by its assignment;
- to effectively initiate the necessary communication to other units of the pertinent work environment, thereby evening up how to proceed in case of conflicts and opportunities.

In their book, Onken and Schulte (2010) further explain what cognitive automation entails, and how both humans and automation can be modelled as cognitive work systems. They present design principles and pitfalls for cognitive automation as well as examples of existing cognitive automation in different fields, among which automotive. A concise overview can be found in Schulte, Meitinger and Onken (2008). The Mediator system would be what they describe as an operating cognitive unit or assistance system, i.e., systems that co-operate rather than solely support the human operator, such as an ACC system.

In the military domain quite some research has been done on aiding the human with their tasks by means of co-operative automation or human-automation teaming (HAT). Onken and Schulte (2010) describe the type of automation needed for such teaming as cognitive automation. The difference between conventional and cognitive automation is clearly illustrated in Figure 2.1.

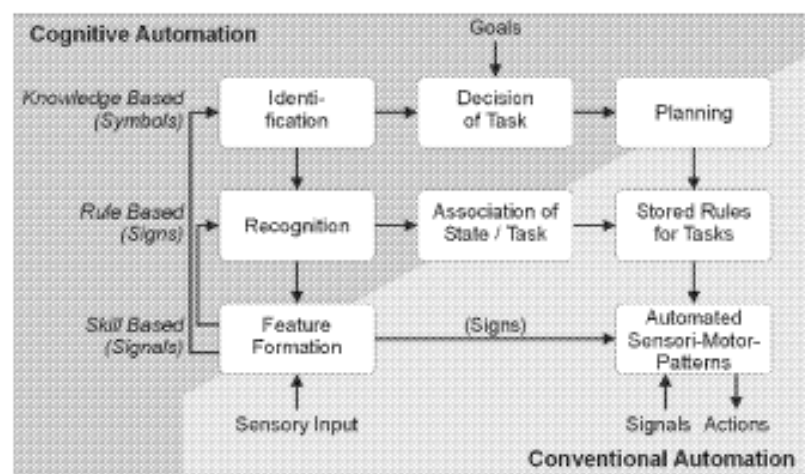


Figure 2.1: Rasmussen's scheme of human cognitive behaviour indicating the difference between conventional and cognitive automation (Onken, & Walsdorf, 2001)

Four cornerstone concepts for the design of these co-operative human-machine systems are described by Flemisch et al. (2011) as ability, authority, control and responsibility. These four cornerstones refer to different aspects of corporation. Having *control* means influencing the situation such that it develops or keeps in a way preferred by the controlling actor. On the other hand, having the *ability* refers to having the competences to execute certain control actions. The *authority* is split into two types: control authority and change authority. Control authority refers to the authority of an actor to execute a control, while the change authority refers to the authority of an actor to change the control authority to another actor. Finally, the *responsibility* refers to the accountability of the actor for certain control tasks. Figure 2.2 shows the relations between these concepts and how to obtain consistency among them.

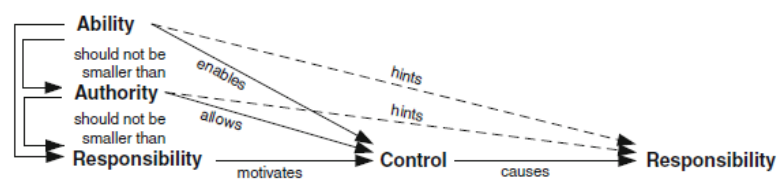


Figure 2.2: Relations between authority, ability, control and responsibility in human-machine co-operation design (Flemisch et al., 2011)

Another concept that is described is that of mental models (e.g., Flemisch et al., 2011; Goodrich, & Boer, 2003). A mental model refers to an actor's representation of the system, which includes the four previously mentioned cornerstones. It is important that the system design aims to obtain consistency among the mental models of all actors. Some of the ironies of automation are related to inconsistencies in mental models (Bainbridge, 1983; Noy, Shinar, & Horrey, 2018). For example, a control deficiency can occur when an inconsistency between mental models regarding control exists. This is related to the irony of mode confusion. The irony of overreliance, on the other hand, is related to inconsistencies between mental models with respect to ability.

For the design of these co-operative human-machine systems an important challenge is to determine which level of automation is appropriate. Parasuraman, Sheridan and Wickens (2000) describe a methodology for choosing appropriate levels and types of automation, in order to minimize the effects that the ironies of automation have on system performance. They propose that automation can be applied to four classes of functions:

- Information acquisition;
- Information analysis;
- Decision and action selection; and
- Action implementation.

These functions are similar to the four stages of human information processes: Sensory processing, perception/working memory, decision making and response selection. By organizing the automation functions in a similar manner as human information processing, the human can develop consistent mental models of the automation functions more easily. Each of the automation functions can be automated to a level from high to low, depending on what is optimal for the complete system performance, as is visualized in Figure 2.3.

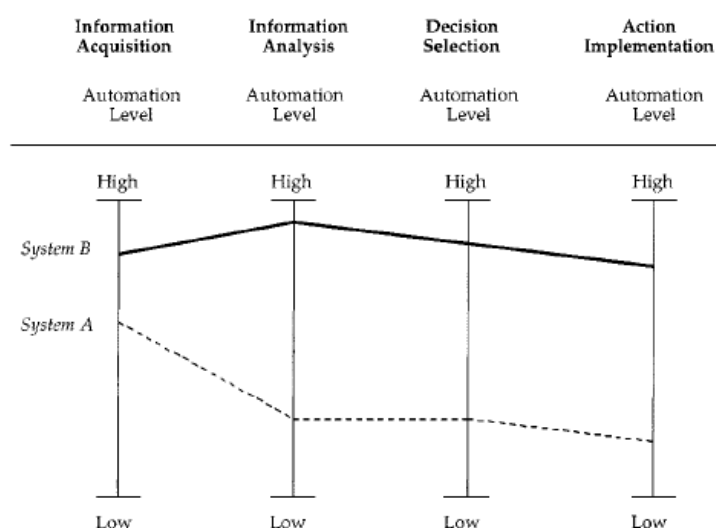


Figure 2.3: Types and levels of automation according to Parasuraman et al. (2000)

In their paper, Parasuraman et al. (2000) describe how to select the appropriate level of automation for what they call adaptive automation. This is described in their paper as context-dependent automation, i.e., levels of automation that can be changed during the use of the system. As the primary evaluation criterion for choosing the level of automation, they use the human performance consequences in terms of mental workload, situation awareness, complacency and skill degradation. As secondary evaluation criteria they mention automation reliability and cost of action outcomes. Their qualitative model for type and level of automation selection is visualized in Figure 2.4.

In addition to this qualitative model, Parasuraman (2000) summarises different quantitative models that can be used to determine the level and type of automation. The computational models that are reviewed in this paper are:

- Signal detection theory;
- Fuzzy signal detection theory;
- Bayesian analysis;
- Expected value models;
- Task load models;
- Cognitive modelling.

These models seem to be very relevant for the Mediator system as well. However, since the time of writing of that paper, probably many developments have taken place. Therefore, it is recommended to look at more recent applications of these models than those referenced by Parasuraman (2000).

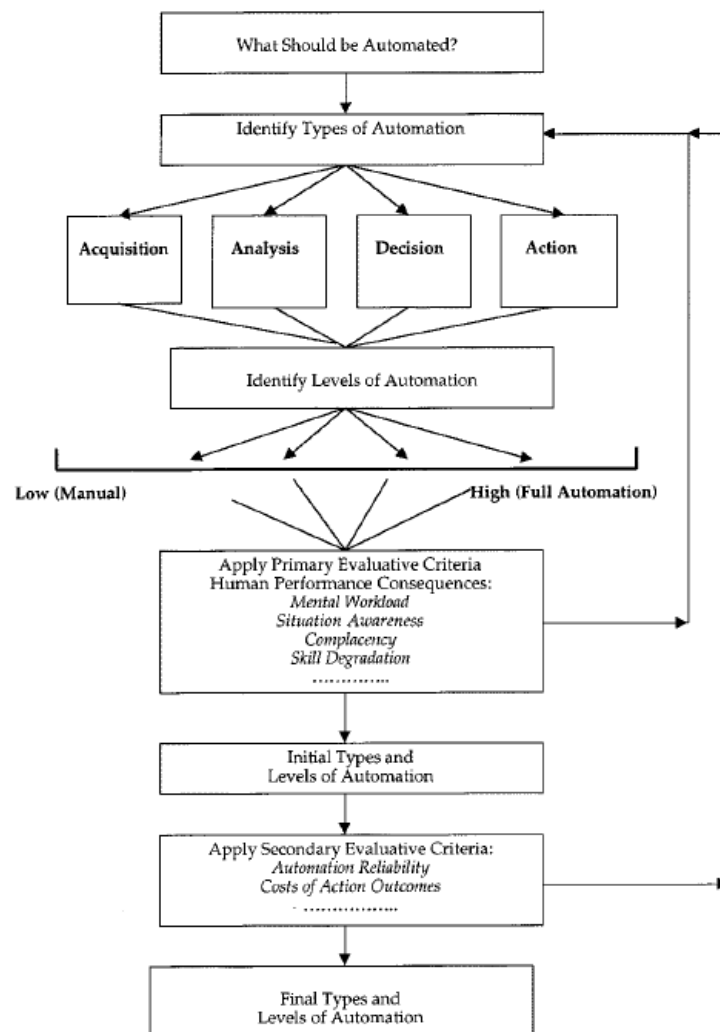


Figure 2.4: Methodology for choosing type and level of automation according to (Parasuraman et al., 2000)

2.3. Mediator-like systems

While no Mediator equivalent systems exist yet, research into human assistance systems in several domain has been around for a while. In this section we discuss some of these systems, distinguishing between early human assistance systems and current driver monitoring systems.

2.3.1. Early Human Assistance Systems

Human assistance systems are designed to assist the human in their work process of vehicle control. Onken and Schulte (2010) describe several existing prototypes of cockpit and driver assistance systems up to the writing of their book in 2010. The prototypes they mentioned for aviation are shown in Table 2.1 and those for driving in Table 2.2.

Table 2.1 Existing Cockpit Assistance Systems (From: Onken, & Schulte, 2010)

Name	Description	Reference
Pilot's Associate (PA), & Rotorcraft Pilot's Associate (RPA)	System that assists the pilot of a single pilot fighter plane, consisting of subsystems that can assess the current situation and plan tactics and missions autonomously and an HMI that includes pilot intent estimation.	Banks, & Lizza, 1991; Miller, & Hannen, 1999
Copilote Electronique	An in-flight mission re-planning decision aid for an advanced combat aircraft.	Hourlier, Grau, & Amalberti, 1999
Cognitive Cockpit project (COGPIT)	Assistant system for fast military aircraft including situation assessment, pilot state (workload, alertness, intent) monitoring, task and timeline management.	Taylor et al., 2002
Assistance for Single Pilot IFR Operation (ASPIO)	System for civil aviation to improve situation assessment which includes pilot and crew monitoring and planning aids.	Wittig, & Onken, 1992
Crew Assistant Military Aircraft (CAMA)	CASSY follow-on for applications in the military domain, including a real-time adaptive individual pilot model.	Onken, & Schulte, 2010; Onken, & Walsdorf, 2001
Tactical Information and Mission Management System (TIMMS)	CAMA add-on for air-to-ground attacks	Schulte, 2003
Cockpit Assistant System (CASSY)	Advisory system for civil air transport based on situation interpretation, e.g., vehicle and environment state and pilot intent and error recognition. Dialogue management and planning.	Onken, 1995; Onken, & Schulte, 2010; Prévôt et al., 1995

Table 2.2 Existing Driver Assistance Systems (From: Onken, & Schulte, 2010)

Name	Description	Reference
Generic Intelligent Driver Support (GIDS)	Adaptive driving assistance system that outputs signals, warnings and advice to support the human driver with the driving task	Michon, 1993
Driver Assistant System (DAISY)	Adaptive driving assistance system that outputs warnings, realized using artificial neural networks	Feraric, & Onken, 1995; Onken, & Schulte, 2010

While these systems have been developed about two decades ago, it is interesting to note that they deal with similar issues as Mediator, e.g., trade of between advising and information overload, assessment of context and situation as well as operator state and online adaptation of cognitive systems to individual driver.

2.3.2. Current Driver Monitoring Systems

With the introduction of SAE level 2 systems in commercial vehicles, the need for driver state monitoring in particular has increased. The automotive industry is actively working on solutions and implementing systems, and several research projects in- and outside of the EU have been started. Regulations are also being introduced that make the presence of monitoring systems mandatory. This paragraph gives an overview of currently running projects on driver state monitoring, solutions from the automotive industry, and relevant European regulations.

2.3.2.1. Other projects

Several research projects related to driver monitoring that are of interest to the MEDIATOR project were identified:

- The project ADAS and Me limits itself to a number of separate driver states instead of a single measure of overall affective driver state. Gaze direction, blink duration and physiological data are used to assess driver fatigue and attention. Information about the different driver states is then fed into the decision system. An effort is made to determine driver emotional state by interpreting speech. Difficulties with environmental sound during vehicle operation make accurate detection of speech difficult and further research is ongoing (Lotz, Faller, Siegert, & Wendemuth, 2017).
- The AutoMate project uses eye tracking to determine when the driver no longer has eyes on the road. Identification of the instrument (phone, dashboard, etc.) the driver is looking at is also provided (Tango et al., 2018).
- The project i-DREAMS plans on combining several indicators of driver state in order to calculate an overall risk level. Combined with measures on task demand this will enable the project to determine if driver state is adequate for the current task.
- The BRAVE project is aimed at improving safety and market adoption of automated vehicles, in part by the development of driver monitoring systems that can be used to enhance current ADAS. By taking into account needs and requirements of users, stakeholders and other road users, systems are developed.
- SENSATION is a project that aims to explore a range of sensor technologies to achieve unobtrusive, real time and cost effective detection and prediction of human wakefulness, fatigue and stress. It is not specifically targeting the transport sector.
- The AWAKE project aims to increase traffic safety by developing a multi-sensor system that can detect driver wakefulness. Included sensors are eye tracking, steering activity, lane position and a steering grip sensor.
- The AdaptIVe project develops automated driver functions based on dynamically adapting the level of automation to the situation and driver status. Methods for driver state monitoring are not the main focus of the project, but guidelines for appropriate interfaces are discussed.
- The HoliDes project address the development of adaptive cooperative human-machine systems. In order to detect operator states, head tracking and hand gestures are recorded and analysed. Driver head orientation can serve as an indicator for distraction similar to eye tracking.
- In (Mioch et al., 2017) a driver readiness ontological model, which determines the current and near-future truck driver's readiness to take over control in a truck platooning scenario, is presented. They distinguish between physical readiness, e.g., hand and feet positions, and mental readiness, including situational awareness and attention.

The results of the relevant research projects mentioned here will be valuable input, especially for the driver state estimation part of the MEDIATOR project.

2.3.2.2. Industry solutions

Compared to the wider approach used in European projects, the industry has a focus mostly on driver distraction and fatigue. Different methods to monitor these two driver states are being installed in consumer vehicles, and development of commercial applications is ongoing. A clear distinction between the two driver states is not always made. The goal of the commercial driver monitoring systems is not to determine which exact state the driver is in, but to monitor whether the driver is actively engaged in the driving task.

Driver states can be estimated using a wide range of methods, and likely a combination of methods is needed for robust estimation. Several of these methods are briefly discussed below.

Eye tracking

Eye tracking systems utilize eye tracking technology in several ways to determine the driver state. Gaze direction is used to verify if drivers have their eyes directed on the road. When this is not the case for an extended period of time, it is assumed the driver is no longer paying attention. Blinking rate is used as a measure of fatigue, with an increase in time spent with closed eyes as indicative of a fatigued driver.

Face and head tracking

Face and head tracking can be used to identify driver distraction, fatigue, mood and intention. Fatigue can be detected from features such as head nodding and yawning, while distraction identified from head orientation and lack of movement. Facial expressions can be extracted to identify the driver's mood and head movements can also be related to driver's intention to change lanes.

Steering activity

These systems measure the amount of steering wheel activity and use this as a measure of driver state. A lack of steering activity or erratic steering movements are indicative of a distracted or fatigued driver. A baseline measure is often established at the beginning of a drive and used to compare further measurements to.

Hands off detection

A simple way of identifying whether a driver is able to control the vehicle is to detect if his or her hands are on the steering wheel. Such detection can be done by measuring the amount of torque applied to the steering wheel or via capacitive sensing. When insufficient torque is applied it is assumed the driver let go of the steering wheel, and is no longer engaged in the driving task. Due to the small amount of torque required from a driver, systems that rely only on this measure are likely to be inaccurate and relatively quick to fool by users. Capacitive sensing is a more sensitive method based on the measure of parasitic capacitance introduced by the driver between the steering wheel and the vehicle's ground.

Pedal activity

These systems measure the amount of gas and brake pedal activity to determine the driver state. Such measures are sometimes used in addition to steering activity to detect driver state.

Control inputs

Control inputs can include the use of turn signal indicators and window wipers, but also the use of the infotainment system. Detection of such control inputs can be used to detect distraction, while the lack of these inputs can aid in determining driver fatigue.

Lane position

Lane position systems utilize the vehicle lane position as a way to determine driver state. When the vehicle gets too close to the lane edge or excessive drifting is detected, the system deems the driver in a deteriorated state. A baseline measure is often performed during the beginning of the

drive when it is assumed the driver is awake and alert. This baseline is then used to compare further measurements to.

Behaviour Learning

To detect irregular driver behaviour, measures of steering wheel and pedal activity or control inputs are often compared to a baseline. This baseline can be adapted to the person driving the vehicle by employing learning algorithms during the first part of a drive.

Other

Measures of lane position are strongly affected by the driving context. To separate irregularities in lane position due to driving context and due to driver distractions, Mercedes-Benz additionally detects side winds and road unevenness.

NAUTO instead measures context information related to other road users, in the form of time headway, to identify dangerous tailgating behaviour of the driver. To this end they also detect speeding and vehicle accelerations due to harsh manoeuvres.

It should be noted that many of these methods relate to the driver actually controlling the vehicle, and can thus only be used to estimate the driver state during SAE level 0 and 1.

During driving with higher levels of automation, only eye, face and head tracking, hands off detection and certain control inputs will provide useful information on the driver state.

An overview of the different driver state estimation techniques by vehicle and equipment manufacturers is given in **Fout! Verwijzingsbron niet gevonden.**². It should be noted that the table is based on information available on the company websites only, and that different brands do not provide equal detail on their driver monitoring systems.

2. Information was retrieved from company websites, see Section **Fout! Verwijzingsbron niet gevonden.**

Table 3: Driver monitoring systems of vehicle and equipment manufacturers.

Manufacturer		Measurements							
Vehicle	Eye Tracking	Face & Head Tracking	Steering Activity	Hands Off Detection	Pedal Activity	Control Inputs	Lane Position	Behaviour Learning	Other
Audi			x						
BMW	x		x	x					
Cadillac	x	x							
Citroën							x		
Ford							x		
Honda			x						
Hyundai			x				x		
Land Rover	x	x							
Lexus	x	x							
Mazda			x			x	x	x	
Mercedes-Benz			x		x	x		x	x
Nissan			x					x	
Renault			x			x		x	
Skoda			x					x	
Tesla				x					
Volkswagen			x						
Volvo							x		
Equipment									
Bosch			x			x			
Seeing Machines	x	x							
Smart Eye	x	x							
Nauto	x	x							x

2.3.2.3. Relevant regulations

Within the European Union there are several regulations that aim at increasing the usage of driver monitoring systems. Euro NCAP will introduce a new assessment protocol for safety assist systems in January 2020 (Euro NCAP, 2019). This updated protocol allows manufacturers to gain extra points for safety when driver monitoring systems are installed. These points are only awarded if the system is active by default and cannot be disabled by a single button press, encouraging higher use. Time-on-task methods of determining driver state are not rewarded, all other measures are.

As of 2022 with the introduction of mandatory driver state monitoring in European regulation (EC, 2019), the Euro NCAP protocol will be adjusted further.

2.4. Conclusion

While mediating between the human and automation is a relatively new concept in the automotive industry, in the aviation and military domain research on this topic dates back several decades. Keeping in mind there are obvious differences between these domains, their research is in many aspects also applicable to the car domain. For instance, both domains benefit from understanding human information processing and decision making. Also monitoring and prediction of human states, such as workload and situation awareness, are integral to human-automation cooperative designs in all domains. In the automotive domain, research and development of driver monitoring systems has recently increased with the advancements in vehicle automation. So much so, that European regulations have been made that make driver monitoring systems obligatory in certain cases.

The short, non-exhaustive literature overview presented here can serve as a starting point for exploring already existing research and design of human-automation cooperative systems during the development stages of our Mediator system.

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3. Assessment of human fitness

This chapter focuses on human related factors that affect drivers' fitness and comfort/trust to drive, i.e., the driver state component of the Mediator system. It presents recent evidence of human degraded performance in the context of manual and automated driving as well as lessons learned other domains, namely, aviation, maritime and rail. Values of fitness and comfort will help deciding who should have the control over the driving task: the human, the automation or both.

We identified five prominent factors that are most likely to affect drivers' fitness and comfort to drive (see Figure 3.1 'Inputs'). The 'output' Fitness to drive will be determined on the basis of three performance measures (Figure 3.1 'Performance measures') depending on the level of automation.

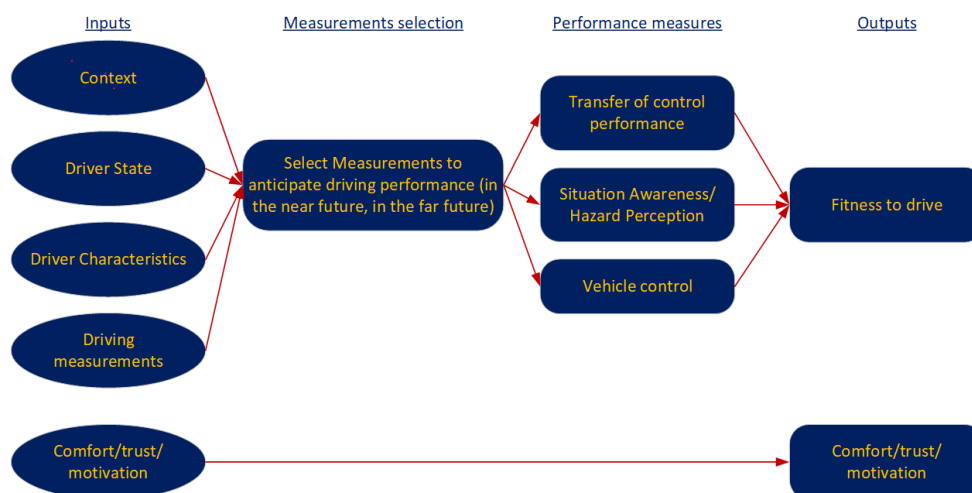


Figure 3.1. Human factors affecting drivers' fitness to drive and driver's comfort/trust and motivation

More specifically, based on extensive brain storming, it was decided to focus this chapter on the effects of the driver competence-related factors experience, age and gender on driving performance (Section 3.1), as well as the effects of driver state related factors on driving performance: mental workload (Section 3.2), distraction by non-driving-related tasks (Section 3.3), fatigue and sleepiness (Section **Fout! Verwijzingsbron niet gevonden.**), and comfort, emotions and trust (Section 3.5). This chapter also looks at hazard awareness as a promising measure of improving drivers' performance in the context of automated driving (Section 3.6). In each of these sections we identified human related key measurements that were found in the literature as reliable and valid to reflect changes in driver's performance and fitness to drive.

3.1. Driving experience, age and gender

Aspects like driving experience, drivers' age and gender play an important role with regard to driving performance and road safety. Substantial knowledge already exists regarding the influence of those aspects on driving safety in manual driving. Hence, these variables need to be considered to determine and predict driver fitness and ability to drive manually or to take-over the driving task. Further, studies revealed that experience with take-over situations generally reduce take-over time,

which is especially important with SAE level 2 automation with a very short time frame for the take-over. For higher automation levels with a longer time frame for a successful take-over, driving experience plays a less important role. For age no influence on take-over time could be found, but take-over performance differed between older and younger drivers. The existing knowledge offers a good starting point for designing human-machine interaction in the context of automated driving with the goal of enhancing safety and mobility (e.g., for older drivers). Knowledge gaps exist regarding the realisation of this interaction, for instance, with respect to the topics driving comfort, pleasure or skill acquisition.

3.1.1. Driving experience

Driving experience, defined as the time or kilometres a vehicle was actively driven, is a very important factor in terms of road safety. Several studies show that drivers who have no substantial driving experience are much more involved in crashes, and that increasing driving experience is positively correlated with lower crash risks (e.g., McCartt et al., 2009). Several deficiencies are examined and discussed as potential reasons for the increased crash risk of inexperienced drivers:

- Unadjusted driving speed and short distances to other road users (e.g., Rudin-Brown et al., 2014);
- Inadequate visual scanning for potential obstacles or hazards (e.g., Underwood et al., 2002);
- Poorer hazard awareness (e.g., Borowsky, & Oron-Gilad, 2013) or prediction (e.g., Crundall, 2016);
- Ineffective attention allocation (e.g., Shinar et al., 1998);
- Longer eyes off road times (e.g., Fisher, 2008);
- Recognition and decision errors (Carney et al., 2015);
- Longer detection and reaction times to hazards (e.g., Whelan et al., 2004);
- Incomplete, slower or even missing behavioural adaptation in response to a changing situation (e.g., Mueller, & Trick, 2012);
- Less anticipatory driving (e.g., Lehtonen et al., 2014).

The elaborated knowledge regarding inexperienced drivers' deficiencies with respect to the driving task offers new possibilities for designing automated driving systems supporting inexperienced drivers in critical situations (e.g. complex intersections with high traffic density, obstacles that are not directly visible but need to be anticipated).

In partial automated driving, drivers' experience can be considered as one variable to determine and predict drivers' fitness or ability to handle a critical driving situation. Further, research could show that experience with take-over situations can reduce take-over times (Zhang et al., 2019) which might be especially important for SAE level 2 automation (i.e., quick take-over is necessary). In higher automation levels (SAE levels 3-4) with longer time frames until a take-over needs to be performed, the influence of experience on take-over time might become less relevant. More research is needed in this regard.

It should be considered that inexperienced drivers need other and probably more support than experienced drivers. Hence, automated systems need to adapt to the experience levels of the drivers. Additionally, it is important to ensure that inexperienced drivers will get enough experience in the driving task to learn and consolidate appropriate driving skills. Further research is needed to examine how inexperienced drivers' driving skills are developing, which elements are important (e.g., successfully cope with a driving scenario at a complex intersection) and how much assistance through automation can be offered without jeopardizing skill acquisition or driving pleasure.

3.1.2. Drivers' age and gender

Drivers' age is often highly correlated with driving experience, because most of the novice drivers receive their drivers' licence as soon as they are legally allowed to drive a car. However, several studies revealed that driving experience and drivers' age have independent effects on driving performance and safety (McCartt et al., 2009) with driving experience as the more pronounced factor (Maycock et al., 1991). Nevertheless, drivers' age also needs to be considered. Regarding driving safety two age groups are especially relevant: very young drivers and elderly drivers.

Younger drivers are often overly confident regarding their own driving skills and take unnecessary driving risks (e.g., driving at night, fatigued or intoxicated) and violate traffic laws more often (e.g., Beirness et al., 2004); they drive at higher speeds, closer distances and accelerate/decelerate more abruptly (e.g., Porter, & Whitton, 2002); and they are more engaged in secondary tasks like smartphone usage (NHTSA, 2015). Together with their lack of experience and inadequate driving skills, especially during the first year (Maycock et al., 2009) or first 1,000 miles (Mc Cartt et al., 2003) of driving, young drivers are a high-risk group with respect to road safety.

For older drivers, several age-related deficiencies and impairments in different driving-related capabilities and skills can influence their driving performance and safety. Potential problems of older drivers according to Langford et al. (2005) are:

- Increased reaction times to potential hazards or obstacles, problems in attention allocation to different tasks, poorer vision (e.g., night vision, contrast sensitivity, peripheral vision);
- Problems in correctly estimating driving speed and distances to other road users;
- Problems in correctly perceiving and analysing especially complex traffic situations;
- Restrictions in body movements (e.g., head movements for shoulder check);
- Vulnerability to fatigue;
- Slowed information processing;
- Feelings of insecurity (e.g., regarding trips to unknown places, heavy traffic situations, bad weather conditions).

Typically, older drivers are aware of their deficiencies and they adapt their driving behaviour accordingly. They drive less than younger people and during low risk times like late in the morning or early in the afternoon when the traffic is not so dense and the light conditions are good (e.g., Memmot, 2006). Additionally, older drivers generally do not drive when fatigued or intoxicated (e.g., NHTSA, 2015), drive at lower speeds (e.g., Otte et al., 2013) and in general are more careful driving with greater headways to other vehicles, smoother accelerations and decelerations and less deliberately violations of traffic laws (e.g., Porter, & Whitton, 2002). Nevertheless, it seems that older drivers still face some problems in detecting hazards and obstacles despite their behavioural adaptation (Bromberg et al., 2012). A further finding suggests that the older the drivers are the less comfortable they feel with the driving task in general (Tuokko et al. 2013). It is important to note that especially for older drivers there is a large interindividual variability regarding age-related deficiencies and driving performance (Midwinter, 2005). However, when adjusted for the amount of driving they do, older drivers crash risk is not higher than that of younger drivers (Shinar, 2017)

The existing knowledge regarding younger and older drivers' characteristics with respect to driving performance and safety can be used to design automated driving systems that support the drivers in an appropriate manner (e.g., enabling older drivers to driver longer trips, in situations or times they feel uncomfortable with and to a higher age in general). Drivers' age can be used as one indicator for drivers' fitness in certain situations, but it needs to be considered that driving experience is the more pronounced variable. Regarding take-over time which is most important in

the SAE level 2 automation, it was found that drivers' age has no influence on take-over times (Körber et al., 2016; Zhang et al., 2019). However, Körber et al. (2016) found differences in the take-over performance like more and stronger braking manoeuvres.

Again, the developed systems need to adapt to the needs of the drivers (e.g., differences between younger and older drivers, but also individual differences within the group of older drivers). Research needs to be done to examine, for instance, how the driving style of an automated vehicle should look (e.g., younger drivers are often driving faster and older drivers are driving slower); what consequences such technical developments have on driving comfort (e.g., how comfortable will an older driver feel when he or she will be driven by night or bad weather conditions with the possibility of a take-over request from the automated system); and how all these aspects will influence the overall acceptance of automated driving functions.

A sub group that needs special attention are young male drivers. Gender plays just a minor role with respect to road safety due to the fact that there are no differences between women and men in their cognitive and perceptual-motor skills. Nevertheless, research revealed some differences regarding attitudes towards driving, especially young men compared to women (Yagil, 1998). It seems like young men are more content to violate traffic laws considering them less important than other laws, show higher confidence in their own abilities to drive a vehicle, and are more willing to take risks when driving resulting in a higher crash involvement (e.g., Ouimet et al., 2010). It seems that gender role (i.e., stereotypical behaviour) could be a better predictor for traffic violations than gender per se (e.g., Oppenheim et al., 2016).

3.1.3. Experience, age and gender effects on take-overs

Further, drivers' experience, age and gender together with certain driving styles could be shown to have an influence on drivers' motivation to resume manual control from an Adaptive Cruise Control (ACC) system in non-safety critical situations. Middle-aged drivers are more likely than young drivers to resume manual control by braking as they approach a slower leader (Xiong, & Boyle, 2012), female drivers and experienced drivers are less likely to overrule ACC by pressing the gas pedal (Varotto, Farah, Toledo, van Arem, & Hoogendoorn, 2017), and drivers with a patient and careful driving style have a smaller acceptable range with the system active (Varotto, Farah, Toledo, van Arem, & Hoogendoorn, 2018). In the same traffic situation, certain drivers are more likely to resume manual control than others (Varotto et al., 2017, 2018; Xiong, & Boyle, 2012).

3.1.4. In conclusion

Driving experience, age and specific gender roles might be good indicators for determining and predicting drivers' fitness in each of the three levels of automation that our Mediator system will cover (e.g., during manual driving for necessary hand-over situations due to decreasing driver fitness or ability to handle the situation, or during automated driving for possible take-over situations due to decreasing fitness of the automated system). Driving experience, more specifically experience with take-over situations has been shown to reduce take-over time, which might be mostly relevant for SAE level 2 automation with very short time frames for take-over reactions.

Further research is needed to examine how human-machine interaction (i.e., the Mediator system) needs to be designed to support inexperienced and older drivers to better handle critical traffic situations, ensure skill acquisition for inexperienced drivers, and to ensure that older drivers feel comfortable when driving under conditions they normally won't drive in due to their own perceived impairments. Also, better understanding is needed on how driver characteristics might influence

motivation to hand-over and take-over vehicle control as well as influence on take-over time and performance for higher levels of vehicle automation.

3.2. Mental workload

Mental workload is an important variable to be considered in the development of Mediator, as both overload and underload influence driver performance. While a low level of workload might result in boredom, a high level might result in the driver being unable to allocate sufficient resources to the intended task. In this Section the concept of mental workload and related factors will be discussed, as well as how workload can be measured.

3.2.1. The concept of workload

According to De Waard (1996), “workload is the specification of the amount of information processing capacity that is used for task performance” (p. 15). In his model (see Figure 3.2), he visualises workload and task performance as (inverted) u-curves: if workload is low, task performance is high and if workload is high, task performance is low. The amount of workload a person subjectively experiences is affected by the task demand. De Waard’s model shows that too high as well as to too low levels of task demand can increase workload and therefore degrade performance. The concept of workload can be related to Fuller’s (2002; 2005) Task-Capability Interface model (see Figure 3.3), which is the model the Mediator concept builds on. The model describes that human performance degrades if the task demand exceeds the human capabilities. This is where the concept of workload fits into the model, as workload is a person-specific concept that is also influenced by one’s capabilities (de Waard, 1996). To get a better understanding of workload, the following subsections will discuss three types of factors relating to the concept: contextual, human and automation. Thereby we follow the Task-Capability Interface model, but also extend it to the for Mediator relevant effect of automated systems.

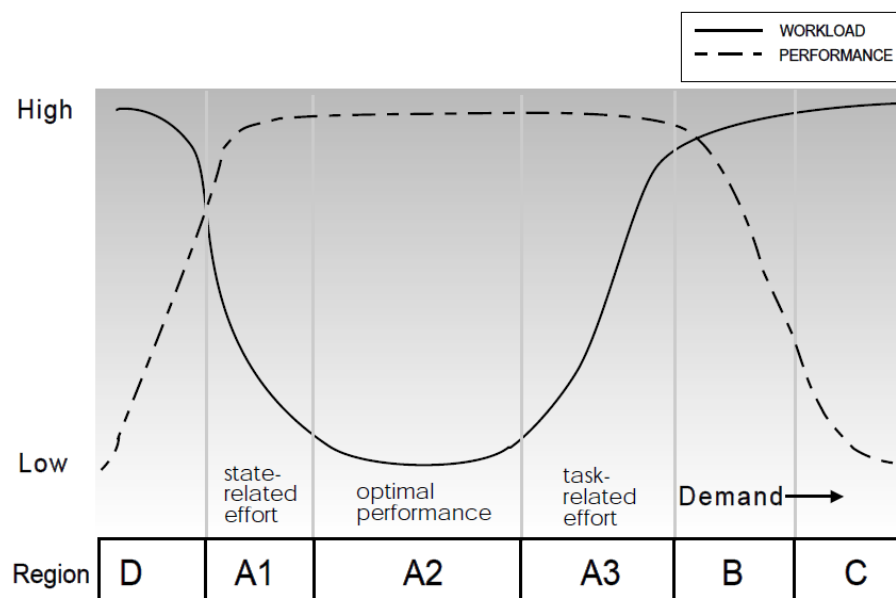


Figure 3.2 De Waard’s model on the relationship between demand, workload and performance (De Waard, 1996).

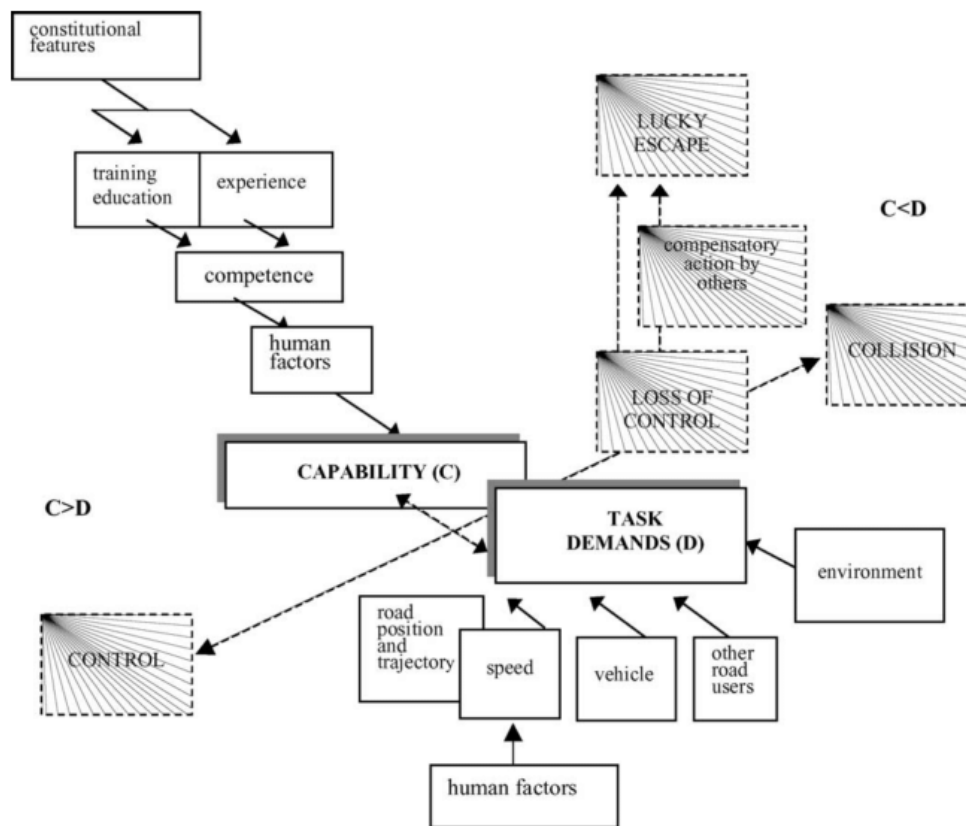


Figure 3.3 Fuller's Task-Capability Interface model (Fuller, 2000; 2005)

3.2.2. Contextual factors

Contextual factors affect the task demands that is placed on the human by the environment or by others moving through the environment. In general it can be said that workload increases with the complexity of the driving context (Törnros, & Bolling, 2006; Cantin, Lavallière, Simoneau, & Teasdale, 2009). More specifically, infrastructural characteristics such as narrower lane width (Dijksterhuis, Brookhuis, & de Waard, 2011), increased road curvature (Heger, 1998) and the presence of intersections (Cantin, Lavallière, Simoneau, & Teasdale, 2009) have been associated with higher levels of workload. The same is true for the presence of other road users: oncoming traffic in the opposing lane (Dijksterhuis et al., 2011), the presence of heavy goods vehicles while merging onto the motorway (de Waard, Kruizinga, & Brookhuis, 2008; de Waard, Dijksterhuis, & Brookhuis, 2009) and increased traffic density (Zeitlin, 1995; de Waard et al., 2008) all have shown an increase of mental workload.

3.2.3. Human factors

Human factors that affect the experienced workload have to do with a person's capabilities and can be congenital, learned or situational. The first human factor to be discussed is age. Research suggests that older drivers experience higher workload compared to younger drivers and are therefore less accurate (Verwey, 2000) and slower (Cantin et al., 2009) when performing secondary tasks while driving. A closely related factor is driving experience. It was found that less experienced drivers showed higher workload levels than experienced drivers (Patten, Kircher, Östlund, Nilsson and Svenson, 2006). Another human factor relating to workload is distraction by secondary tasks. Törnros and Bolling (2006) found that workload increased when participants had

mobile phone conversations while driving. This was found for hands free and handheld conversations.

3.2.4. Automation factors

Automation factors related to the experienced workload have to do with vehicle automation. Although automation has the potential to decrease mental workload by taking over part of the driving task, Stapel, Mallakkal-Babu, & Happee (2019) found that inexperienced drivers reported no decrease in workload while using the ACC. However, De Winter, Happee, Martens, & Stanton (2014) found that self-reported workload was highest during manual driving and lowest in highly automated driving, with driving using ACC in between. Additionally, using the ACC reduced driver mental load (Ma, & Kraber, 2005; Rodun-Brown and Parker, 2004; Vollrath et al., 2011) but with the addition of a secondary task the driver mental load increased, worsening driving situational awareness (Ma, & Kraber, 2005; Merat, Hamish Jamson, Lai, & Carsten, 2012). This could pose problems, especially during critical moments like a take-over request, as found by Merat, Hamish Jamson, Lai, & Carsten (2012).

3.2.5. Measuring workload

Workload measuring methods are often used to assess how humans work with systems. Most often, three types of workload measures are used: (1) subjective assessment scales, (2) psychophysiological responses and (3) task performance (Matthews, de Winter, & Hancock, 2018).

3.2.5.1. Subjective assessment of workload

Subjective workload is often measured using the Rating Scale for Mental Effort (RMSE; de Waard, 1996), the NASA Task Load Index (NASA TLX; <https://humansystems.arc.nasa.gov/groups/TLX/>) and the Subjective Workload Assessment technique (SWAT: Reid, & Nygren, 1988), amongst others.

The aforementioned questionnaires require the participants to answer questions regarding their experiences, often reflecting on their current state. However, when workload has to be monitored continuously, using self-reporting questionnaires is insufficiently feasible when used to monitor driver performance.

3.2.5.2. Task performance measures

Several aspects of primary task performance can be used as an indicator of mental workload. Primary task performance is very task specific, however, in driving context all primary task measures are speed and accuracy measures (de Waard, 1996). Workload has been associated with an increased standard deviation of the lateral position (SDLP) and an increased standard deviation of the steering wheel (SDSWH; de Waard, 2001). On the other hand, increases in mental workload during a non-visual secondary task have also been shown to improve lateral position variability (Brookhuis, de Vries, & de Waard, 1991; Reimer, 2009).

Secondary task performance is often a task implemented to determine the workload of drivers while driving (de Waard, 1996). Because the Mediator system will not provide drivers with additional tasks that might decrease driver safety, secondary task performance will not be elaborated upon.

3.2.5.3. Physiological measures

This subsection discusses physiological measurements for assessing workload. These are derived from the driver's physiology and have the advantage that they do not require a response from the driver. Also, multiple measurements can be done simultaneously (de Waard, 1996)

ECG

An electrocardiogram (ECG) measures the electrical activity of the heart, which is used to contract the cardiac muscle (Paxion, Galy, & Berthelon, 2014). Two indicators that are measured are known to be sensitive to mental workload: the heart rate (and the differential of the heart rate) and heart rate variability (HRV). When the mental workload is increased, the heart rate and the differential of the heart rate increases (Lenneman, & Backs, 2010; Mehler, Reimer, Coughlin, & Dusek, 2009). Also, heart rate variability decreases when workload gets higher (Brookhuis, & de Waard, 2010; Mulder et al, 2004). However, the heart rate is not solely influenced by workload and the heart rate variability does not always sufficiently discriminate the amount of experienced workload (Paxion, Galy, & Berthelon, 2014).

Blood pressure

Blood Pressure has been found to be affected by workload: systolic blood pressure and blood pressure variability both increase while driving in a high workload demanding simulated traffic environment (Stuiver et al. 2014).

EEG

Electroencephalography (EEG) is also used to evaluate mental workload. The EEG records bands of frequencies and event related potentials (Paxion, Galy, & Berthelon, 2014). A decrease in the alpha band and an increase in the theta band indicate an increased workload state (Wascher et al., 2018; Getzmann et al., 2018; Borghini et al., 2014). Additionally, it is possible to derive electrophysiological responses from the continuous EEG measurements. These are specifically linked in time with sensory, cognitive or motor events (Lohani, Payne, & Strayer, 2019). In driving research, certain event related potentials (P3b and N1) latencies and amplitudes show to be sensitive to cognitive demands related to processing information from in vehicle systems; they decrease with increased task demands. Also, increased latencies in mismatch negativity (MMN) have been associated with a high mental workload (Ying et al., 2011). However, Getzmann et al. (2018) found no influence of workload on the mismatch negativity.

Functional near infrared spectroscopy

Functional near infrared spectroscopy is a neuroimaging method that measures local changes in cerebral hemodynamic activity (Lohani, Payne, & Strayer, 2019). Cognitive load increases oxygenated hemoglobin in the brain (Liu et al. 2012) and more specifically, systematic increases in the bilateral inferior frontal and temporal occipital brain regions were found when workload was increased incrementally (Unni et al., 2017).

Pupillometry

Blink rate has been seen to decline when workload increases from both processing visual stimuli and from memory tasks (Wilson, 2004). However, the correlation is weak (Castor, 2003). Additionally, pupil diameter has been found to be sensitive to rapid changes in workload and it increases with higher cognitive load (Wilson, 2004; Palinko et al. 2010). Also, pupil size rapidly widens and narrows corresponding to cognitive effort: more cognitive effort leads to more and faster pupil size changes (Hampson, Opris, & Deadwyler, 2010; Vogels, Demberg, & Kray, 2018).

Pupil dilation was also found to be able to detect increases in cognitive load within a one second time frame (Prabhakar, 2018). This suggests that pupillometry could be used as a real time measurement of workload

Electrodermal Activity (galvanic skin response)

Skin conductance levels are higher during increased workload in driving situations (Mehler et al., 2012). Skin conductance responses have also been found to be higher during traffic situations that elicit higher workload levels (Schneegass et al., 2013). The same effects were found in simulation studies that required texting and navigation (Seo et al., 2017) and speeding (Kajiwara, 2014).

Thermal Imaging

Facial skin temperatures could be measured by using an infrared camera. The physiological mechanism relating to the response to workload is that the skin surface temperature changes according to blood perfusion and muscular contraction (Reyes et al., 2009). Nasal temperatures seem to drop when workload is increased (Or, & Duffy, 2007). Another study found that nasal and forehead temperatures increased in difference during increases of mental workload (Kajiwara, 2014).

Feasibility and knowledge gaps

Depending on the setting, some physiological measures are more feasible than others. While on the road, some equipment may influence the driver, compromising his safety (Lohani, Payne, & Strayer, 2019). More importantly, there is a need to prevent misinterpretation of physiological signals of cognitive processes. Physiological measures such as heart rate are impacted by multiple processes such as fatigue, exertion, stress, medication and workload, which might lead to interpretation issues (Lohani, Payne, & Strayer, 2019).

A related concern in multi-model measurements is the fact that individuals respond differently, are more reactive when assessed by one measure compared to another (Lohani, Payne, & Strayer, 2019). Additionally, different measurements are all utilized in their own paradigm when studied, showing relative changes in the outcome across conditions. Currently, we do not have a well-understood threshold for these measurements to make definitive judgements regarding driving fitness. There is not a fixed threshold for physiological measures that can be used across multiple individuals to define high or low workload levels (Lohani, Payne, & Strayer, 2019). It is therefore difficult to define a general threshold for being unfit to drive due to workload.

Defining an individual's baseline while driving under "normal" circumstances could give insight to the individual's physiological state. Calibrating a "normal" range for individuals could be a way to identify significant variations from this range. This could be a method for detecting workload levels that may be suboptimal for driver performance (Lohani, Payne, & Strayer (2019).

3.2.6. In conclusion

In conclusion, workload seems to influence many aspects of the driving task. Measuring workload can be done using many possible methods, mainly focusing on subjective workload, physiological measurements and task performance. Whereas subjective workload measurements are often very useful in controlled studies, they seem to be less useful for our Mediator system as they require driver's responses. Physiological measures show some promise, but here arises the largest knowledge gap. There is a lack of dependable thresholds to decide whether a driver is fit to have or take over control of the vehicle. More importantly, measures such as heart rate are impacted by

multiple processes such as fatigue or exertion. Finally, task performance in itself is a relevant measure, even without it being used to measure workload. Naturalistic driving data (such as the UDRIVE dataset, Van Nes et al. 2019) could be studied to better understand the relation between task performance and workload.

It is therefore necessary to evaluate the need to measure workload for the Mediator system. The Mediator system might need to recognise high and low workload states of drivers (and probably not how high or low exactly) and adjust task demands accordingly for optimal performance levels. The question arises whether workload is the best estimator when performance indicators may provide a more accurate and dependable assessment of driver fitness. On the other hand, measuring workload could be crucial in understanding these performance indicators. Using workload as a human fitness indicator thus requires filling in many knowledge gaps.

3.3. Distraction by non-driving related tasks (NDRTs)

This Section contains recent evidence of the effects of drivers' engagement in non-driving related tasks (NDRTs) on their driving performance in manual and automated driving. It begins with manual driving and recent evidence of the performance costs associated with NDRT engagement. Next, we continue with automated driving and performance costs associated with NDRT engagement. Notably, since the role of the driver is different, depending on the level of automation, this second section is further divided into two: (1) driver distraction in the context of low levels of automation, and (2) driver engagement in NDRTs in the context of high levels of automation. Finally, this section contains suggested directions for future research.

3.3.1. Driving performance costs associated with NDRT in manual driving

Distracted driving is a major cause of crashes worldwide. In the USA, distracted driving has been found to be a contributing factor to the 15% increase in fatal crashes from 2014 to 2016 (Kidd, & Chaudhary, 2019). In a recent observational study across four northern Virginia communities during day time, Kidd and Chaudhary (2019) observed 11,837 drivers and found that compared to their study in 2014, about the same amount of drivers (23%) were engaged in at least one secondary task. Notably, mobile phone use was not significantly different between 2014 and 2018, yet, the likelihood of holding a mobile phone (holding but not interacting or conversing) significantly decreased while the likelihood of manipulating a mobile phone (interacting with a hand-held mobile phone) significantly increased. In addition, the authors indicated that 14% of drivers were engaged in non-cell-phone secondary tasks behaviour (e.g., grooming, talking and singing, eating), which exceeded mobile phone use in both 2014 and 2018. This finding is in line with older studies that indicate that drivers tend to engage in many tasks including listening to music/radio while they are driving (e.g., Ho, & Spence, 2017). It has also been proposed that shifting attention between different regions of space contributes to distraction: the personal space (wherein the phone conversation takes place), and the peri-personal and extra-personal spaces (wherein most of the driving tasks are executed). Attentional problems within the personal space will tend to have a more adversarial effect on drivers' risk taking and decision making (Ferlazzo, Fagioli, Nocera, & Sdoia, 2008).

A large body of evidence examined the effects of driver distraction on performance costs. In a recent systematic review and meta-analysis that examined the effects of talking on a mobile phone, with a passenger or dialling on driving performance it was found that mobile phone (either handheld or hands-free) and passenger conversation produced moderate performance costs, but were not substantially different from one another (Caird, Simmons, Wiley, Johnston, & Horrey, 2018). Dialling while driving, on the other hand, which is a visual-manual task, had large

performance costs. Performance measures that were examined in this study included longitudinal control, lateral position, eye movements and hazard perception abilities. The most significant performance costs while conversing the mobile phone included:

- Slower response to emergency events in the driving environment, such as a lead vehicle braking or a pedestrian suddenly entering a crosswalk.
- Lower detection rate of targets that did not necessarily require an immediate response (e.g., secondary probes and traffic signs).

These performance costs are associated with poor eye movements, which can be monitored and measured. Notably, the authors argue that the smaller effect size of performance decrement that was found for emergency events compared to targets that did not require an immediate response indicate that drivers prioritize the tasks and manage the workload such that nonessential tasks will suffer larger performance costs compared to essential and driving critical tasks such as lateral and longitudinal control and hazard perception.

As aforementioned, visual-manual tasks such dialling a phone number, composing text messages, entering destination into a navigation system lead to a greater degradation in driving performance. In a recent literature overview it was found that typical visual-manual tasks (e.g., input a destination manually, interacting with a smartwatch) lead to longer eyes-off-road times and poorer longitudinal and lateral control of the vehicle (Goodsell, Cunningham, & Chevalier, 2019). Notably, although audio-vocal interactions lead to better driving performance compared with visual-manual tasks, they are nevertheless distracting, significantly increase cognitive load, and result in degraded driving performance (Goodsell et al., 2019).

While engaging a non-driving related task may result in degraded driving performance, evidence show that manual drivers often compensate for additional workload caused by the secondary task or for underload caused by 'easy' driving conditions. They do so by making deliberate decisions whether to attend to a secondary task or initiate a secondary task in a given situation (Schömig, & Metz, 2013; Christoph, Wesseling & van Nes, 2019) and by prioritizing the tasks and managing the workload such that non-essential tasks will suffer larger performance costs compared to essential tasks (Caird et al., 2018). This compensation mechanism is often termed self-regulation (Young, Regan, & Lee, 2009). According to Lin et al. (2019) self-regulation in manual driving studies was mainly exhibited in longitudinal vehicle control such as speed reduction, time headway increment and the management of the interaction with the secondary task. Recent evidence of self-regulation mechanism with respect to child passengers-related distraction has shown that the risk of fatal crashes due to this type of distraction is higher on non-intersection parts of the road presumably because drivers may try to self-regulate their interactions with child passengers and focus on driving in more demanding traffic situations such as intersections (Maasalo, Lehtonen, & Summala, 2019)

Management of the interaction with the secondary task depending on the driving task demands has been proposed to follow a model containing three hierarchical levels that follows Michon's conceptual model (1985): planning (strategic), decision (tactical), and control (operational; Schömig, & Metz, 2013). At the planning level drivers generally anticipate the secondary task before driving (e.g., a driver must call her boss during the drive). At the decision level drivers evaluate if the current situations are appropriate for engaging in secondary tasks (e.g., a driver may reject answering a call if he is approaching a dangerous intersection). Typically, drivers tend to reject more secondary tasks or delay their beginning with a higher driving demand (Lin et al., 2019), but not always (Tractinsky, Ram, and Shinar, 2013). Finally, at the control level, drivers

regulate the current secondary task processing through disengagement with the secondary task if necessary. There is some evidence that when the driving demand is high, self-regulation at this level is typically manifested by interacting less frequently with secondary tasks, allocating more percentage of gaze on the road or exhibiting a shorter duration of eyes-off-road (Lin et al., 2019).

3.3.2. Driving performance costs associated with NDRTs in automated driving

So far, evidence was provided regarding the types of secondary tasks that manual drivers perform while driving, how it affects their driving performance and how drivers self-regulate their engagement with secondary tasks to maintain reasonable driving performance. The current section provides evidence of the types of NDRTs that drivers engage with, in the context of automated driving: what are the performance costs associated with engagement in these tasks and how drivers self-regulate their engagement with NDRT in the context of automated driving. First, we discuss the situation at a low level of driving automation (SAE level 2) in which the drivers' role shifts from an active controller to a supervisor of the automation (Fisher, Lohrenz, Moore, Nadler, & Pollard, 2016). Then, the discussion expands to higher levels of automation (SAE levels 3 and 4) in which the driver is out of the driving loop for either short (level 3) or long (level 4) periods of time, and may lose situation awareness and be more likely to engage in a diversity of NDRTs.

3.3.2.1. Low levels of driving automation (SAE level 2)

At SAE level 2 drivers are supervisors of the automation, meaning that they must continuously monitor the driving task (Fisher et al., 2016). According to Lin et al. (2019) the main driving task demand is to monitor road hazards while taking into account the mental model of the driver regarding the automation functioning (Beggiato, & Krems, 2013; Fisher et al., 2016) as well as the driving context (i.e., road conditions). There are two critical challenges that drivers must face during SAE level 2 automation:

- drivers must remain vigilant so they will notice changes to the system, and
- drivers must keep track of the changing road environments and monitor for hazards, or in other words keep their situational awareness intact (Fisher et al., 2016).

The effects of NDRTs on driving performance can be discussed in terms of vigilance and situation awareness. In terms of vigilance, there is evidence that engagement in a secondary task can actually relieve drowsiness (Lin et al., 2019) and help drivers to maintain alertness (Naujoks, Höfling, Purucker, & Zeeb, 2018). Naujoks et al. (2018), for example, showed that while driving for long periods of time in a driving simulator drivers' visual and mental demand associated with secondary tasks (playing on the phone) decreased the take-over reaction time in response to a sudden brake of a lead vehicle. This finding is in line with studies on boredom and fatigue in manual driving that showed that secondary tasks may be beneficial in such circumstances (Oron-Gilad, Ronen, & Shinar, 2008).

Although engagement with NDRT may help keeping drivers alert and vigilant, engagement with NDRT may increase drivers' mental workload, impede situation awareness, and as a result impede driving performance. In fact, there is some recent on-road evidence that SAE level 2 automated driving can actually lead to an increase in mental workload demands due to the fact that drivers need to monitor the environment as well as the automation (Solís-Marcos, Ahlström, & Kircher, 2018; Stapel, Mullakkal-Babu, & Happee, 2019 – see also Section 3.2). As indicated in the previous subsection, drivers typically self-regulate their engagement with the secondary task depending on the demands of the secondary task and the driving task. In a recent study, Lin et al. (2019) used a non-driving vigilance task to simulate the monitoring condition during automated driving at level 2. While performing the vigilance task, participants received monetary incentives to engage with a secondary task (deciding whether a number is odd or even). The display was

showing either the primary or the secondary task and participants had to press a button in order to shift between the two tasks. Within the framework of the three level model of self-regulation (Schömig, & Metz, 2013), the study's findings showed that on both the planning and decision levels participants' anticipation of a higher hazard event rate or a higher urgency level apportioned more attention to monitoring the hazard. Furthermore, at the decision level, as the expectation for a hazard increased, the higher the percentage of time spent on the primary task, the shorter average time off the primary task, and the higher the frequency of switching-off the digit task. On the control level participants tended to disengage from the secondary task with the anticipation of a more urgent hazard but to continue the secondary task with frequent switching-back for a less urgent hazard.

One model that can be used as a metric to study how drivers apportion their attention between the various tasks and driving context is the SEEV (Horrey, Wickens, & Consalus, 2006). In brief, this model describes how operators sample information in an environment with multiple sources of information. Four factors can determine to where and when operators will direct their attention: Saliency, Effort, Expectancy and Value (SEEV). Saliency and Effort are bottom-up factors that refer to how salient the display or event within the environment and how much effort (mostly physical) one needs to make in order to sample information (e.g., looking back one's shoulder when driving backwards). Expectancy and Value are top-down factors that refer to where and when we expect to find a certain information and what is the value of that information (e.g., looking at the engine temperature display may not provide much value compare to the speedometer).

While these findings show that drivers can regulate their mental resources depending on the urgency of the hazard, there are evidence showing that on the control level drivers may still suffer loss of situation awareness that lead to poor hazard identification performance. In a recent driving simulator study, it was shown that drivers who were interrupted by a visual working memory task for only two seconds performed poorly in identifying hazards (based on eye fixations) that were pre-cued prior to the interruption (Borowsky et al., 2016). Furthermore, a recent driving simulator study showed that drivers who continuously received situation-related information from an automated driver had no benefit in mitigating a hazardous situation that appeared 4 seconds after an automation failure (Cohen-Lazry, Borowsky, & Oron-Gilad, 2017). The authors explained that since the last situational detail was given to drivers more than two seconds before the failure, drivers lost their situational awareness during these two seconds and had no advantage in mitigating the hazard over drivers who did not receive this type of information.

This subsection dealt with drivers' engagement with NDRTs in the context of a low level of driving automation. While evidence shows that drivers regulate their engagement by considering the demands of the secondary task as well as the driving context, they may still suffer driving performance decrement. The picture in SAE level 2 seems to be complex in terms of drivers' performance. While driving with level 2 automation may be perceived as a less demanding task than manual driving, it can in fact lead to interactions between vigilance, increased mental workload, and engagement with NDRTs. With respect to the Mediator system, distraction in SAE level 2 driving conditions should be monitored in terms of eye movements, levels of mental workload and types of secondary tasks, and the way these interact to affect situation awareness and take-over performance. It should be noted that since drivers at SAE level 2 may perform some parts of the driving tasks, inputs such as lane deviation, response to hazards and speed should be included to evaluate fitness to drive.

3.3.2.2. High levels of driving automation (SAE levels 3 and 4)

Unlike at SAE level 2 where drivers must continuously monitor the driving task and the automation, in higher levels of automation drivers may relieve themselves from the driving and monitoring task for longer periods and may engage in a variety of secondary tasks (Wandtner, Schömig, & Schmidt, 2018). Nevertheless, when asked to do so, drivers still have to be able to take over control of the driving task. This subsection is focused on how secondary task engagement affects the take-over quality and driving safety in these conditions with a focus on SAE level 3 automation, but similar principles apply to SAE level 4 automation.

As indicated, drivers of level 3 automation may be out of the driving loop for some time. Hence, one of the most important proxies for drivers' fitness to drive is their ability to get back into the driving loop, gain awareness of the situation, and take over control smoothly and safely. A recent meta-analysis explored 129 studies to identify the determinants of the take-over time in the context of level 2 and higher driving automation (Zhang, de Winter, Varotto, Happee, & Martens, 2019). With regard to engagement with NDRTs it was found that performing a NDRT with a handheld device strongly increases the mean take-over time. Notably, while the take-over time in high levels of driving automation may take more time than in lower levels of automation (Zhang et al., 2019), some studies did not find evidence of direct influence of engagement with NDRTs on take-over performance (Naujoks et al., 2018).

A prominent factor that can be seen as a moderator for the effect of NDRTs on drivers' performance is self-regulation, that is, drivers' ability to manage the interaction with the secondary task considering the driving task, automation monitoring task, and secondary task demands. Wandtner et al. (2018) recently used a driving simulator to examine how drivers voluntarily schedule secondary task processing according to the availability and predictability of automated driving modes. One group of drivers had a preview on the availability of the automated driving system in upcoming sections of the track (predictive HMI), while the other drivers served as a control group. Participants were free to accept or reject a texting task that was offered during both driving modes and also prior to take-over situations. Within the three levels model framework (Schömig, & Metz, 2013), tasks were rejected more often prior to take-over situations in the predictive HMI group than the control (planning and decision levels). Since the take-over performance was much worse when participants engaged in a secondary task during the transfer of control (reflected by a longer time until automation override, increased standard deviation of lane position, longer time until steering, more lane exceedances and higher maximum acceleration) participants in the predictive HMI group who rejected more secondary tasks performed safer take-overs than the control. At the control level, however, once engaged in a task and regardless of the HMI type, drivers tended to continue texting even in take-over situations, which eventually lead to poor control take-over performance. This finding, with respect to the control level, is consistent with previous studies showing that drivers who decide to engage in a secondary task on the control level, that is, the level where the driver must concurrently handle the driving task and the secondary task, may lose situation awareness and fail in handling the primary driving task even if they self-regulate their behaviour (e.g., poor take-over performance, poor hazard identification).

This subsection dealt with drivers' engagement with NDRTs in the context of SAE level 3 automation and how it affects their take-over performance. Since level 3 automation enables drivers to be out of the driving loop for some time, it is highly important to keep track of the type of task that the driver engages with and to provide the driver the appropriate support to resume situation awareness and prepare them for the upcoming take-over. Monitoring eye movements, head movements and facial expressions are highly important for being able to decide whether the driver is ready to take over control. The take-over performance can then be evaluated on vehicle

dynamics parameters and hazard perception. There is yet no agreement of how to determine the level of drivers' fitness to drive after a period of being out of the loop on the basis of these measures and this is what we expect to explore within the scope of MEDIATOR.

3.3.3. In conclusion

Distraction by non-driving related tasks is a major cause of crashes worldwide. While engagement in non-driving related tasks during manual driving generally results in degraded driving performance, evidence shows that to some extent manual drivers compensate for additional workload caused by the secondary task or for underload caused by 'easy' driving conditions. They do so by making deliberate decisions whether to engage in a secondary task or to initiate a secondary task in a given situation. For understanding and managing distraction by non-driving related tasks, a distinction must be made between planning/strategic elements of the driving task, decision making/tactical elements, and control/operational elements.

For automated driving, engagement by non-driving related tasks can be expected to have different effects on driving performance and safety. Moreover, the effects will depend on the level of automation. At lower levels of automation (SAE level 2) drivers have to monitor the automation all the time and be prepared to take over any moment. While monitoring elicits drowsiness, the task also requires constant vigilance as well as situation awareness. Engagement in a secondary task can help to remain vigilant. On the other hand, secondary non-driving related tasks have found to impede situation awareness, and, consequently, adequate take-over performance. A mediator system for an SAE level 2 vehicle would need to monitor distraction in terms of eye movements, levels of mental workload and types of secondary tasks, and define how these factors affect take-over performance.

At higher levels of automation (SAE levels 3/4) the driver can be out of the driving loop for shorter or longer periods of time. At these levels, engagement in non-driving related tasks is much more likely. The consequence, though, can easily be a loss of situation awareness, needing more time to resume manual driving when needed. Monitoring eye movements, head movements and facial expressions are highly important in order to decide whether the driver is ready to take over control. It still has to be studied how best to determine whether a driver is sufficiently fit to take over after a period of being out of the loop.

3.4. Sleep-related and task-related fatigue

The term fatigue has been “defined so inconsistently and applied so loosely in the scientific literature that its meaning is now obscure” (Balkin, & Wesensten, 2011). Here we define fatigue according to Fischler (1999) as a “decline in performance that occurs in any prolonged or repeated task ... However, it is also [experienced as] a subjective sensation”. Or as Phillips (2014) defined it (page 12):

“Fatigue is a suboptimal psychophysiological condition caused by exertion. The degree and dimensional character of the condition depends on the form, dynamics and context of exertion. The context of exertion is described by the value and meaning of performance to the individual; rest and sleep history; circadian effects; psychosocial factors spanning work and home life; individual traits; diet; health, fitness and other individual states; and environmental conditions. The fatigue condition results in changes in strategies or resource use such that original levels of mental processing or physical activity are maintained or reduced.”

Driver fatigue is often divided into sleep-related and task-related fatigue (Phillips, Kecklund, Anund, & Sallinen, 2017). *Sleep-related fatigue*, i.e. sleepiness or drowsiness, is defined as a “a physiological drive to fall asleep” (Dement, & Carskadon, 1982), which is affected by sleep deprivation, extended duration of wakefulness and time of day. Certain characteristics of driving, like task demand and driving environment, can produce *task-related fatigue* in the absence of any sleep-related cause. Task-related fatigue can then also be subdivided as fatigue due to overload and underload, respectively (May, & Baldwin, 2009; Phillips, 2015). Examples of overload include high density traffic, poor visibility, or the need to complete an additional task, whereas underload is associated with monotony and boredom (Gimeno, Cerezuela, & Montanes, 2006).

Sleep deprivation has a detrimental effect on sustained attention, working memory, reward processing (risk taking, sensation seeking, impulsivity), aversive emotional processing (irritability, anxiety, aggression) and hippocampal memory processing (post-learning, memory consolidation). This leads to disruptions in human behaviour across nearly all domains of cognition and affect (Krause et al., 2017). Not all changes in brain function that occur after sleep deprivation result in deficiencies though. Some neural alterations are compensatory and aim to preserve task performance. This is particularly important in driving where a sleepy driver is fighting to remain awake. The extent and duration of compensatory brain function and which behaviours are maintained is however poorly understood (Krause et al., 2017).

3.4.1. Factors that control or affect the level of alertness

The primary processes that impact sleepiness are the homeostatic and circadian processes (see Figure 3.4). The homeostatic drive for sleep, which involves continuous time awake and loss of sleep, decreases waking neuro-behavioural performance and alertness (and increases fatigue) as it accumulates over time. The circadian process, which drives 24h rhythms in the brain and body, represents a sinusoidal increase and decrease of wake pressure across time of day. Sleep inertia occurs just after awakening from sleep and is characterized by reduced vigilance, increased sleepiness and impaired cognitive and physical performances. The severity of sleep inertia is associated with several factors such as prior sleep deprivation, awakening near the circadian trough of body temperature and awakening from deep slow-wave sleep (Vallat, Meunier, Nicolas, & Ruby, 2019). Cognitive throughput and reaction times on a simple visual search task is reduced for about 10 to 30 minutes after awakening as a consequence of sleep inertia (Ritchie et al., 2017).

Internal factors include psychological states (mood, anxiety), pharmacological substances (e.g., caffeine, prescription drugs) and individual characteristics (e.g., age, genetics, gender, medical conditions, recent history, socio-cultural background). External factors include environmental conditions (posture, ambient temperature, light, noise), time constraints (task load, time pressure) and stress. More context relevant factors are environmental factors such as light conditions, road curvature, traffic density, and sound or vibrations. It is also often assumed that driver fatigue is countered by the alerting effect of a more stimulating environment, such as in the city (Horne, & Reyner, 1999). However, available research on effects of environmental factors on driver sleepiness is sparse (Ahlström, Anund, Fors, & Åkerstedt, 2018; Arnedt, Geddes, & MacLean, 2005; Horne, & Reyner, 1999; Tal Oron-Gilad, & Ronen, 2007; Thiffault, & Bergeron, 2003), and from a driver sleepiness detection perspective (e.g. Fu et al., 2016; Barua et al., 2019) it is even sparser.

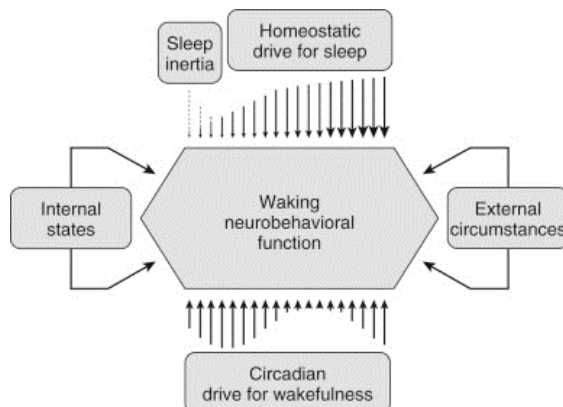


Figure 3.4 Schematic representation of the speculative oppositional interplay of circadian and homeostatic drives in the regulation of alertness, performance and related neurobehavioral functions (Gabehart, & Van Dongen, 2017).

3.4.2. Countermeasures

Overt signs of different types of fatigue may overlap, but the countermeasures are different (May, & Baldwin, 2009). If the driver is suffering from high levels of task-related fatigue due to overload, an appropriate countermeasure implies to stop driving and temporarily shut off demands of sustained attention. This could be done either by a short break at a rest stop, or by vehicle automation. If fatigue is due to underload, then activation (e.g., engagement in NDRT) rather than rest may help (Gershon, Ronen, Oron-Gilad, & Shinar, 2009; Oron-Gilad, Ronen, & Shinar, 2008; Rayes, Short, Meyer, & Llaneras, 2019). If fatigue is sleep-related, due to sleep deprivation or driving at night-time, only sleep will recuperate the driver in the long run (Ruggiero, & Redeker, 2014).

3.4.3. Fatigue and sleepiness indicators

The most commonly used, and probably also the most trusted, fatigue and sleepiness indicator is subjective self-assessments such as the Karolinska Sleepiness Scale (Åkerstedt, Anund, Axelsson, & Kecklund, 2014). Self-ratings are therefore often used as ground truth, i.e. as the target value, when designing sleepiness classification systems. In addition to subjective measures, numerous objective fatigue and sleepiness indicators have been suggested over the years. These are summarized in Table 3.1.

- Electroencephalography (EEG) measures brain activity, typically quantified as powers in the theta (4–7 Hz), alpha (8–15 Hz) and beta (16–31 Hz) frequency bands. An increased theta power reflects sleep need (Aeschbach et al., 1997; Cajochen, Brunner, Krauchi, Graw, & WirzJustice, 1995), but in a driving setting, increased alpha power appears to be a more reliable indicator (Kecklund, & Åkerstedt, 1993; Simon et al., 2011). EEG-based measures are obtrusive and suffer from noise in naturalistic settings, large interindividual variability, and some individuals do not respond despite being clearly sleepy (Sparrow, LaJambe, & Van Dongen, 2019).
- Heart rate, heart rate variability (HRV) and respiration have also been used to quantify driver sleepiness (Apparies, Riniolo, & Porges, 1998; Patel, Lal, Kavanagh, & Rossiter, 2011; Tran, Wijesuriya, Tarvainen, Karjalainen, & Craig, 2009; van den Berg et al., 2005; Vicente, Laguna, Bartra, & Bailón, 2016; Yang, Lin, & Bhattacharya, 2010). The parasympathetic influence when falling asleep slows down the heart and make its beating less regular (Egelund, 1982; Milosevic, 1997). At the same time, the sympathetic nervous system is activated to resist falling asleep while driving (Vicente et al., 2016). However, since both environmental factors, intra-individual time-varying differences as well as inter-individual differences obscure the relationship between HRV and sleepiness, it is difficult to

use HRV-based metrics in naturalistic settings. These difficulties are amplified by measurement noise when HRV is estimated remotely via cameras or wearable devices.

- Eye movements and blink behaviour are typically quantified in terms of blink durations or eyelid opening/closing velocities (e.g., Schleicher, Galley, Briest, & Galley, 2008; Åkerstedt, Peters, Anund, & Kecklund, 2005). Camera-based solutions based on computer vision and deep learning has matured over the past years, but there are still issues related to lighting, squinting, posture and some types of glasses. There are also individual differences regarding what should be considered a long blink duration, a low percentage of eye closure, etc.
- Vehicle control measures, such as increased lateral variability, have been used as indicators of sleepiness, but driving behaviour measures can clearly not be used for sleepiness detection in an automated vehicle.

All in all, eyelid parameters appear to be the most promising objective sleepiness indicator, given that it can be measured in a robust manner. Vehicle control measures are also of interest to assess driver fitness in general, but only during unassisted driving.

Table 3.1 Objective fatigue and sleepiness indicators

Methods	Fatigue and sleepiness indicators
Electroencephalography (EEG)	Increasing theta and/or alpha power/activity; decreasing amplitudes of ERP components;
Eye movements and blink behaviour	Increasing blink frequency; increased blink duration; more often and longer high (>80%) percentage eyelid closure (PERCLOS); higher saccade latency and/or duration; increased number of glissades; less smooth pursuit gain and phase; delayed pupil constriction; slow rolling eye movements (SEM)
Facial expressions and body movement	More frequent and extreme head movements (e.g. blink/eye closure, outer brow raise, tongue show, jaw drop, lip corner depressor and yawning) and physical activation (e.g. chewing, talking or changes in sitting posture).
Heart rate (variability)	Increased high frequency (HF) power
Respiration	Increased respiration rate variability; increased respiration amplitude
Temperature	Decreased body temperature; increased distal-peripheral temperature
Skin conductance	Decreased skin conductance; increased skin resistance
Vehicle control measures	Less micro-corrections; larger erratic steering; larger and faster steering corrections; slower driving; closer to centre of road; increased line crossings
Speech volume and pitch	More flattened/monotonic voices; lower tone (pitch); lower speech volume

Most research focuses on classification or detection rather than prediction of driver sleepiness, but there have also been attempts to predict future target values (Damousis, Damousis, Tzovaras, & Tzovaras, 2008; de Naurois, Bourdin, Stratulat, Diaz, & Vercher, 2017; Golz, Sommer, & Krajewski, 2016; Kaplan, Itoi, & Dement, 2007; Liang et al., 2019; Murata, Ohta, & Moriwaka, 2016; Watson, & Zhou, 2016). For example, Golz et al. (2016) found that 8s EEG segments contained enough information to predict subsequent microsleep events, and that the achieved accuracy dropped from 97% to 87% when predicting rather than detecting microsleep events. Another approach is to use a biomathematical model to predict the alertness level based on time of day and prior sleep (Åkerstedt, & Folkard, 1997).

3.4.4. Fatigue and sleepiness in the context of automated driving.

As the Mediator system is focused on deciding of whether the human is fit to drive given the driving context, it is important to understand what are the most important fatigue and sleepiness related factors that should be monitored at different levels of automation and what are the key performance measurements that might be affected.

For SAE level 2 automation it seems that fatigue-related problems due to underload are of crucial importance. There are some preliminary driving simulator results on increased fatigue due to automation where it is suggested that drivers are unable to stay alert during extended periods of monitoring the automated driving unless they engage in non-driving related tasks (NDRTs) (Jamson, Merat, Carsten, & Lai, 2013; Neubauer, Matthews, Langheim, & Saxby, 2012; Schömig, Hargutt, Neukum, Petermann-Stock, & Othersen, 2015; Vogelpohl, Kühn, Hummel, & Vollrath, 2019).

SAE level 3 automation allows the human to be out of the loop for short periods of time. However, when the driver is called back to drive, he or she must be brought back in the loop, gain situation awareness and take-over control of the vehicle. When fatigued, the time to driver fitness may be too long to resume control in time, possibly resulting in unfitness of both the human driver and automation. Recent evidence shows that take-over performance decreased when drivers were fatigued (Vogelpohl et al., 2019). In level 3 automated driving, the main issue of fatigue seems to be in its influence on take-over performance. To ensure successful take-over, it is necessary to ensure the driver is “fresh” enough. Therefore, fatigue must be monitored during automated driving and adapted to in take-over situations.

3.4.5. Lessons learned from aviation, maritime and rail

In the aviation, maritime and rail industry, fatigue issues have mostly been managed through design, regulations of work hours, fatigue management, and other operational and human resources policies. Sleepiness detection systems are rare since most unobtrusive solutions (such as cameras) depend on a stationary operator facing forward. On a ship bridge, the “driver” can move around, facing all directions, which pose higher demands on the detection system. Similarly, a pilot’s glance behaviour is more scan-oriented and not focused forward to the same extent as during car driving. In automated driving, the user will be more inclined to face away from the direction of movement and to shift their focus of attention away from the road. This is why driver monitoring systems might soon face similar challenges as in other transportation modes.

3.4.6. In conclusion

Fatigue, both sleep-related and task-related, has been found to have a substantial effect on manual driving and affect alertness and situation awareness. Except for some early results obtained from driving simulator studies (Jamson, Merat, Carsten, & Lai, 2013; Neubauer, Matthews, Langheim, & Saxby, 2012; Schömig, Hargutt, Neukum, Petermann-Stock, & Othersen, 2015; Vogelpohl, Kühn, Hummel, & Vollrath, 2019) very little is known about driver sleepiness and fatigue in an automated driving setting. Hence, there is a wide variety of relevant knowledge gaps. Will fatigue due to overload increase due to added workload during partial automation when the driver must monitor both the surroundings and the automation system? Will fatigue due to underload develop faster when the driver is disengaged from the driving task during conditional automation? And what is the effect of sleep inertia on task performance in cases where the driver has slept during conditional or full automation?

When it comes to driver sleepiness detection in a conventional driving setting, Mårtensson, Keelan & Ahlstrom (2019) listed three major shortcomings that many studies suffer from (page 422): “

- The results are often based on rather small datasets with 5 to 20 participants. This small amount of data does not allow for proper validation of the sophisticated methods that are used (e.g., Fu, Wang, & Zhao, 2016; Golz et al., 2016; Jiřina, Bouchner, & Novotny, 2010; Kong, Zhou, Jiang, Babiloni, & Borghini, 2017; Li, & Chung, 2015; C. T. Lin et al., 2010; F. C. Lin, Ko, Chuang Su, & Lin, 2012; Mu, Hu, & Min, 2017; Papadelis et al., 2007; Patel et al., 2011).
- The data has often been acquired in driving simulators and not from real-road driving (e.g., Damousis, Cester, Nikolaou, & Tzovaras, 2007; Golz, Sommer, Chen, Mandic, & Trutschel, 2007; Golz et al., 2016; Hu, Zheng, & Peters, 2013; Jiřina et al., 2010; Khushaba, Kodagoda, Lal, & Dissanayake, 2011; Kong et al., 2017; Li, & Chung, 2015; Li, Lee, & Chung, 2015; C. T. Lin et al., 2010; F. C. Lin et al., 2012; Mu et al., 2017; Patel et al., 2011; Picot, Charbonnier, & Caplier, 2012; Yang et al., 2010). An important limitation of using driving simulator data is that the drivers do not perceive any risk, which may cause a behaviour that is different from that on real roads (Ranney, 2011).
- Many studies are not actually using data from sleepy drivers. Instead “sleepy” data is invoked by driving for about an hour in a monotonous setting (e.g., Fu et al., 2016; Khushaba et al., 2011; Kong et al., 2017; Li, & Chung, 2015; Li et al., 2015; C. T. Lin et al., 2010; F. C. Lin et al., 2012; Mu et al., 2017). Such an experimental design gives rise to fatigue caused by under-stimulation rather than to physiological sleepiness (May, & Baldwin, 2009).”

There is also an emerging trend in the driver sleepiness community to use deep learning on video data (Du, Wang, Huang, & Hu, 2018; Guo, & Markoni, 2018; Liu, Qian, Yao, Jiao, & Pan, 2019; Massoz, Verly, & Van Droogenbroeck, 2018; Wang, Huang, & Guo, 2019). This is a much-needed development in the field. However, many of these studies stop after the detection of facial features (like yawning) or eye closures (like PERCLOS), neglecting the final step of linking the features to actual sleepiness in actual driving. The lack of publicly available real-road datasets is a concern here.

3.5. Driving comfort, emotions, trust in automation

Driving comfort, emotions as well as trust in technical systems are important aspects for safe driving and successful human-machine interaction whatever the level of automation. A Mediator system should be able to act as a team player with the driver and thus, be aware of and take account of current comfort, emotions and trust of the driver/user. Uncalibrated trust, negative emotional states or discomfort due to perceived compromised safety in automated modes may lead to reduced situation awareness and safety critical interventions by the human. This will significantly reduce the possible positive impact of such a Mediator system on traffic safety, efficiency and user acceptance. This Section summarises current knowledge on each of the three topics, potential state-of-the-art measurements and knowledge gaps.

3.5.1. Driving comfort

Comfort is considered as one of the main motivators for higher levels of automated driving next to safety, efficiency, social inclusion and accessibility (ERTRAC, 2019). Although there is no common definition of comfort, it can be considered a feeling of well-being and an attribution of positive valence, associated with the absence of discomfort and uneasiness (Bellem et al., 2018).

Aspects of driving comfort have been investigated in a long research tradition: vibrations, noise, smell, light, climate and anthropometrics were identified as main variables affecting comfort in vehicles (Bubb, & Spanner-Ulmer, 2009). Potentially uncomfortable situations are known from manual driving studies:

- Infrastructure-related discomfort factors include situations with higher complexity such as construction zones, intersections, enter and exit situations at the highway as well as roundabouts (Cahour, 2008; Healey, & Picard, 2005).
- Own driving manoeuvres that are perceived as potentially critical and uncomfortable are turning, entering and exiting roads, overtaking (including avoiding obstacles), as well as distance keeping in complex situations such as intersections or high traffic density (Cahour, 2008; Engelbrecht, 2013; Healey, & Picard, 2005; Meng, & Siren, 2012).
- Discomfort inducing behaviour of other road users is related to short distances (Siebert et al., 2013; Vos et al., 1997), unpredictable or unclear behaviour of others (Dorantes Argandar et al., 2016), manoeuvres of larger vehicles such as trucks (Meng, & Siren, 2012) as well as behaviour of vulnerable road user (Cahour, 2008; Meng, & Siren, 2012).
- External factors that could lead to increased discomfort comprise adverse weather conditions, icy roads, darkness, obstacles on the road as well as bad road conditions such as potholes (Cahour, 2008; Dorantes Argandar et al., 2016; Engelbrecht, 2013; Meng, & Siren, 2012).

As the human role in automated driving shifts from active driver to passenger, additional psychological determinants of driving comfort are discussed, such as apparent safety, trust in the system, feelings of control, motion sickness, familiarity of driving manoeuvres, and information about system states and actions (Beggiato et al., 2015; Bellem et al., 2016; Elbanhawi et al., 2015; Iskander et al., 2019; Varotto et al., 2018).

In automated driving conditions, these new comfort aspects are not only relevant for a pleasant driving experience and acceptance of automated systems, but they can also have safety impacts. Unnecessary interventions by the human driver due to uncomfortable situations (e.g., when apparent safety appears as compromised) could lead to safety-critical and unnecessary take-over situations (Hergeth, Lorenz, & Krems, 2016; Techer et al., 2019). As these new comfort aspects are primarily related to dynamic situations, constant comfort evaluation is required in order to prevent discomfort by, for instance, adapting automation features such as the driving style. Traditional comfort measurements usually make use of questionnaires³. However, there is a continuous research effort to get more objective human comfort measures that can be assessed by sensors in real-time. Current approaches use heart rate, heart rate variability, electrodermal response, pupillometry, oxygen saturation, electromyography, electroencephalography, pressure distribution by seat mats and posture analysis (Beggiato et al., 2018; Ikeda et al., 2018; Tan et al., 2008).

3.5.2. Emotions

Closely related to comfort as an affective state is the topic of emotions in driving. Negative emotions in (manual) driving may change cognitions of traffic-related stimuli, narrow attentional focus or processing, and modify interpretations of other drivers and their activities, thus eventually increasing the potential for risky, harmful, or unsafe driving (Hennessy, 2011).

Study reviews show that emotions and moods may affect driving-related performance in a number of ways (De Groot-Mesken et al., 2008). The clearest results were found for feelings of anger and

³ a collection of recent comfort questionnaires can be found at <http://www.icc.tudelft.nl/Questionnaires/Questionnaires.htm>

hostility, which seem to affect general task performance, but are also related to the committing violations and to aggressive and risky driving. Furthermore, some results suggest that anxiety and feelings of tension are related to errors. Roidl et al. (2014) found that anger leads to stronger acceleration and higher speeds; anxiety and contempt yielded similar but weaker effects, yet showing the same negative and dangerous driving pattern as anger. Shahar (2009) found that anxiety can have a negative impact on the number of errors, lapses, and ordinary violations, mainly due to distraction and attention deficits. Other emotions, such as sadness, may have an indirect impact on driving outcomes: According to Pêcher et al. (2009), drivers who listened to sad music in a simulator felt calmer but were unable to focus as much attention on the driving task. Similarly, Bulmash et al. (2006) found slower steering reaction times and a higher number of accidents among depressed participants in a simulator.

A direct comparison of studies on emotions in driving is difficult because different affective concepts are used such as emotion, mood, affect or personality (De Groot-Mesken et al., 2008). Anger, for example, is sometimes used as a mood, sometimes as an emotion and sometimes as a personality trait. A conceptual distinction between affect, feelings, mood and emotion is proposed by Mesken (2006). Affect is most often used as an umbrella term for emotions, feelings and moods. Feelings differentiate affective from non-affective experiences; i.e., those elements of experience that cannot be reduced to bodily sensations or cognitions. Moods are diffuse and longer lasting affective states for which the cause or object is not clear, whereas emotions are intentional in the sense that they are always related to an event or object.

Measures of emotions include a variety of questionnaires (e.g. Mood Adjective Checklist, Driving Anger Scale, self-developed questionnaires), psychophysiological measures (cardiovascular signals, electrodermal reaction, electromyography, respiration, speech - overview in Cowley et al., 2016) as well as the manual or automated analysis of facial expressions (Ekman et al., 2002). Recent developments in video-based face tracking technology gives promising results in automated detection of emotions (Bryant, & Howard, 2019; Ko, 2018). However, there is still very little knowledge on emotions during automated driving. Techer et al. (2019) found that driving a highly automated vehicle in urban areas may have adverse effects on the user's emotional state. As long as drivers are uncomfortable with the vehicle behaviour, they may decide to take over in complex situations. Therefore, the authors conclude that it is important to consider the emotional dimension of driving highly automated vehicles. Otherwise, expected benefits of automation for traffic congestion and safety may be compromised.

3.5.3. Trust in automation

The penetration rate of automated vehicles near-term markets is considered as directly contingent on, and dominantly controlled by perceived trust (Hancock, 2019). Trust in automation has been researched intensively over the past several decades and is considered a key element in human–technology relationships, affecting safety, performance and use rate (Schaefer et al., 2016). A widely used definition by Lee and See (2004) describes trust as “... the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability”. Trust is particularly relevant to misuse and disuse of automation and depends on the performance, process, or purpose of an automated system (Lee, & See, 2004). Performance-based trust varies depending on how well an automated system executes a task. Process-based trust fluctuates based on the operator's understanding of how an automated system performs tasks and purpose-based trust is contingent upon the designer's intended use for an automated system.

Hoff and Bashir (2015) presented a model of factors influencing trust in automation based on a review of 127 empirical studies. The authors distinguish between trust prior to an interaction and

trust formation during an interaction. *Before an interaction*, trust can be distinguished on three layers as dispositional trust, situational trust and initially learned trust:

- Dispositional trust represents an individual's overall tendency to trust automation (independent of context or a specific system) and relates to culture, age, gender and personality traits.
- Situational trust depends on external situational factors including system type and complexity, task difficulty, workload, perceived risks and benefits, organisational settings and the framing of the task. Internal context-dependent situational trust characteristics of the operator include self-confidence, subject matter expertise, mood and attentional capacity.
- Learned trust represents operator's evaluations of a system drawn from past experience or the current interaction. Initial learned trust before an interaction is influenced by attitudes/expectations, the reputation of the system/brand, experience with similar systems and understanding of the system.

During an interaction, dynamic learned trust is formed based on the system's performance, which includes reliability, validity, predictability, dependability, timing and difficulty of errors and usefulness. Design recommendations for creating trustworthy automation are mainly related to providing continuous transparency / feedback to the user in an adequate communication style, simplifying the ease of use as much as possible and adjusting the level of automation based on user preferences.

Common measures for trust in automation include trusting behaviours (e.g., reliance on or compliance with automation) and self-report questionnaires. Attempts to assess dynamic learning trust in real-time are primarily based on eye tracking to assess monitoring behaviour (Hergeth, Lorenz, Vilimek, & Krems, 2016; Walker et al., 2019).

3.5.4. In conclusion

Driving comfort, emotions as well as trust in automated systems are important aspects for safe and successful human-machine interaction in all automation levels. Although there is substantial knowledge on each of the three topics for manual driving, knowledge gaps are apparent for all levels of automated driving. As a Mediator system should act as team player by intelligently assessing the strengths and weaknesses of both the driver and the automation, constant evaluation of current comfort, trust and emotional state is required. Traditional evaluation approaches using questionnaires / subjective data from users are fruitful for evaluation studies. However, these approaches are not suitable for constant real-time assessment. Thus, research priorities should be given to investigating non-intrusive behavioural markers for comfort, trust and emotions in automated driving modes. Recent developments in video-based face tracking technology (see Appendix) offers promising options for non-intrusive real-time assessment of eye and head movements, facial expressions, emotions and posture. However, methodological issues need to be investigated on the one hand, e.g., how reliable are video-based measures compared to state-of-the-art eye tracking systems. On the other hand, the obtained measures need to be related to the constructs of comfort, emotion and trust, e.g., which patterns of eye or head movements indicate over-trust or discomfort.

3.6. Hazard awareness

It is reasonable to assume that as the levels of driving automation increase, drivers' control of certain aspects of the driving task, their situation awareness and their ability to identify and adequately respond to safety-critical events will be compromised (Fisher, Lohrenz, Moore, Nadler,

& Pollard, 2016). This ability of the driver to pay attention to critical situations in driving is defined by researchers as 'hazard awareness' (Horswill, & McKenna, 2004). Hazard awareness includes the ability of drivers to read the road and detect actual hazards or decipher the location from where a potential hazard instigator might enter the driver's path (Horswill, & McKenna, 2004). Hazard awareness has received considerable attention over the years, as it is among the few driving skills found to correlate with traffic crashes (Boufous et al., 2011; Congdon, 1999; Horswill et al., 2010; Horswill et al., 2015; McKenna, & Horswill, 1999; Wells et al., 2008). Hazard awareness is commonly measured via drivers' eye movements variables (e.g., fixations durations on areas of interests such as mirrors, potential pedestrian location etc., horizontal and vertical gaze dispersions) alongside with drivers' response time and/or response rate to actual or potential road hazards.

While hazard awareness (often termed hazard perception) has been substantially investigated in manual driving, there are only a few studies that investigated hazard awareness in the context of automated driving (e.g., Zeeb et al., 2015; Hergeth et al., 2016; Louw, & Merat, 2016; Louw et al., 2016; Seppelt et al., 2017). Results show that drivers' eye movements are generally more dispersed as automation level increases, with less focus towards the centre of the road and road environment (de Winter et al., 2014), and more focus, for instance, towards secondary, non-driving related tasks (Carsten et al., 2012; Louw, & Merat, 2016).

3.6.1. Fatigue and hazard awareness in partially automated vehicles

Drivers in automated vehicles are especially prone to fatigue, even more than manual drivers with acquired lack of sleep, and even if they did not previously suffer from a lack of sleep (Vogelpohl, Kühn, Hummel, & Vollrath, 2019; see also Section 3.4). Thus, task induced fatigue occurs sooner in automated driving than in manual driving. Feldhütter et al. (2016) found indicators for the development of fatigue during an automated drive of only 20 minutes based on eye-tracking measurements compared to fatigue signs that appeared after 45 to 50 minutes of manual driving. Saxby and colleagues (Saxby, Matthews, Warm, Hitchcock, & Neubauer, 2013) demonstrated situational awareness decrement in a SAE level 2 automated vehicle, when the driver must switch from a possibly inattentive state during full automation to maintaining alertness following manual take over. In this study, 170 drivers had to respond to a single roadway hazard after a simulated drive in a partially automated vehicle. Results suggested that for drivers of a simulated automated vehicle, the likelihood of collision with a roadway hazard was greater after driving for 30 minutes in an automated more than after a 10 minute drive. These findings emphasize the loss of situation awareness during automated driving that eventually may compromise hazard awareness. Interestingly, their findings did not find evidence for loss of motor control under fatigued conditions, highlighting the negative relationship between fatigue and cognitive aspects of attention rather than between psychomotor aspects.

3.6.2. Recovery of HA during and after a manual take-over in automated driving

One interesting question with regard to automated driving and hazard awareness is how long does it take a driver to recover his hazard awareness abilities from the moment the driver began taking manual control over the vehicle? The term 'take-over time' is commonly used to define the recovery period that is needed to resume control from partial or highly automated driving after a critical event in the environment or after receiving a take-over request (Zhang et al., 2019).

Little is known about the take-over time in terms of hazard awareness, although researchers agree that disengaging the automation after a take-over request might be better identified through measures of awareness of the situation after the take-over request (Vlakveld, 2015; Vogelpohl et al., 2018). Vogelpohl et al. (2018), for example, measured eye-movements after a take-over

request and found that the first glance to the side mirror and the first glance to the speed display was delayed for up to 5 s for highly distracted drivers in automated driving conditions compared to manual drivers. In a later study, Vogelpohl et al. (2019) measured proxies for hazard awareness immediately after a take-over request, by analysing the drivers' braking and steering reactions to the onset of a braking lead vehicle. The researchers found that after a take-over request warning signal, drivers under automated driving conditions used their brakes more often compared to manual drivers and choose to stay behind the braking lead vehicle in the same lane. Manual drivers on the other hand who had better situation awareness, tended to overtake the lead vehicle instead of using their brakes. It seems that shifting from automated driving to manual driving requires additional time to regain situation awareness and hazard awareness abilities. This process can take longer depending on the driver's state prior to the take-over request (e.g., distracted, fatigued). A small number of studies showed that under low mental workload conditions drivers of automated driving may keep their hazard awareness abilities intact (Louw et al., 2017; Louw, & Merat, 2016), but more research is needed to better understand how situational awareness and hazard awareness are affected by different drivers' states prior to a take-over request.

3.6.3. In conclusion

In conclusion, this section shows the importance of utilizing hazard awareness as an important measure of drivers' fitness to drive. The evidence shows that driving in an automated mode for even a short period hampers drivers' ability to identify road hazard and mitigate these hazards as a result of distraction. Eye movements are crucial for evaluating drivers' ability to anticipate road hazards and thus should be monitored continuously by the Mediator system.

3.7. Conclusions

This chapter focused on human related factors that were determined as most likely to affect drivers' comfort and fitness to drive in different levels of automation. The chapter provides an overview of the most recent findings of drivers degraded performance in the context of automated driving. Based on these findings we identified key human related variables that should be monitored and measured by our Mediator system in order to determine the driver state (e.g., fatigued, distracted, bad mood). For each driver state, we identified three performance measures that must be evaluated in order to assess the driver's fitness to drive.

Table 3.2 summarizes the knowledge presented in the chapter according to the following categories:

- The first column defines the measures that needs to be monitored in order to identify a certain driver's state.
- The second column defines the driver states that were identified as most important for investigation with the highest likelihood to affect drivers' fitness to drive.
- The third, fourth and fifth column define the three performance measures that are crucial for evaluating the driver's fitness to drive. Note: not all measures can be evaluated for each level of automation. The fitness to drive will be determined on the basis of all relevant performance measures that are available.
- The sixth column is a separate output that will be provided to MEDIATOR and reflects the driver's willingness to drive, as well as comfort and motivation.

The main challenge with respect to human degraded performance refers to the way the key variables as presented in Table 3.2 interact and affect driving performance and how driving performance is translated to fitness and comfort to drive. This is the major research gap that needs to be resolved in the scope of the current MEDIATOR project.

Table 3.2. Overview of measures, driver states and constructs for evaluating and predicting human (degraded) performance

Potential measures to evaluate a driver's state and performance	Driver state	Fitness to drive			Comfort, Trust and Motivation
		Time to physical take over control	Quality of take over control	Vehicle control performance	
Physiological measures Eye movements: Eyes off road, active visual scanning, blink rate EEG, ECG Peripheral detection task (PDT) Subjective evaluation: NASA-TLX, etc. Understanding the nature of the NDRT in terms of cognitive and motor demands Prior knowledge	Distractions (and workload)		Detection and reaction times to hazards, proper visual scanning, Glances off-road – number and duration.	Speed Variability, lane position, SDLP, braking manoeuvres, SDSWH	N/A
EEG ECG, eye movements and blink behaviour Facial expressions and body movements, Respiration, temperature, skin conductance Peripheral detection task (PDT) Subjective evaluation: KSS Understanding the nature of the NDRT in terms of cognitive and motor demands Prior knowledge	Fatigue (and underload)	Take-over time	Detection and reaction times to hazards, proper visual scanning, Glances off-road – number and duration.		Willingness to complete the driving
psychophysiological measures (cardiovascular signals, electro-dermal reaction, electromyography, respiration, speech, facial expressions, patterns of eye-/head movements Prior knowledge	Comfort, Trust, Emotion and mood				Trust, Willingness to complete the driving, Mood Adjective Checklist

3.8. References

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4. Assessment of automation fitness

4.1. Introduction

This Chapter focuses on the automation part of the Mediator system, i.e. what do we need to know to assess whether the automated system is sufficiently fit to take over or continue the driving task? It explains the purpose of the information transfer between the automated system and the decision making component of the Mediator system (see Chapter 6). Furthermore, the demands from the decision making component on such an interface are discussed. It should be noted that the Mediator project will not develop automated systems that can perform (parts of) the driving task. Existing automated systems are the starting point, like the other mediated party - the human driver - is. Analogous to estimating the human fitness as discussed in the previous chapter, estimates of the automation state must provide the decision making component with three types of relevant information to enable decision making, each of which are discussed in detail in Section 4.3:

- Automation Fitness Values
- Automation State Contextual Information
- Appropriate Intervention Type

The consequence of a decision by the Mediator system could be an HMI action which convinces the driver to activate or deactivate a specific feature or the complete automation system, or which aims to increase the fitness of the human driver, the fitness of the automated system, or both. This process is visualised in Figure 4.1 below.

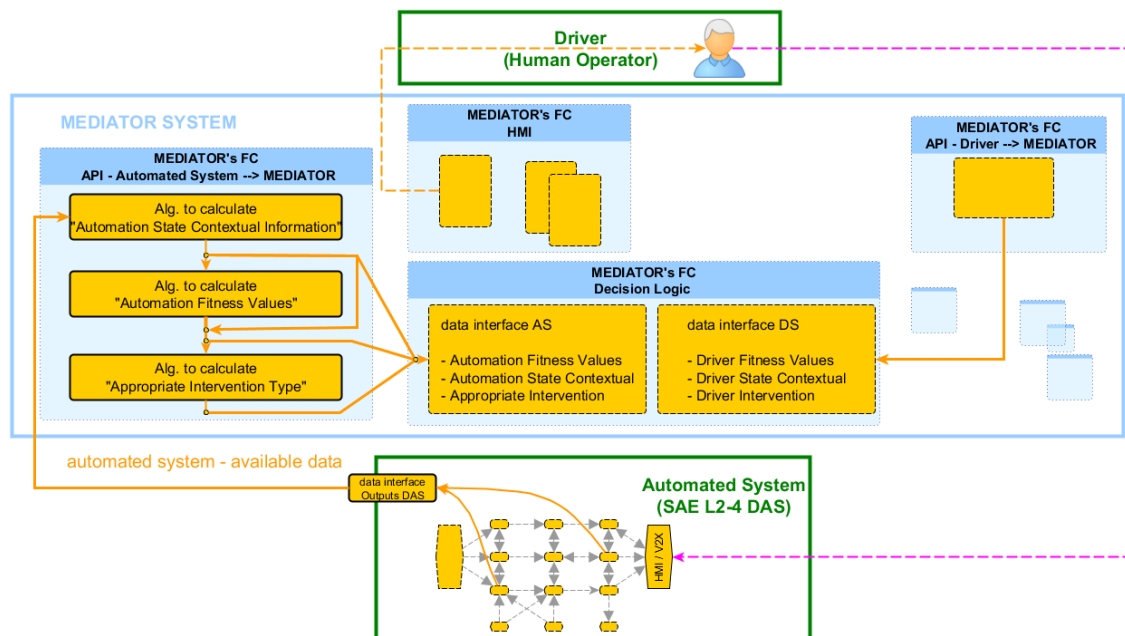


Figure 4.1 The solid orange arrows show how the information from the automated system gets processed into useable information for the Mediator decision making component. The dashed arrows show how an appropriate intervention could be triggered in the automated system via the Mediator system's HMI and the human driver.

The structure of the current Chapter is as follows:

Section 4.2 provides some basic background knowledge, introducing the terminology of automated driving, concepts for analysing the driving task, and a generalised model of a functional architecture of driving automation systems.

Section 4.3 describes the output from the automated system for the decision making component of the Mediator system. It explains the current drawbacks by using driving automation systems, especially in the context of mode confusion and mode awareness by unexpected degradation of the driving mode. It offers a collection of different sources of degradation and shows the impact of the available sensor configurations for such an event.

Section 4.4 specifies the driving automation system as a source of information for the Mediator system. It explains the development constraints of driving automation system, in particular at higher levels of automation (SAE levels 3+), the significance of modelling and describing context information, the necessary self-awareness of the system and how it has to deal with uncertainties.

The final section (Section 4.5) provides the main conclusions and formulates the resulting knowledge gaps, proposing a research strategy as preparatory work for the next steps in the MEDIATOR project.

This chapter will adopt the taxonomy of the Society of Automotive Engineers (SAE, 2018) concerning the context of the *level of driving automation*. More information is available in Subsection 4.2.1. The terms used in this chapter to describe *context information* will follow the definitions of scene, situation and scenario of Ulbrich, Menzel, Reschka, Schuldt, & Maurer (2015).

4.2. Background knowledge

First, this section discusses the taxonomy and definitions of levels of driving automation (4.2.1) and subsequently a driving model and functional system architecture (4.2.2).

4.2.1. Levels of driving automation

The use of taxonomy and definitions, which are common in the automotive industry, simplifies the integration of information from the automation system into the mediator system. Helpful here is a 2014 article of Bengler et al. which still gives an up-to-date review of the evolution of driving automation systems during the last three decades.

Since 2010, different expert groups around the world have worked on definitions of automation levels of the driving task. Most well-known is probably the taxonomy of the Society of Automotive Engineers (SAE). In 2011 in the United States, the SAE established the working group *On-roads Automated Vehicle Standards Committee*. Most recently, they published the standard J3016 "Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems" (SAE, 2018). This standard includes the definition of six levels in the evolution of autonomous driving known as the SAE levels of driving automation. These are explained in more detail below.

In Germany the Federal Highway Research Institute BASt established the working group *Legal Consequences of an Increase of Vehicle Automation* in 2010. BASt published the results of this working group in a report in January 2012 (Gasser, & Vogt, 2012). In 2013 the BASt refined its nomenclature of automated driving to align with the SAE definitions (Gasser, 2013).

Also in the United States, the National Highway Traffic Safety Administration (NHTSA) published its concept "Levels of vehicle automation" in 2012 (Wood, Chang, Healy, & Wood, 2012). In 2013 the NHTSA published its "Preliminary Statement of Policy Concerning Automated Vehicles" (NHTSA, 2013) to align with SAE and BAST. The most significant difference with the concepts of the SAE and BAST is that the NHTSA does not distinguish between level 4 and level 5 automation.

As indicated the most well-known taxonomy and definitions are those of the SAE. The SAE categorises vehicle automation into six levels ranging from no-automation (level 0), where the human driver has full control of the vehicle, to full automation (level 5) where the vehicle controls all the driving tasks. Since the SAE terminology is also very useful for the MEDIATOR project, we introduce the most essential ones here, based on and cited from the SAE Standard J3016 (SAE, 2018):

- The Dynamic Driving Task (DDT) includes all real-time operational and tactical functions required to operate a vehicle in on-road traffic. The DDT excludes strategic functions such as trip scheduling or route planning.
- Driving automation system (DAS) is a technical system containing hardware and software, collectively capable of performing part or all of the DDT on a sustained basis.
- Each level of automation is designed to work in specific conditions referred to as the Operational Design Domain (ODD). The ODD is defined as 'the specific conditions under which a given driving automation system or feature thereof is designed to function, including, but not limited to, driving modes. An ODD may include geographic, roadway, environmental, traffic, speed, land/or temporal limitations'. The ODD for all levels of automation, except for full automation (i.e. SAE Level 5), is limited.
- SAE Level 2 of vehicle automation (i.e. partial driving automation) refers to "sustained and ODD specific execution by a driving automation system of both the lateral and longitudinal vehicle motion control subtasks of the Dynamic Driving Task (DDT) with the expectation that the driver completes the Object and Event Detection and Ranging (OEDR) subtask and supervises the driving automation system". By partial driving automation, the driver needs to determine whether/when engagement and disengagement of the driving automation system are appropriate and immediately perform the entire DDT whenever required or desired.
- At SAE Level 3 of vehicle automation (i.e. conditional driving automation), the Automated Driving System (ADS), while engaged, performs the entire DDT. The ADS also determines whether ODD limits are about to be exceeded and/or whether there is a DDT performance-relevant system failure of the ADS and if so, it issues a timely request to intervene to the DDT fallback ready user. It disengages at an appropriate time after issuing a request to intervene.
- At SAE Level 4 of vehicle automation (i.e. high driving automation), the ADS performs the entire DDT and the DDT fallback within a limited ODD. The ADS performs an automatic transition to a minimal risk condition when: a DDT performance-relevant system failure occurs; the user does not respond to a request to intervene, or the user requests that it achieves a minimal risk condition.

Original Equipment Manufacturers (OEMs) and Suppliers in the automotive industry brand the description of Advanced Driver Assistance Systems (ADAS) over the last two decades. Today, there are many ADAS that support the human drivers in their driving task, ranging from systems to enhance comfort, energy-efficiency and safety. The SAE Standard J3016 does not mention ADAS, but instead, it has a definition of Driving Automation System (DAS) that covers SAE levels 1-5 of the driving automatization. In contrast, an Automated Driving System (ADS) concerns SAE level 3+ of the driving automatization.

4.2.2. Driving model and functional system architecture

The Mediator project aims to design a technical system which is capable of dealing with SAE automation levels 2 to 4 in vehicles from different OEMs or suppliers. It is a good guess to assume that the complete functional architecture of these driving automation systems will not be available in terms of trade secrets. A generalised model of a functional system architecture of the driving automation system should allow the development of a generalised interface between the automation and the Mediator system and to adapt it to the different SAE automation levels. In the following subsections, the two underlying concepts and the generalised functional system architecture will be introduced.

4.2.2.1. A three-level hierarchy of the driving task and categories of human target-oriented behaviour

The primary purpose of driving a vehicle is to transport people or goods from one place to another safely. To understand and describe how humans solve the driving task is the subject of models of human driving behaviour. In the development of automated driving, models of human driving behaviour play a critical role to increase safety, to increase the usability of the developed features and to design the system architecture. Two major concepts are of importance here: the requirements of the driving tasks, and the human behaviour to deal with those requirements.

Regarding the driving task, according to the models of Donges (1982) and Michon (1985) three hierarchical levels can be distinguished. Both models aim to describe what has to be solved in order to drive a vehicle. The SAE used Michon's model as a basis for the definitions and taxonomy of automated driving:

- The first level of the driving task has anticipation time horizons of more than 1 minute and is defined as "Navigation" or "Strategic Level". It contains the planning of the route based on available information.
- The second level of the driving task hierarchy has anticipation time horizons between 1 second and 1 minute. It is defined as "Guidance" or "Manoeuvring Level". The drivers have to guide their vehicle by performing and coordinating various driving manoeuvres, like following another traffic participant.
- The third level of the driving task hierarchy has anticipation time horizons under 1 second and is defined as "Stabilisation" or "Control Level". Drivers continuously control the current lateral and longitudinal movement of their car.

In order to structure human behaviour, Rasmussen (1983) provided a model for describing target-oriented human activities. He distinguished three levels of performance of skilled human operators (drivers): skill-based behaviour, rule-based behaviour, and knowledge-based behaviour. On the skill-based level, reactive, sensory-motor activities take place without conscious control. On a rule-based level, decisions are taken based on an earlier collected set of rules. If no learned rule for a situation is available, the knowledge-based behaviour has to be used.

Donges (1993) combined the hierarchy of driving tasks and the processing levels of the human operator to a single model (see Figure 4.2). Donges also offers a good summary of the current use and development of driver models in the context of ADAS and ADS development (Donges, 2015).

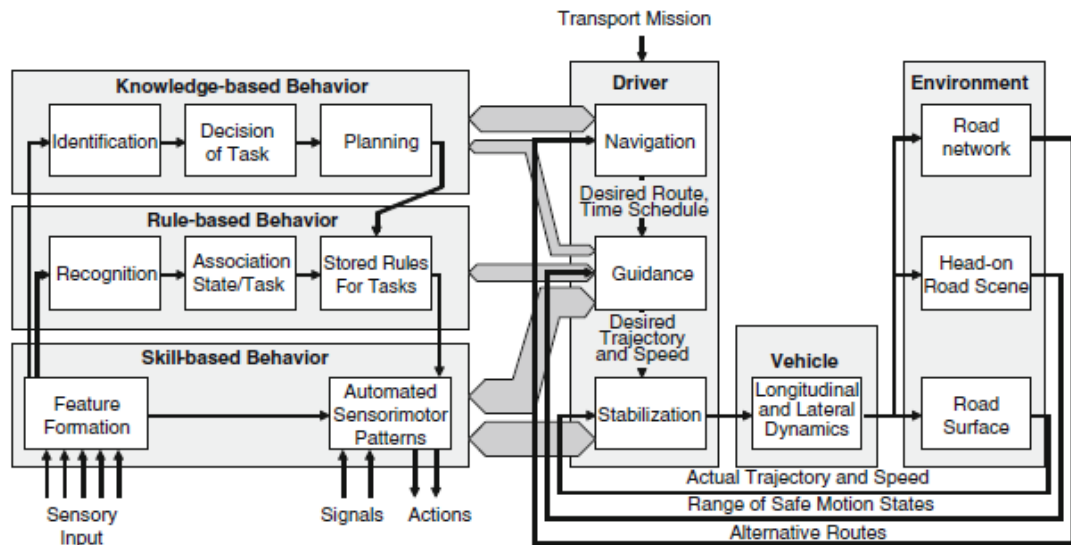


Figure 4.2 Categories of human target-oriented behaviour and three-level hierarchy of driving task (Source: Donges, 2015).

4.2.2.2. The driving automated system as a rational agent

A second concept in the development of driving automated systems is the concept of a cognitive system or a rational agent (Russell, & Norvig, 2010). Such a system or rational agent observes its environment, calculates a decision of further behaviour and performs actions on its environment. The focus of this consideration is the flow of information in such a technical system.

A driving automation system could be seen as a rational agent; it observes the environment, computes a decision and performs actions on its environment. In robotics, the information flow to allow such behaviour demands functional components of perception, planning and control (Behere, & Torngren, 2015). Due to the technical problems in the development of driving automation systems, it is feasible to separate localisation from perception (Ulbrich, & Maurer, 2015; Ziegler et al., 2014).

4.2.2.3. The generalised functional system architecture of a driving automation system

The model of the generalised functional system architecture, as depicted in Figure 4.3, combines both concepts. The horizontal axis represents the concept of the necessary information flow of rational agent (cognitive system) with columns for the localisation module, the perception module and the planning and control module. The vertical axis represents the three-level hierarchy of the driving task with its different anticipation time horizons. The main tasks of the generalised functional system architecture are to locate the necessary information for the decision making component (Chapter 6), explain the correlation between the different data sources and the level of information processing.

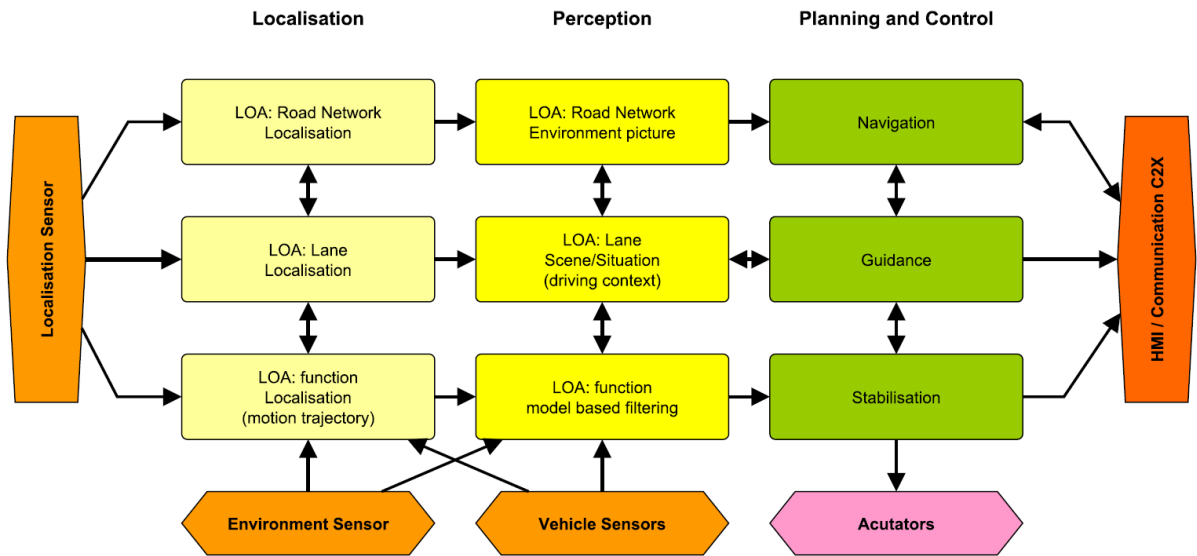


Figure 4.3 Generalised model of a functional architecture of driving automation system (LOA = Level of Automation) .

4.3. Required output of the automated system

In this section we discuss what the automated system has to deliver to the Mediator system and which data sources are available. First we look at what input the decision making component needs in order to determine whether the automation is sufficiently fit to be in charge of the driving task (Section 4.3.1). Subsequently, we describe the need for information about the driving context (Section 4.3.2). Finally, we discuss the appropriate intervention types (Section 4.3.3).

4.3.1. Automation state fitness values

The automation fitness value(s) constitute one or a few variables which summarise the automation's performance on the (full or partial) driving task, or its 'suitability' for that driving task, both now and in the near future.

These summary variables of the automation should be such that it will be possible for the decision making component to compare them (potentially after additional calculations and estimations) with the analogous fitness values of the driver (Chapter 3). As stated, these variables should reflect the fitness "now and in the near future"; i.e., not be limited to just the automation's fitness *right now*, but also take into account *predicted* fitness in the next period. The length of the next period will depend on the level of automation.

This prediction is essential to offer the human driver sufficient transition time to take over parts or the full driving task if needed. For SAE level 4 vehicles, it is more a question of comfort to organise a smooth transition of the Dynamic Driving Task (DDT) from the Automated Driving System (ADS) to the human driver before leaving the Operational Design Domain (ODD). However, in case of a DDT fallback situation when using an SAE Level 3 vehicle, providing the driver with sufficient time to take over is necessary to increase safety.

The automation fitness summary variables should be accompanied by *confidence* measures as an indication of how certain the automation system is about its values and how can it deal with

uncertainties. Again, this is important information for the decision making component of the Mediator system, because that component will be designed to act conservatively when it comes to safety (see Chapter 6), and thus be able to estimate the probability of the automation (and the driver) becoming unfit to drive.

One possible and plausible operationalisation of this type of automation fitness summary variables, at least for SAE level 3 vehicles (short duration transfer of control) and SAE level 4 vehicles (long duration transfer of control) is the estimate of the *Time To Automation Unfitness* (TTAU) and *Time To Automation Fitness* (TTAF), together with corresponding confidence values (or intervals). The TTAU reflects the estimated time until the automation can no longer drive safely. This value would neatly take into account current fitness as well as the predicted fitness in the near future. Having similar values for the fitness of the driver (i.e. Time To Driver Fitness (TTDF) and Time To Driver Unfitness (TTDU)) allows the decision making component to monitor and compare them and ensure safe transitions of control.

In case of SAE level 2 vehicles which require continuous mediation, the focus of the automation fitness summary variables is somewhat different. Here, the automation fitness value reflects the performance of the partial driving automation, while the overall monitoring and supervision has to be done by the human driver. Nevertheless, the principle is still the same: these summary variables also take account of the current performance of the automated system, the predicted performance in the near future and the associated confidence estimates in order to provide the decision making component with meaningful information about whether the automation is safe and comfortable to use now and in the near future.

An important aspect of switching between automation and human driver as the main operator of the vehicle is mode awareness of the driver. Sarter and Woods (1995) define the mode awareness as ‘the ability of the user to track and to anticipate the behaviour of a given driving automation system feature’. The driving mode, i.e. which automated driving systems are currently on and their performance, affect the level of automation and the level of degradation in performance, respectively.

For example, if a vehicle with SAE level 2 automation approaches a road section with poor lane marking, the lane-keeping system might become unable to (fully) control the lateral movement of the car requiring immediate human intervention. While automated driving systems aim to improve road safety, limitations of the technologies might (still) require the intervention of the human. Timely notification by the Mediator system to the driver through the HMI is needed to prevent mode error and increase the mode awareness.

The proper timing and mode of communication with the driver via the HMI highly depend on the driving context and the environment's complexity (e.g., approaching a sharp curve or a busy intersection) as well as the driver state (e.g. related to fatigue, distraction, workload). In these driving situations, the automated vehicle could support the decision regarding the timing and mode of communication by continuously monitoring the user state and as well the driving environment complexity. This opportunity is particularly useful for SAE level 2 and 3 vehicles. The availability of High Definition (HD) maps and Infrastructure-to-Vehicle (I2V) communication can increase the awareness of the automated vehicle of its surrounding environment and any upcoming events down the road. For example, in case the vehicle is approaching a sharp curve in which the lane-keeping system cannot operate appropriately, this should be communicated to the driver in sufficient time before approaching the curve. Figure 4.4 illustrates the recommended type and mode of communication during manual driving when approaching a curve. As shown in Figure 4.4,

the visual demands are high during the entry and negotiation section, and medium to high during the curve discovery. Therefore, presenting complex information (e.g. that requires reading and/or interpretation) should be avoided 4-5 seconds before the point of curvature.

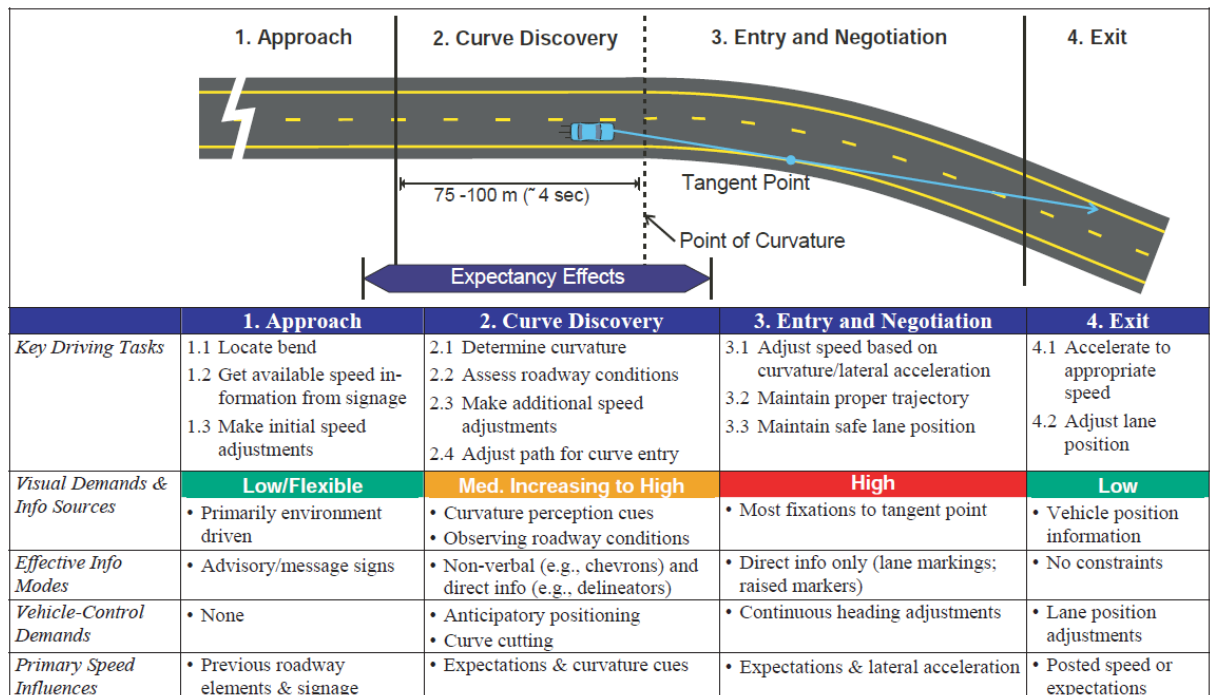


Figure 4.4 Different curve segments, key driving tasks and constraints (Source: Campbell, et al., 2012).

4.3.2. Automation state contextual Information

In addition to the automation fitness summary variables, the automation state component must provide information about the *contextual* information. This information should constitute information that helps the decision making component to make better, context-sensitive decisions, as well as potentially provide selected relevant context information to the human driver (through the HMI component).

An example connected to an SAE level 3 vehicle might illustrate this. If the *Time To Automation Unfitness* value (see Section 4.3.1) is dropping, it could have several different reasons. One reason could be that the vehicle is about to leave the defined ODD. Another reason could be an unexpected incident that the automation had not previously foreseen. Yet another reason could be that road lane markings are no longer as visible as before. These reasons result in qualitatively very different situations that might require very different actions of the Mediator system. In some situations, however, reaching the end of the ODD can be foreseen for a longer time. It might be that in these situations the driver has been preparing for some time to resume control and therefore, the HMI interaction would be different from a situation of unexpected incident. In the case of an incident more urgent take-over procedure might be needed, for example together with an 'alarm-like' signal. Furthermore, in the latter case, the take-over by the human driver would probably be significantly facilitated if he or she received information about the context or type of incident, as assessed by the automation system.

However, even when there is no immediate need for a transition of control from automation to human driver or vice versa, contextual information is a useful input to the decision making component and the HMI of the Mediator system. Contextual information will help to decide how to maintain and/or improve human fitness (anticipating on a potential future take-over request), as well as to maintain trust, comfort, and transparency for the human driver. For example, trust by and comfort of the driver may benefit very much if the HMI provides some information derived from this automation-provided contextual information by having transparency on its functioning, e.g., by displaying the (accuracy of) lane position estimates or other relevant road users around the vehicle, including some representation of the time headway to the lead vehicle. In case of a SAE level 2 vehicle that requires continuous human supervision and monitoring, displaying contextual information and potentially engaging the human driver in some interactive process based on that, may help to make the human driver less prone to distraction and drowsiness.

4.3.2.1. Causes of disengagements of the automation

As indicated, there are several reasons why it is very important for the Mediator system to have information about the driving context. The next question then is how to collect, process, and interpret the contextual information in a reliable way.

Collection of this information may employ several different types of sensors (such as camera- or LIDAR-based), either individually or in combination (i.e. sensor fusion). In addition, certain sensors may be employed to perform multiple tasks. For example, a LIDAR can be used for both roadway object detection and 3D mapping of the environment (Hillel, Lerner, Levi, & Raz, 2014). However, the sensors underlying the systems that control the longitudinal movement (such as Adaptive Cruise Control (ACC)) as well as the systems that control the lateral movement (such as Lane Detection and Tracking (LDT) and Lane Departure Warning (LDW) systems) are affected by several factors in the driving context which can lead to a degradation of their performance or even stopping the performance of their intended functions.

The disengagement reports from the different OEMs conducting trials on California public roads provide insights into the current factors influencing disengagements of autonomous mode. Dixit, Chand and Nair (2016) categorise these disengagements to automatic and manual disengagements. Automatic disengagements are those initiated by the driving automation system and occurred due to failure either in the software (such as detection technology, communications breakdown, improper sensor readings) or hardware issues. Manual disengagements, on the other hand, are those initiated by the human and occurred when the test drivers reacted in response to other road users, due to discomfort with the automated mode, adverse weather conditions, construction activities, to perform lane changing in heavy traffic, and poor road infrastructure. The authors found a relatively high correlation of 0.73 ($p\text{-value} < 0.01$) between the monthly automatic disengagements/mile and manual disengagements/mile indicating that drivers form their trust based on their experience of automatic disengagements. Road infrastructure (including poor road conditions such as improper lane marking, holes and bumps) and the unexpected/reckless behaviour of other road users (such as cyclists, pedestrians, and other drivers) were also found to be a major cause for disengagements. Finally, construction zones and weather due to rain and sun glare also caused disengagements.

Considering vision-based systems (such as LDT and LDW), for road marking detection or road sign detection, the consistency in design, quality, reflectivity, and high visibility of the road markings and road signs are critical (Lawson, 2018). Type of road (i.e. highway, urban road or rural road), existing discontinuities (such as weaving sections, on-ramps and off-ramps), and road surface quality (smoothness, wetness or dust/slush) are also important factors. In addition, the traffic state

of surrounding vehicles on the road and their behaviour (such as vehicle cut-in situations) might affect the performance of these systems. Table 4.1 identifies factors affecting the performance of automated driving systems (the list is not exhaustive) based on the studies by Schoettle (2017), Hillel et al. (2014), and García (2019).

Table 4.1 Factors Impacting the Performance of the driving automated system.

Factors	Impacts on Performance
Extreme weather (heavy rain, snow, or fog)	Reduces maximum range and signal quality (acuity, contrast, excessive visual clutter) for audio/visual systems (cameras, Light Detection And Ranging (LIDAR)), and Dedicated short-range communications (DSRC) transmissions (though to a lesser extent).
Excessive dirt or physical obstructions (such as snow or ice) on the vehicle	Interferes with or reduces maximum range and signal quality (acuity, contrast, physical occlusion of field of view) for all basic AV sensors (cameras, LIDAR, radar).
Darkness, low or abrupt changes in illumination	Reduces maximum range and signal quality (acuity, contrast, possible glare from external light sources) for AV camera systems. For example: When exiting a tunnel; Glare, bright sunlight, oncoming headlights
Large physical obstructions (buildings, terrain, heavy vegetation, nearby vehicles, etc.)	Interferes with line of sight for all basic AV sensors (cameras, radar, LIDAR); some obstructions can also reduce the maximum signal range for DSRC. For example: Nearby vehicles creating severe occlusions; Shadows from nearby trees, noise barriers and buildings creating misleading edges and texture on the road;
Road design	Several road design elements affect the performance of ADS: Sharp curves and S curves Narrow lanes Change in lane markings' type or width near discontinuities (such as: on-ramps, off-ramps, and weaving sections) Remaining of old lane markings
Dense traffic	Interferes with or reduces line of sight for all basic AV sensors (cameras, radar, LIDAR); can also interfere with effective DSRC transmission caused by excessive volumes of signals/messages.
Road users behaviour	Sudden or abrupt behaviour of road users, such as: Vehicle cutting-in Sudden appearance of a pedestrian/cyclist
Systems limitations	LKAS are designed to function only under certain speed ranges. For all speeds outside the specified ranges, the LKAS either stops functioning or its performance reduces. LIDARs: range ~ 200m Radar: range ~ 250 m Camera systems: Field of view (horizontal): ~ 45° to ~ 90°

4.3.2.2. Impact of the sensor equipment on the performance of automation

Figure 4.5 summarises an assessment of how different sensor strategies can handle individual driving tasks compared to the human driver. Each sensor strategy has its strengths and weaknesses, and it clearly shows that sensor fusion can contribute to compensating for the limitations of each sensor strategy on its own.

Performance aspect	Human	AV			CV	CAV
		<i>Radar</i>	<i>Lidar</i>	<i>Camera</i>	<i>DSRC</i>	<i>CV+AV</i>
Object detection	Good	Good	Good	Fair	n/a	Good
Object classification	Good	Poor	Fair	Good	n/a	Good
Distance estimation	Fair	Good	Good	Fair	Good	Good
Edge detection	Good	Poor	Good	Good	n/a	Good
Lane tracking	Good	Poor	Poor	Good	n/a	Good
Visibility range	Good	Good	Fair	Fair	Good	Good
Poor weather performance	Fair	Good	Fair	Poor	Good	Good
Dark or low illumination performance	Poor	Good	Good	Fair	n/a	Good
Ability to communicate with other traffic and infrastructure	Poor	n/a	n/a	n/a	Good	Good

Figure 4.5 Assessment of sensor performance across driving tasks (Source: Schoettle, 2017).

4.3.3. Appropriate intervention type

The third type of information that the automated system has to deliver to the Mediator system is the appropriate intervention type. This is directly related to the second type of information described above, the contextual information. The appropriate intervention type refers to what the automation, based on its information and assessment, thinks might be possible and suitable actions, given the driving context. In many cases this may be limited to "shut the automated driving system off", e.g. when the system leaves its ODD because the vehicle leaves the highway, or because of an incident. Alternatively, vice versa, when the system enters its ODD, the suggested appropriate intervention type may be "the automated driving system can be turned on".

In some other cases, however, there may be other options. For example, it is conceivable that in case the lane markings are currently not sufficiently visible, the intervention "change lanes", which may have to be executed (or perhaps approved and monitored) by the human driver, would result in better visibility of the lane markings, and thus in better automation fitness values and the potential to keep the automated driving system on for longer. Similarly, for SAE level 4 vehicles, the suggested intervention could be to "take a different route" because that might mean that the vehicle could remain in the Level 4 automated driving zone longer, providing more comfort and rest for the human.

4.4. Driving Automation Systems as a source of information

The current section describes how the information that is collected for the driving automation systems can be used for our Mediator system. First, it describes the information that stems from internal performance assessments by the automated system (4.4.1); then it focuses on context information: what is available (Section 4.4.2) and what can be improved (Section 4.4.3), and finally it discusses various issues related to confidence, values, and uncertainties (Section 4.4.4).

4.4.1. Degradation strategy and key performance indicators

As mentioned in Section 4.2.1 the standard (SAE, 2018) classifies the transfer from total control from the human driver to driving automated systems as a stepwise process on a scale from 0 to 5.

SAE Level 0 involves no automation and SAE Level 5 means full-time performance by a driving automated system on all driving aspects, under all road and environmental conditions.

During the operation of an SAE Level3+ vehicle, the safe behaviour must be guaranteed, as the human driver is not requested to supervise the driving permanently. To cover the enormous variety of situations, which must be handled by an SAE Level3+ systems, the design and development of the system must follow an ISO 26262 compliant development process. The ISO 26262 standard demands a functional safety concept, which means that the SAE Level3+ automated driving systems must be continuously aware of its current performance and its remaining capabilities (Reschka, & Maurer, 2015; Serban, Poll, & Visser, 2018).

Depending on the current situation, including the intention of the automated system, a decrease in performance of a certain system module has a different impact. For example, suboptimal but still sufficient performance of the front radar has a lower impact on the performance of the complete automated system in a traffic jam scenario compared to a highway scenario.

The internal key performance indicators (KPIs) and degradation strategies of individual modules or the complete driving automation system will take the internally available context information into account. In order to assess the usability of this information for the Mediator system it is important to examine the difference between the automation fitness values as required inputs to the Mediator system (see Section 4.3.1) and the internal KPIs of the automated system. In connection with the additional context information from the human operator, it could be worthwhile to re-evaluate the internal KPIs before the computation of the Automation Fitness Values.

4.4.2. Context information and driving context

In case of lower levels of automation (SAE level 1 to 2), the human driver has to monitor the environment and supervise the performance of the driving automation systems. With higher degrees of automation (SAE level 3+), the driving automation system is responsible for the monitoring of the environment and its performance.

This fact does not mean that the lower level automation does not monitor the environment. For example, most SAE level 2 systems are responsible for the driving task at the stabilisation level, like lane-keeping assists, or offers the human driver advice in certain traffic situations. To perform these parts of the driving task, monitoring of the traffic environment is necessary. However, the scale of perception, the understanding of complicated traffic situation, is one of the differences between supervised and unsupervised automated driving systems.

Another difference is the scale of the planning and control module and the perception module in the functional system architecture (Pink, Becker, & Kammel, 2015). To allow safe planning of further driving behaviour, the planning and control module needs a representation of the real world. Not only the information of the distance to a leading vehicle or the relative position to the lane marking localisations, the planning of a feasible and safe trajectory also requires context information. Will the slower leading vehicle perform a lane change to the slower lane or is there a sufficient gap between the vehicles on the faster lane to perform a lane change for an overtaking manoeuvre. The extraction of more but also relevant context information is an opportunity to allow more foresight with the same hardware equipment (Ulbrich, Nothdurft, Maurer, & Hecker, 2014).

Our Mediator system is meant to operate for different levels of automation (SAE levels 2 to 4). Hence, it will have to use a generalised functional system architecture (see Figure 4.2), with a consistent definition of the terms to describe the context information. Terms to describe the context

information like situation, hazardous event or operation scenario are widely used in the field of automated driving. In this respect we refer to Ulbrich et al. (2015) who differentiate and define these terms based on a comprehensive literature review.

The context information that is relevant for the decision making component and for the human driver will be collected as part of the automation state contextual information, as described in Section 4.3.2. This information will be part of the driving context part of the Mediator system. The driving context information is meant to assist the driver in completing his knowledge about the surrounding situation; it transfers information that the driver might have missed because of inattentiveness or mental overload, or because it was hidden behind an obstacle, or even because the information was inaccessible for human senses. Such assistance is not only beneficial for safety, but it also might increase the trust of the driver in the automated system.

As explained by Ulbrich et al (2015), context information is always subjective depending on the observer point of view and the relevance for the observer's operational tasks. For our Mediator system, it is an important task to find out how to extract the relevant context information for the human driver from the context information of the automated system. A second important task is to achieve a balance between available context information, the hardware constraints of the interface to the Mediator system, and the hardware and software capabilities of the Mediator system to handle the context information.

4.4.3. Ways to improve the context information of the driving automation system

Currently, the available context information is not yet optimal for the purposes of our Mediator system. The design of SAE Level 3+ vehicles is constrained by the ISO26262 design process and especially by the requirements concerning the safety validation and safety verification of the system. In the developed countries, the risk of an accident is relatively low, but the required proof that the automated driving system is at least as safe as a human driver will be hard to achieve (Winner, Wachenfeld, & Junietz, 2018). One important reason is the massive amount of possible situations (Junietz, Wachenfeld, Klonecki, & Winner, 2018). A certified SAE Level 3+ vehicle will only operate if it has enough relevant context information to identify a situation and to plan a feasible and safe trajectory for that situation.

Various reasons could limit the quality of the context information. Some reasons may originate from the kinds of uncertainties discussed in Section 4.4.4. Other may originate from deficiencies in the process of context information building or be the result of an ambiguous traffic scene. For example, it may be ambiguous which of the perceived markings belong to the host lane.

For the longer term, solutions will become available to avoid insufficient or low quality context information, both infrastructure-based and vehicle-based. For this, the availability of a highly accurate digital map and the opportunity of dedicated short-range communications (DSRC) should be mentioned. For the shorter term, finding a solution is more challenging. The current design of an automated driving system compliant with ISO26262 would not allow direct feedback from the Mediator system. It would be only possible if the Mediator system design is also compliant with ISO26262. Thus, the interaction between the automated driving system and the Mediator system should be part of the development process of the automated driving system. However, if the Mediator system uses the human driver as bypass, it could use the user interface of the automated driving system. If the human driver has the necessary information via the HMI of the Mediator system, it could advise the automated driving system with the existing user interface of the automated system to initiate a behaviour change (see Figure 4.1). For example, in case of poor

lane markings on a right lane, due to the heavy use of this lane by trucks, the driver could advise a lane change to the left lane with better lane markings.

4.4.4. Confidence values and uncertainties

The planning and control module (see Figure 4.2), and especially the trajectory planning, has to deal with uncertainties (Nolte, Ernst, Richelmann, & Maurer, 2018), with incomplete parts and noisy parts of the context information. In a simulation, it is possible with a perfect representation of the environment, combined with an ideal representation of the host vehicle and all other traffic participants to model complete and accurate context information.

A first type of uncertainties relate to the completeness of the information. In reality, there are many reasons that the context information is incomplete. Nolte et al. (2018) call this this epistemic uncertainty. Reasons include the impossibility of observing from parts of the environment due to missing sensor equipment, limited sensor range, the occlusion of the sensor's field of vision, missing knowledge about the intended behaviour of other traffic participants, and simplified model of vehicle dynamics. Simplified, the epistemic uncertainty has its origin in a lack of information (Der Kiureghian, & Ditlevsen, 2009).

A second type of uncertainties has a statistical origin, also named aleatoric uncertainties (Nolte et al., 2018). These uncertainties could be, for example, unavoidable measurement and process noise in evaluation algorithms of sensor data or in algorithms to estimate the state of the host vehicle.

Both types of uncertainties have an impact on the evaluation of the internal key performance indicators and the internally used context information. It is a challenge to increase the usefulness of the automation fitness values and the automation state contextual information while taking account of both types of uncertainties.

4.5. Conclusions

The ISO 26262 standard covers the development process of driving automation systems. It demands a functional safety concept concerning the defined functional range and system boundaries. It defines Automotive Safety Integrity Levels (ASIL), which provides Failure In Time (FIT) targets for hardware and software components. It defines how the software should be designed, developed, and tested. All these development constraints lead to a technical system which could provide the required input information of the decision making component of our Mediator system.

However, in order to realise the desired functionality of the Mediator system, we need to achieve a balance between the available relevant information on the one hand, and the hardware constraints of the interface to the Mediator system and the hardware and software capabilities of the system on the other. This is a challenging task. It requires the examination of the uncertainties, the available context information and the internal key performance indicators of each module of the generalised functional system architectures and also possible combinations to fulfil the trade-off. Existing studies of the performance and usability of the existing driving automation system will allow focussing the necessary investigations.

In order to be able to define and quantify the required information from the automation several knowledge gaps have to be closed, which can be summarised as follows:

- How to calculate the automation fitness summary variables, including prediction and confidence values, while driving and for the different levels of driving automation? Furthermore, how to choose the most relevant combination of weighted internal information, like internal key performance indicators, the ODD or context data for this calculation?
- How can the automation fitness for the SAE level 3 vehicles be improved to exceed the transfer time from the few seconds, guaranteed by the automated system, to larger values to allow the driver more comfortable take-over, considering the automation and driver state contextual information in a given driving context?
- Which automation state contextual information is needed to enable the decision making component of the Mediator system to provide a consistent and usable classification of traffic situations? Furthermore, for different levels of automation, which automation state contextual information is available and how should it be processed for the Mediator's HMI to provide the driver with useful information on the current performance of the automated system and useful information about the traffic situation in order to improve transparency, trust, and take-over performance?
- Which automation state contextual information, in combination with driver state contextual information would allow creating the necessary driving context information to enable the decision making component to advise on or perform an appropriate intervention type?
- How should the application programming interfaces (APIs) for all these relevant sources of information look like and how can they be realised effectively, within the constraints of the vehicle computing hardware and software?

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5. The Human Machine Interface (HMI)

5.1. Introduction

Automotive systems will allow the driver to be supported by smart tutors, during a trip or during a parking manoeuvre. The purpose of such systems is to increase the driving comfort (allowing the driver to be also involved in non-driving tasks) and most of all road safety. The path to vehicle automation has to follow different steps and before full automation is provided, different aspects have to be deepened. The analysis of the autonomous-driving innovation feasibility involves many different perspectives (e.g.: technology maturity, regulations, infrastructure, etc), but last and not least we are facing vast challenges in human factors. In particular, the Human Machine Interface (HMI) design is a fundamental key to ensure safe control transfers between human and automation.

The HMI of a vehicle can be defined as “a set of all interfaces that allow the user of a vehicle to interact with the vehicle and/or devices connected to it” (Wetzel, 2013). Carsten & Martens, (2019) define the “HMI” as the set of explicit and implicit communications between human operator and the vehicle, comprising all vehicle controls that provide channels (input to the vehicle and feedback for the driver) in between. The HMI should take into consideration several demands that need to be evaluated and balanced; such as driver and passenger needs, available technology, applicable regulations, and costs. Note that the MEDIATOR project focuses on mediating between a driver and his/her vehicle, but not on interactions with other road users. By adopting the above HMI definitions of a vehicle, the external HMI of the vehicle (e.g. potential indications on the automation status to other road users) will be acknowledged but is not part of the project scope.

The flow diagram of Figure 5.1 illustrates how the HMI of the Mediator system is expected to be positioned in relation to the other components of the Mediator system. Driver interaction with the HMI i.e. inputs and outputs are interpreted and controlled by the HMI software. In turn, the HMI software communicates with the decision logic component. The latter informs the HMI software when an action *from* the driver (e.g. resume lateral control) or *to* the driver (e.g. a wake-up call) is required. In other words, the HMI software does not decide *if* and *when* an action is needed, but it does determine *how* an action is best materialized. Furthermore, the decision logic component informs the HMI software on the automation options that are available to the driver (i.e., functionalities related to SAE level 4 automation may not always be available in each driving context). Again, it is up to the HMI component to translate such signals into an appropriate interaction with the driver (see Chapter 7 on functional requirements). Finally, the HMI software informs the decision logic component of the current HMI state (e.g., if a warning signal is currently being transmitted) and of any inputs by the driver (e.g., driver’s preference to activate longitudinal and lateral automation).

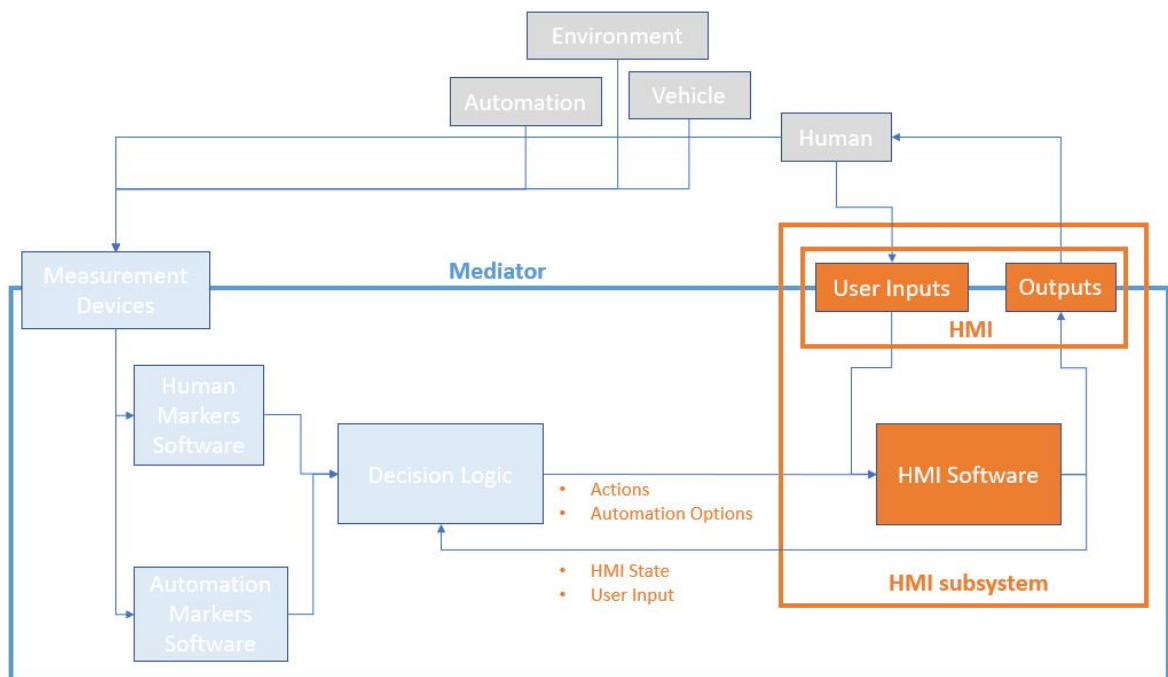


Figure 5.1. Expected signal flow of the HMI component within the Mediator system. From the perspective of the driver, the HMI comprises the user inputs and outputs.

The aims of this chapter are:

- To identify main HMI challenges related to different levels of automation and the functional requirements (Section 5.2);
- To identify (knowledge on) potential design space to address these challenges, which may be applied in the HMI component and/or in the Mediator system as a whole (Section 5.3);
- To identify recommendations from general HMI design principles (Section 5.4);
- To identify lessons that can be learned from other transport modes (Section 5.5);
- To identify missing knowledge related to these challenges (Section 5.6).

5.2. Challenges

Chapter 7 describes the top-level functional requirements for our Mediator system, distinguishing between different levels of automation (SAE levels 2-4). From the perspective of the HMI component, these functional requirements elicit several questions. For example, how do we implement interventions for the different automation levels? Which controls do we need for this? How do we ensure that drivers understand, trust, and use the Mediator system within the boundaries it is designed for? Should we personalise the HMI, and if so, how? How much information does the driver need and when is it too much?

In addition, the European Road Transport Research Advisory Council (ERTRAC, 2019) lists several questions about the path to higher levels of automation, some of which are (indirectly) related to the HMI. How to understand the interaction between humans and automated vehicles (in-vehicle and outside the vehicle) at different levels of automation? How will driver training and an awarded driving licence handle the differences between the functionalities of semi-automated cars, and between the environments and conditions in which they operate? Will driver training decrease over time with increased levels of automation? How to adapt the vehicle automation to different user needs and group? These questions are addressed by a number of HMI challenges: trust,

fatigue, distraction, mode awareness, information overload and underload, learning and unlearning, user acceptance, and industry acceptance. The relations between challenges and functional requirements are summarized in Table 5.1. In terms of HMI and user acceptance, a forced take-over procedure must likely be implemented differently than a voluntary take-over procedure. Therefore, we have divided the original functional requirement ('take-over procedure') into two functional requirements. Each of these HMI challenges are discussed in the next subsections.

Table 5.1 HMI Challenges. Each challenge is related to one or more functional requirements (indicated by orange fields). 1 = The challenge is to elicit trust that the Mediator system will indeed improve human fitness. 2 = The challenge is to elicit trust that the Mediator system informs the driver in time. 3 = The challenge is to elicit trust that a forced take-over by automation was justified. 4 = Mode confusion is a challenge within the driving mode, but not likely during transfer of control. 5 = Challenge when an unfit driver wants to resume control. 6 = This challenge is mostly relevant for the SAE levels 2 and 3 automation. 7 = Not a challenge, because urgency of the situation overrules the desire for differentiation in terms of brand identity.

Challenge	Functional requirements							
	Transfer control automation to human			Transfer control human to automation		Within driving mode		
	Improve human fitness	Voluntary take-over procedure	Forced take-over procedure	Voluntary take-over	Forced take-over	Improve/maintain human fitness	Maintain trust, comfort, transparency	Establish shared control
Trust	1		2		3			
Mode awareness						4		4
Fatigue		5						
Distraction		5				6		
Information load								
User acceptance								
Industry acceptance			7		7			
Learning								
Unlearning								

5.2.1. Trust

Trust is a multi-faceted challenge (see Section 3.5.3). On the one hand, if drivers do not trust the Mediator system, they are unlikely to obtain it, let alone make use of it. If, on the other hand, drivers have too much trust in the system, they may wrongly expect the system to function outside its operational domain. Both facets (i.e., insufficient trust and overreliance) are discussed next.

5.2.1.1. Trust prior to an interaction

People appear to differ in their trust regarding the prospect of self-driving cars. A recent survey that BMW conducted amongst their customers, whom may be identified as enthusiastic self-drivers, revealed that while they indeed like to drive themselves, they would be perfectly happy to have the car driving autonomously half of a four-hour trip (BNR, 2019). In contrast, a market research

carried out in 2015 among the residents of the metropolitan area of Austin in Texas revealed that half of the respondents were inclined to use a self-driving car, while the other half did not have trust in this type of technology (Zmud, Sener, & Wagner, 2016). The responses were independent of demographic variables such as age. The variables that instead influenced the propensity to use new technologies were mainly psychological, such as the perception of security, anxiety for the context, the fear of losing privacy, and social influences. Although neither BMW drivers, nor residents in Austin, are representative for the entire European population of drivers, these findings do indicate that not all potential car buyers will initially trust the Mediator system. The challenge for the Mediator HMI, then, is to improve and elicit trust by addressing factors that impact trust while driving.

5.2.1.2. Overreliance as a result of using the system

Trust in a system can change as a result of using a system. Traditional drivers are used to being supported by active systems (Advanced Driver Assistance Systems - ADAS) that are able to be more sensitive to danger than drivers, and able to warn them promptly when necessary. Drivers seem to be slightly passive in the interaction with traditional ADAS: they drive and act more readily in critical situations when the system does not intervene itself, than what is expected during the interaction with automated vehicles. While “warn-act” systems do not require high levels of decision making or contextual interpretation, in aviation the autopilot system has been known to be affected by automation surprise (e.g., Sarter et al., 1997), which occurs when an action by the system is not expected by the pilot. If automation surprise persists in the automotive domain, this means that future drivers will face new fleets of vehicles, potentially more comfortable and safer. But that will require the driver to be more capable to properly “interpret” the situation considering that the vehicle will intervene in his/her turn. The HMI design will have an important role in making this “interpretation” easy, avoiding surprise effects.

During manual driving, the driver experience allows him/her to adapt flexibly to other road user’s behaviour and to the external context complexity and variability (Horswill, & McKenna, 2004). The automated vehicles will not be able to see and interpret the world as a human driver does, and sometimes will be unable to adapt equally flexible to the environmental complexity. This discrepancy in approaching the different scenarios (due to a conflict between the driver mental model and the vehicle actions path and/or decision-making strategies) would generate misinterpretations and misuses, that could become the cause of severe incidents. For example:

- SAE level 2 and 3 automated systems that brake promptly in front of various obstacles have to adapt to the driver’s mental model, so that drivers may wrongly assume that the system is able to brake in case of all “frontal dangers”, and not intervene when required;
- SAE level 2 and 3 automated systems that are able to manage some, but not all types of curved roads, could adapt the driver’s mental model to expecting that the automated vehicle will always intervene (e.g., by braking) when it is not able to, again causing the driver not to react when required.

The first example is illustrated in a study by Victor et al. (2018), in which three experiments were conducted with a level 2 vehicle on a test track. Drivers were driven for 45 minutes until the vehicle approached a dummy vehicle parked on the road. Although the level 2 vehicle was programmed to stop at the latest possible moment, the aim of the study was to test if drivers would perform an evasive manoeuvre themselves (i.e., braking or steering). In the first experiment, many drivers did not do so, in part because they fell asleep or because they were not looking at the road. In the second experiment, drivers were reminded through the HMI to keep their hands on the steering wheel and keep their eyes on the road. Despite these instructions, some participants still

failed to perform an evasive manoeuvre. Just as in the first experiment, the drivers indicated that they thought the system would be able to handle the dummy vehicle.

Therefore, in the third experiment, drivers were explicitly told that the level 2 vehicle would not be able to handle vehicles parked on the road, so they would have to perform an evasive manoeuvre themselves. Despite these additional instructions, some drivers again failed to perform an evasive manoeuvre. Some of them indicated they were doubting on whether to react, but eventually decided not to because they judged the level 2 vehicle would be able to handle the situation. This study shows that overreliance can develop over a relatively short time-span; the authors refer to this as dynamic trust.

5.2.2. Mode awareness

Complex automated systems could pose the potential risk of confusing the users and therefore provoke erroneous behaviour termed as mode error (Sarter and Woods, 1995). Multiple modes in a computerized device could lead to mode error (Lewis and Norman, 1986). This is inherently a human machine system breakdown which occurs when users lose track of which mode the system is in. Poor system feedback, high complexity of the automated system and insufficient mental models have found to result in erroneous behaviour of pilots which led to the cause of several accidents in the aviation sector (Sarter, 2008). Alike in aviation, the automotive sector also faces a similar set of challenges in implementing different levels of automation in a vehicle, thereby increasing the complexity of the system.

In general, there are two approaches to avoid mode error. Firstly, mode error may be prevented by an adequate HMI that ensures the user is aware of the system mode and its behaviours. A study by Feldhütter et al. (2019) indicates that this is indeed an HMI challenge, both in terms of design and in terms of evaluation. The researchers reported from a driving simulator study that participants failed to distinguish between two modes (partial automation and conditional automation) due to their similarity in system behaviours. The study findings also reported that overreliance and not the lack of mode awareness was the main cause for participants reduced monitoring behaviour. A second approach to avoid mode error is to avoid the necessity of knowing the (theoretical) system mode in the first place, by creating an environment that makes the driver aware of his/her responsibility (i.e., the tasks assigned to the driver).

5.2.3. Fatigue and distraction

As described in Section **Fout! Verwijzingsbron niet gevonden.**, driver fatigue can be divided into sleep-related and task-related fatigue, the latter of which can be due to overload as well as underload. Each type of fatigue requires a different approach in terms of countermeasures, and therefore, in terms of HMI interventions. First, for sleep-related fatigue only sleep will recuperate the driver in the long run.

A challenge for the HMI is posed for situations in which the vehicle cannot maintain operation at e.g. SAE level 4, in which sleeping is optional. Should the HMI convince the driver to stop driving altogether? Secondly, for task-related fatigue due to overload, drivers should stop driving and temporarily shut off demands of sustained attention by taking a short break at a rest stop, or by vehicle automation. Thus, the HMI challenge is to either convince drivers to take a break, or to handover control. Third, for task-related fatigue due to underload, activation rather than rest is to be recommended. The HMI challenge is to either provide the driver with a (non-driving) task or, if vehicle automation is activated, to activate the driver by convincing him/her to resume control, given that the driver has (re-)established situation awareness.

Continual proliferation of in-vehicle information systems present drivers with opportunities for distraction (or activation, in case of task-related fatigue due to underload). Especially during level 3

automation, drivers will likely simultaneously manage driving-related activities (DRAs) and unrelated but cognitively demanding non-driving related activities (NDRAs). Vehicle designers need ways of understanding human capability in such situations to provide solutions that accommodate these conflicting demands. This could assist in the development of interfaces that enable drivers within different levels of automation to achieve high performance with various NDRAs without inhibiting or constraining performance for DRAs.

5.2.4. Information underload and overload

The amount of information provided to the driver is directly associated with the level of task demand for the driver. As described in Section 3.2, high subjective workload can be a result of too low task demands, as well as too high task demands. In turn, high subjective workload has a negative impact on driving performance. Therefore, the amount of information provided to the driver by the HMI should be balanced with the total load of information for the driver to process, as depicted in Figure 5.2.

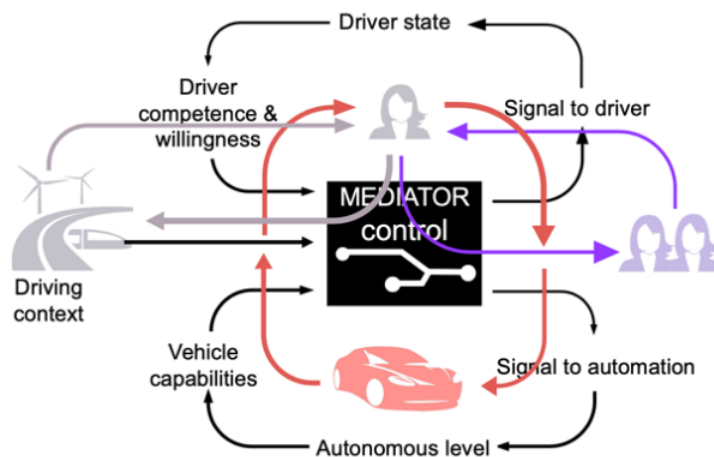


Figure 5.2 System (black lines) and real-world information streams (grey, red, and purple lines).

In cognitive processes the abundance of information while driving a vehicle is structured in layers and sorts of information. The correlation between required driver alertness (concentration) and the HMI's ability to steer or properly frame the total information load (reference) indicates that the HMI task comprises of providing information as well as shielding information. Identified information streams (Figure 5.3) are:

- HMI information on driving task and future driving context (anticipated task changes);
- Non-driving tasks of the HMI, such as entertainment systems and augmented information about the context (e.g., environment, commercial triggers);
- Social media interaction
- Visual and haptic noise of the vehicle interior design, e.g., design ornaments and interior lighting;
- Social interaction with passengers in the vehicle as well as with other road users;
- Physical information about vehicle movements through hands, feet, seating and balance from e.g. temperature, lateral and transversal movement, acceleration and deceleration, and road conditions;
- Observation of the driving context, i.e. the environment of the vehicle.

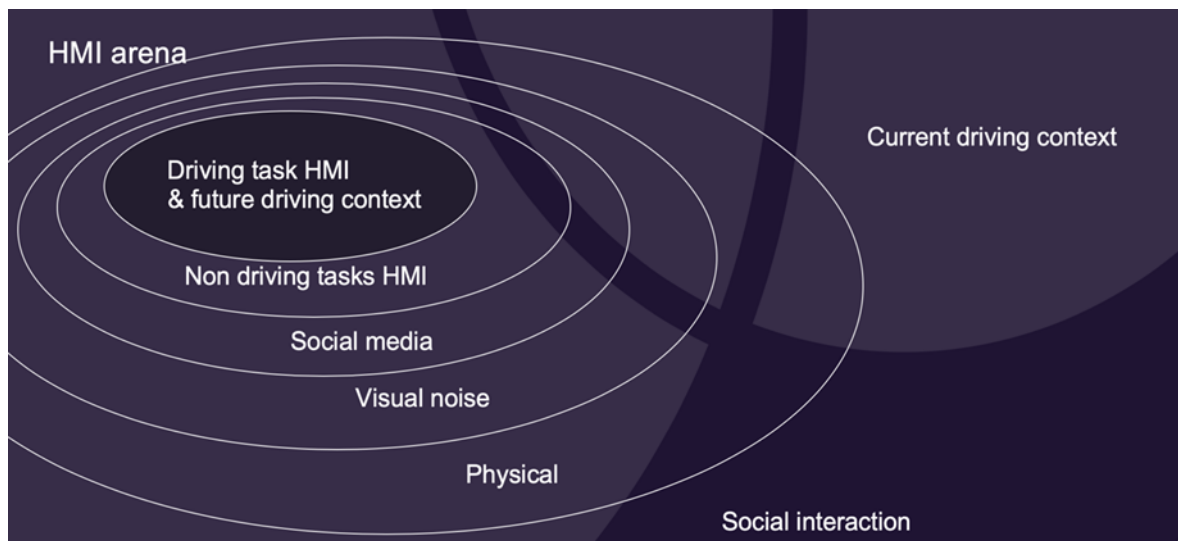


Figure 5.3 Layers and sorts of information.

Note that a driver will collect individually, through senses, the same information as the Mediator system does through its variety of sensors. While the Mediator system processes this information into a preferred driving mode, the driver may interpret the same information differently and draw another conclusion.

In principle, the design scope includes all identified information layers within the vehicle interior. In the design task the level of detail and inclusion of each must be determined, depending on the experimentation scope and available resources, to avoid information underload and information overload.

5.2.5. User acceptance

Abbink, Mulder and Boer (2012) conclude that there is an ample body of literature that provides arguments and evidence for the need for human-automation interaction. Or as they put it (page 26): “In some cases, the human will accept that someone/something else takes over his/her tasks and might even prefer this. In other cases, the human will want to feel free and in control. But how do we ensure as engineers that the human operator feels free to act? Sociologist Zygmunt Bauman (2000) argues that “...to feel free means to experience no [...] resistance to the moves [that are either] intended, or conceivable to be desired.” [...] If we can make human-automation interaction in such a way that the human agrees with the actions of the automation, the human is likely to feel free and in control.”

This requires an even better understanding of the human, especially in potential conflict situations, like a forced take-over while the driver wants to remain in control, or when convincing the driver to refrain from a preferred non-driving task-related activity when a take-over request is imminent.

5.2.6. Industry acceptance

The automotive industry as a whole has developed into a vast economic power with the corresponding social and economic responsibility. It reached unprecedented scale and mass manufacturing efficiency, derived from integrating the full scope of exact and social sciences, giving the automobile its essential presence and role in contemporary human mobility. The core mechanism on which the industry is built is that of branding i.e. offering a unique proposition

based on qualities such as individual expression, status and the notion of adventure and exploration.

The origin of strategic brand differentiation may be contributed to Alfred P. Sloan, President of General Motors early last century. Ford, considering the car to be a commodity product, pursued a strategy of economies and offered a simple car at a low, decreasing price (Edson Armi, 1988). The downside of Ford's mass manufacturing was that the degrading, unskilled, heteronymous work on assembly lines no longer allowed the individual American worker to express its, formerly craft related, identity. Rival General Motors was smaller and could not compete on price while Ford's commodity automobiles did not offer any variation. Sloan decided to introduce a graded hierarchy of 'styled' products blanketing all markets (Gartman, 1994), making the automobile a vital part of the worker's quest to re-establish their individuality (Doorman, 1995).

In today's context, i.e., the unbalance between those individual mobility wants as they are portrayed in brand identities, and collective mobility needs, the automobile has surpassed its epitome in its contemporary manifestation and technologies. While early generations were defined by abundant innovations and true progression, after more than a century everybody has found the optimum. The innovation curve flattened out with only minor improvements from one generation to the next. Formerly brand specific unique qualities, like safety, performance or reliability, are no longer inspiring differentiators for designers. Next to qualitative inspiration, quantitative differentiators have also largely been eliminated from their vocabulary and means to create distinctive designs (Doorman, 1995), Platforms and powertrains, which determine proportions and stance (Doorman, 1995; Gartman, 1994) are now shared between brands (Mantle, 1996), reducing brand differentiation even further.

Contemporary and near future developments, such as electric cars, new ownership models and autonomous driving reignite the automotive innovation curve, but they also entail a twofold risk. From a qualitative perspective, it may reduce driving experience as another important brand differentiator. Quantitatively, electronics do not inspire distinctive vehicle design. Nor does it allow strategic brand differentiation because electronic development has a different dynamic which does align with vehicle development. While in automotive design we advocate that brand identity must be coherently expressed in use, technology and form, in reality the weight has shifted away from technology in favour of use (interaction) and form. To maintain visual brand identity, which is the core design strategy on which the economic viability of the automotive industry is build, branding must be framed strategically (van Grondelle, 2000; Person et al., 2007).

5.2.7. Learning and unlearning

Confusion and user errors can be expected whenever a new system is used. Within the scope of the MEDIATOR project, it is not yet anticipated that the Mediator system will be part of the driver's licence training, in contrast to aviation, where pilots learn how and when to make use of the autopilot (Trösterer et al., 2017). A direct consequence is that people will familiarize themselves with the system while they are driving on public roads. A challenge for the HMI is to aid drivers during these first steps, which is especially important given the potential consequences of incorrect use (e.g. misunderstanding a take-over request as explained in Section 5.2.2 on mode awareness).

One of the pitfalls of automated driving is skill degradation (Noy et al., 2018). While drivers may learn to use and to rely on the Mediator system, they may unlearn how to drive manually (e.g., diminished skills, loss of situational awareness, reduced intervention effectiveness when disengagement of automation is requested). A common solution to prevent skill degradation in

aviation is to require frequent practice of manual flying skills (Trösterer et al., 2017). Translated to the automotive context, a Mediator HMI challenge may be to convince drivers to drive manually for a yet to be determined minimum proportion of the time. This minimum proportion of time is not an arbitrary value. In the driving simulator study by Feldhütter et al. (2019) authors suggest that overreliance in the automation explains why intermediate manual driving was observed to be an ineffective measure to help participants to regain adequate monitoring behaviour after changing from conditional to partial automation. Thus, the challenge to prevent skill degradation is potentially intermingled with the challenge to minimize overreliance. Furthermore, the challenge to prevent skill degradation may be interacting with the challenges on trust and user acceptance: will drivers understand and accept when and why they cannot use their vehicle in a preferred automation mode?

5.3. Design Space

The design of the vehicle's HMI will be only be successful if one considers how humans process, understand and experience information. In addition, there will be certain (system) limitations or challenges caused by the modes/levels of the automation and technological limitations. In order to design a certain HMI output or input, one should consider the Human Information Processing model (van Egmond et al., 2019). In Figure 5.4, a version of this model is presented. The stages identify in which stage the information given by the HMI is processed. The choice of a specific sensory modality (vision, audition, touch, olfactory) will be determined by the type of information and the level of the attentive value of the signal. The amount of attention needed will be determined by the urgency of the situation and the time needed to react. In addition, the HMI may also consider personalization based on user needs such as reflecting her/his lifestyle, ease of operation, intuitiveness, quality feel and flexibility and will become more and more important in establishing the brand identity of the vehicle.

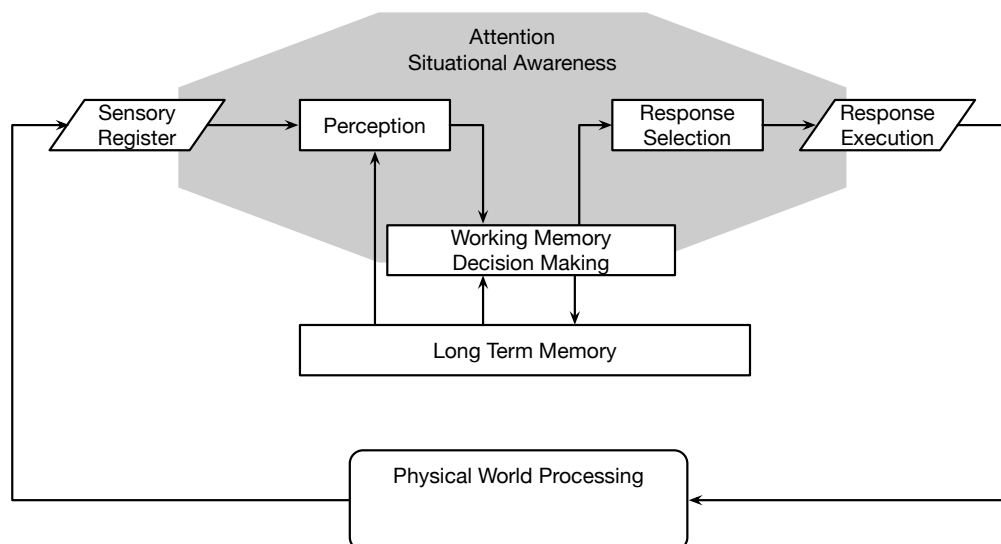


Figure 5.4 Visualisation of human information processing.

Organisations such as NHTSA, FHWA, European Commission, JAMA, TRL and others have established a detail set of guidelines and recommendations for in vehicle HMI. Naujoks et al., 2019) compiled a set of initial guidelines (checklist) formulated based on the applicable international standards (NHTSA, SAE, ISO 9241), recommendations for design and assessment of IVIS (In Vehicle Information Systems, ATIS (Advance Traveller Information Systems), driver-

vehicle interfaces and in-vehicle warning systems for the design of automated vehicle HMIs. The guidelines address mode indicators for automated driving systems and the information processing perspective as a basis for design. The guidelines could be used as a verification tool to guide the development of automated vehicle HMI in the early stage of the development process. Lilis et al. (2019) empirically validated the checklist in their driving simulator study that measured the usability and acceptance of two automated HMI variants (low compliance HMI and high compliance HMI) constructed from the guidance of the checklist measures. It was found that, when the HMI guidelines did not meet the checklist requirements, the self-reported usability, usefulness and satisfaction to automated driving HMI decreased significantly.

As also described in Chapter 4, SAE J3016 (last version SAE, 2018) defines six levels of automation ranging from no-automation (level 0), where the human driver has full control of the vehicle, to full automation (level 5). These levels give direction to the design of automation in vehicles. Although the SAE document does not specifically provide design guidelines, the document provides system boundaries for the design of an HMI. Especially, the definitions 3.20 through 3.29 have to do with the sensing and responding defined by SAE as Object and Event Detection and Response (OEDR). OEDR are subtasks of the *DDT (Dynamic Driving Task)* “that include *monitoring the driving environment* (detecting, recognizing, and classifying objects and events and preparing to respond as needed) and executing an appropriate response to such objects and events (i.e., as needed to complete the *DDT* and/or *DDT fallback*)”. Figure 5.5 gives an overview of who is in control during the DDT and, more importantly, who is in responsible of the OEDR. Note that for level 0 through 3 the fallback is on the driver, whereas in 4 and 5 the fallback is on the system. The latter fallback is however within an Operational Design Domain (ODD). If one leaves the ODD in which level 4 and 5 are possible, one transcends to another level in which the driver is the fallback.

Level	Name	Narrative definition	DDT		DDT fallback	ODD
			Sustained lateral and longitudinal vehicle motion control	OEDR		
Driver performs part or all of the DDT						
0	No Driving Automation	The performance by the <i>driver</i> of the entire <i>DDT</i> , even when enhanced by <i>active safety systems</i> .	<i>Driver</i>	<i>Driver</i>	<i>Driver</i>	n/a
1	Driver Assistance	The <i>sustained</i> and <i>ODD</i> -specific execution by a <i>driving automation system</i> of either the <i>lateral</i> or the <i>longitudinal vehicle motion control</i> subtask of the <i>DDT</i> (but not both simultaneously) with the expectation that the <i>driver</i> performs the remainder of the <i>DDT</i> .	<i>Driver and System</i>	<i>Driver</i>	<i>Driver</i>	Limited
2	Partial Driving Automation	The <i>sustained</i> and <i>ODD</i> -specific execution by a <i>driving automation system</i> of both the <i>lateral</i> and <i>longitudinal vehicle motion control</i> subtasks of the <i>DDT</i> with the expectation that the <i>driver</i> completes the <i>OEDR</i> subtask and <i>supervises</i> the <i>driving automation system</i> .	System	<i>Driver</i>	<i>Driver</i>	Limited
ADS (“System”) performs the entire DDT (while engaged)			System	System	Fallback-ready user (becomes the driver during fallback)	Limited
3	Conditional Driving Automation	The <i>sustained</i> and <i>ODD</i> -specific performance by an <i>ADS</i> of the entire <i>DDT</i> with the expectation that the <i>DDT fallback-ready user</i> is <i>receptive</i> to <i>ADS</i> -issued <i>requests to intervene</i> , as well as to <i>DDT performance-relevant system failures</i> in other <i>vehicle</i> systems, and will respond appropriately.				
4	High Driving Automation	The <i>sustained</i> and <i>ODD</i> -specific performance by an <i>ADS</i> of the entire <i>DDT</i> and <i>DDT fallback</i> without any expectation that a <i>user</i> will respond to a <i>request to intervene</i> .	System	System	System	Limited
5	Full Driving Automation	The <i>sustained</i> and unconditional (i.e., not <i>ODD</i> -specific) performance by an <i>ADS</i> of the entire <i>DDT</i> and <i>DDT fallback</i> without any expectation that a <i>user</i> will respond to a <i>request to intervene</i> .	System	System	System	Unlimited

Figure 5.5 An overview of who is in control during the Dynamic Driving Task and who is responsible of the Object and Event Detection and Response (OEDR) for each of the six SAE levels of automation (Source: SAE, 2018).

Driver experience and instinct determine the throughput time from signal to action, and are one factor of the vehicle's total response time. In SAE level 2 to 4 vehicles, drivers are expected to resume manual control when the automation fails or reaches its operational boundaries. Several studies have analysed the mean take-over time of drivers in response to a take-over request or a safety critical event in automated driving. In a meta-analysis of 129 studies, Zhang et al. (2019) found that previous experience with take-over requests has a significant impact on the mean take-over time. Drivers showed shorter mean take-over times when they were asked to take-over control for the second time in the same driving session or in a similar scenario during a second driving session. The mean take-over times were also moderately shorter when drivers could anticipate the request to take over (e.g. the take-over requests occurred periodically or they could be anticipated based on the traffic situation). The main conclusions are that experience and anticipation are important factors influencing take-over time, and therefore results from experiments with repeated trials should be interpreted with caution. In addition, being able to anticipate take-over requests is facilitated by an understanding of the capabilities of the automated driving system. Thus, drivers may need to know and understand the automation mode (e.g.,

through automation transparency), which potentially re-introduces mode confusion problems that were otherwise circumvented by only informing the driver about his/her task responsibilities (see Section 5.2.2).

5.3.1. HMI input controls and available technologies

In-vehicle HMI input devices could either be explicit (touch, gestures, speech, dashboard controls) or implicit (gaze/head tracking, physiological parameters) and their modalities are mainly classified into keypads and pointing elements. The keypad elements include dashboard switches as well as complex systems like speech recognition. The pointing elements refer to either relative or absolute pointing method like touch (Lilis et al., 2019) through physical switches or touchscreen interfaces. Direct input devices, suitable for discrete pointing and ballistic tasks are better than rotary controllers. Ability to convey a vast amount of information, adaptivity and intuitiveness are the main advantages. Readability due to sunlight glare, lack of physical feedback are the key drawbacks. Gesture interfaces provide a more natural interaction and are more intuitive than physical interfaces. Research on gestural interaction in automotive focus on handling the secondary tasks using non-intrusive one hand gestures (Ohn-Bar & Trivedi, 2014). Lack of direct physical feedback and recognition errors are the main drawbacks of gestural interfaces.

Multimodal interface systems (MMI), capable of using two or more inputs have advantages over unimodal inputs in terms of improved recognition, understanding, intuitiveness and adaptivity (Oviatt, 2016). Manawadu et al. (2017) evaluated a multimodal HMI for tactical level controlling of intelligent vehicle using three modalities (touch screen, hand gesture and haptics) and reported that MMI has effectiveness on perceived workload, efficiency, reduce error and situation adaptability.

An important issue when discussing HMI input controls involves maintaining driver situation awareness to keep the driver in the loop so that he or she can respond timely and adequately when needed to take-over control. Uchida, Hirano and Itoh (2019) investigated the effect of verbal communication between driver and system. They hypothesized that the driver can cognitively participate in vehicle operation even if he/she is not physically in the control loop. In a driving simulator study, they compared two conditions. In one condition, the 'talking' condition, the system asked the driver about the peripheral situation and/or vehicle control and the driver had to respond. In the other condition there was no talking of the system. In the experiment, the driver was confronted with two events that required their intervention. The results showed that in the talking condition, as compared to the non-talking condition, the number of collisions were significantly higher, and the event response time was significantly longer. This indicates that the verbal interaction with the system does not improve drivers' situation awareness. Self-reports showed that verbal interaction did not improve the usability of the driving automation system either.

5.3.2. HMI output controls and feedback mechanisms

The available output devices mainly include screens (i.e. visual displays), speakers, vibration (tactile) motors, and augmented reality displays, with respective modalities on visual, auditory and haptic. The next subsections discuss each of these modalities in more detail.

5.3.2.1. Visual displays

For more than decades visual displays are used in the vehicle to assist the driver with safety-related information and to improve driving performance. Manca et al. (2015) identified six types of visual displays that are used in autonomous driving related research studies:

- Display with three main components (automation scale, automation monitoring and a message field)
- Birds' eye view display
- Informative speedometer
- Head-up display
- Eye catching lights for informing
- Eye catching lights for guiding

Yang et al. (2018) investigated the use of LED bar on the bottom of windscreen to communicate the status of automated vehicle, its intentions and system boundaries. Their findings showed that the LED bar increased the drivers trust in automation. Besides that, the findings showed that drivers preferred visual modalities compared to auditory.

In the field of visual displays new developments in head-up displays in combination with augmented reality seems promising. Lindemann, Lee and Rigoll (2018) simulated an explanatory windshield display (WSD) interface for automated cars to increase drivers' situation awareness in a mixed-reality driving simulation presenting an urban environment. The interface combined screen-fixed elements and world-registered augmented reality overlays. The results showed a significant improvement of the situation awareness with the WSD interface as opposed to having only speed and navigation information. Situation awareness improved both in high and low visibility conditions (good versus bad weather). The authors conclude that an WSD interface with augmented reality elements can help to increase situation awareness in urban environments and that this in the end may prevent loss of trust or even increase trust in the automated vehicle.

5.3.2.2. Auditory displays

An advantage of auditory messages or signals compared to visual signals is that auditory signals can draw attention to an occurring event although the attention of the driver is focused on something else. Auditory signals can be distinguished in: auditory icons (referring to an existing source); auditory ear cons (abstract sound of which the meaning has to be learned), and spoken words (e.g., Kramer, 1994).

A disadvantage of auditory messages is that it often takes time to convey a message. These signals are often longer in duration than abstract signals and are often masked by surrounding noise. The latter inhibits interpretability of the message. Levels of urgency can be evoked by adjusting sound parameters like frequency, timbre and temporal structure (van Egmond, 2008; Özcan and van Egmond, 2020). Modern cars are mostly equipped sound surround systems which opens up new interaction scenarios for design of the HMI in which sound can be radiated from a certain position in the car in order to draw attention to that position (e.g., Heydra et al., 2014).

Research shows that human vocalisation (speech and non-linguistic) generates a greater activation in the bilateral superior temporal sulcus of the brains. This could indicate specific processing for the human voice and a possible greater attention (Fecteau, Armony, Joannette, & Belin, 2004). Besides, the human voice makes it possible to make clear to the driver what is the request and the time remaining before the take-over. From the literature, the preference for a female voice for auditory messages seems to emerge, but there is some conflicting research (Bazilinskyy, Petermeijer, Petrovych, Dodou, & de Winter, 2018; Bazilinskyy, & de Winter, 2015). Sonorous signals do not allow a clear communication with the driver, but in particular, looming sounds generate more activation in amygdala, causing a faster initial response (Bach et al., 2007), and are perceived from the driver as more urgent (Bazilinskyy et al., 2018).

5.3.2.3. Haptic output

Haptic or tactile feedback has proven to be efficient way of informing a driver about the approaching threats. The tactile cues or stimuli mainly depend on four variable that could be altered to get a distinguishable signal: amplitude, rhythm, frequency and spatial location (Huimin, Kuber, & Sears, 2017). Wan and Wu (2017) investigated the effects of vibration patterns on a vehicle take-over request to the driver engaged in a secondary task. They reported that faster response times were observed when the vibration pattern was presented in the order: seat back-seat back-seat pan-seat pan.

Abbink et al. (2012) refer to a 2010 paper of Abbink and Mulder who define haptic shared control as “a method of human-automation interaction that allows both the human and the [automation] to exert forces on a control interface, of which its output (its position) remains the direct input to the controlled system”. Subsequently, Abbink et al. (2012) state (page 21):

“This implies that—depending on the direction and magnitude of the force that either human and automation exerts on the control interface—there can be a rich two-way interaction between human and automation” (page 21). Haptic shared control has been investigated in areas such as vehicle control, robotic control and for learning and skill transfer. However, this approach has not (yet) received substantial attention in the automation and human factors domain.” and can be explored as a means of feedback in autonomous driving.”

Abbink et al. (2012) also mention (page 26):

“Experimental results in a driving simulator showed that when avoiding objects in highly critical situations, the designed extended haptic shared control system—compared to unsupported, manual control—, helped to reduce the number of crashes, with reduced control effort (forces) and control activity (steering actions) (Della Penna et al., 2010). Essentially, the haptic shared control system allowed drivers to choose their preferred trajectory around the object and helped to quickly execute this choice without deteriorating overshoot that might result from excessive steering.”

5.3.3. Comparing different modalities and multi modal cues

Take-over time is a very relevant factor in different levels of automation, so it is important to understand which are the most effective take-over requests, between multimodal and unimodal cues. Bazilinskyy et al. (2018) showed that multimodal signals are preferred in high-urgency situations. In low-urgency the most preferred cues are auditory messages. The same authors divide take-over requests in three categories that may be used in different levels of urgency for take-over transition i.e. visual, auditory and vibrotactile, each with their own draw-backs:

- Visual take-over requests can be written messages or signals shown on cluster, head unit or other in-vehicle displays. The issue with visual-only signals is the high probability the driver might not see the visual message during autonomous driving session.
- Auditory take-over requests can be sonorous signals or voice messages. They are more effective than visual, but it may not be sufficient in the case of drivers with hearing problems.
- Vibrotactile take-over requests can be generated by vibration of the steering wheel or seat. To use these types of signals, physical contact with the object is necessary, so in a situation of autonomous driving, where the driver can remove his hands from the steering wheel, the vibration on the steering wheel is practically useless.

Given that these draw-backs are mitigated, Zhang et al. (2019) found that the modality of the take-over request has a significant impact on the mean take-over time. Auditory and vibrotactile take-over requests have a similar impact on the mean take-over time. The mean take-over times are shorter with auditory or vibrotactile take-over requests than with just visual take-over requests or no take-over request. Drivers, especially when they are engaged in a visually distracting non-driving task, may overlook visual warnings or may not consider a visual signal as urgent (Petermeijer, Doubek, & De Winter, 2017). Drivers' attention may be attracted more effectively using auditory take-over requests that have omni-directional characteristics (Bazilinskyy, & de Winter, 2015), and using vibrotactile take-over requests on the seat, which can be perceived even when drivers are engaged in visual or auditory non-driving tasks (Petermeijer, de Winter, & Bengler, 2016). Combining auditory and vibrotactile take-over requests can result in slight reductions in take-over time compared to unimodal auditory and vibrotactile take-over requests (Petermeijer, Bazilinskyy, Bengler, & de Winter, 2017). The main conclusion is that auditory and vibrotactile feedback reduce drivers' take-over time in automated driving and are therefore recommended as warnings during take over requests.

Some studies also investigated driver behaviour after resuming manual control in automated driving at a manoeuvring or tactical level. Vibrotactile and auditory warnings are not effective in conveying complex information such as the direction of a lane change in order to avoid a stationary vehicle (Petermeijer, Bazilinskyy et al., 2017). Appropriately designed visual messages, on the other hand, can effectively support drivers in making the right manoeuvre (braking or changing lane) after resuming manual control (Eriksson et al., 2019). The main conclusion is that visual and vocal messages can effectively provide drivers with complex information and therefore are recommended to support drivers in the tactical decision making after resuming manual control.

In safety critical situations, presenting information to operator via multisensory channels seems to exhibit a promising effect on their performance in multitasking and attentional management (Sarter, 2002; Wickens, 2008). A detection task presenting the information using trimodal cues (visual, auditory and haptics) received shorter response time than presenting the information using bimodal and unimodal cues. Pitts and Sarter (2018) looked at how well younger and older adults respond to nonredundant simultaneous cues provided in three different sensory channels and reported that the response time and accuracy was affected by both age and cue combinations. In general, the response times decreased with addition of cues (uni-, bi-, and trimodal cues: 529.7, 475.3 and 457.7 milliseconds).

5.4. Recommendations

In this section we define five general recommendations for the development of human-machine interface (HMI) relevant for the HMI in general and for the Mediator system HMI in particular.

5.4.1. Embrace a holistic approach

The HMI must be addressed in a holistic manner. In particular, the in-vehicle human-machine interface should be designed to integrate all interactions between the vehicle and the driver, as well as the interaction with other sources which require the driver's attention, thus adding to the overall cognitive load, either active or passive.

Embracing the complexity of the HMI in its full scope is not only important in the design process, but also required during the experimentation phases. While experiments in principle benefit from reducing the number of variables, a holistic approach dictates the opposite i.e. involve as many

variables as close to reality as possible. Furthermore, each study will benefit from the highest possible fidelity level of a former study.

5.4.2. Design for user acceptance

In the rational system exercise of designing human mobility, facilitating human efficiency and improving human experiences while eliciting sustainable behaviour, are paramount. The design of the Mediator system HMI must build on vital ‘irrational’ emotional values i.e. the automotive brand experiences, as they are instrumental in inspiring the aforementioned behavioural change and how to elicit that (van Grondelle, 2013).

In the scope of control transfer scenarios that will be initiated, monitored and managed by the Mediator system (Figure 5.6), driver preference is no factor in scenarios with a high level of urgency, because of safety reasons (driver state) or vehicle performance (autonomous ability). In all other situations however, the system must facilitate driver preference. Driver perception is historically formed in self-driving, which suggests driver autonomy and freedom of choice. To preserve user acceptance of a Mediator system it is important that driver autonomy remains to be facilitated when possible, and up to the level of autonomy which is possible in any scenario. Similar to the design space of the manufacturer, driver-autonomy is likely to be the highest in the middle of the scope of scenarios, where there is no Mediator system preference towards the level of control by either driver or vehicle.

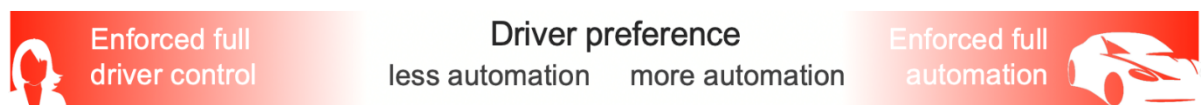


Figure 5.6 Scope of human-machine interactions, crucial for user acceptance.

5.4.3. Design for industry acceptance

The automotive industry, which is structured by, and built upon deeply rooted emotional automobility values (‘irrationalities’ for lack of a better word) is now facing future human mobility design as a mere rational system design exercise, predominantly driven by logistics and technological developments. While the revival of the electric car is an opportunity to fundamentally rethink the automobile and reignite the innovation curve, autonomous driving poses a risk towards the aforementioned automotive merits and structure (van Grondelle, 2016). Because its rational parameters do, in principle, not inspire variation. For industry acceptance though, diversification in brand identity i.e. brand specific design of the human-product interaction, and manifestation of the HMI system (look and feel) are crucial.

In the scope of control transfer scenarios that will be initiated, monitored and managed by the Mediator system, variation in design is unwanted in scenarios with in which driver preference is not a factor because of safety reasons (driver state) or vehicle performance (autonomous ability). See Figure 5.7. In all other situations however, design space may be identified in which consecutive OEMs have design freedom to create brand specific variation. Design freedom is likely to be the biggest in the middle of the scope where there is no Mediator system preference towards the level of control by either driver or vehicle.

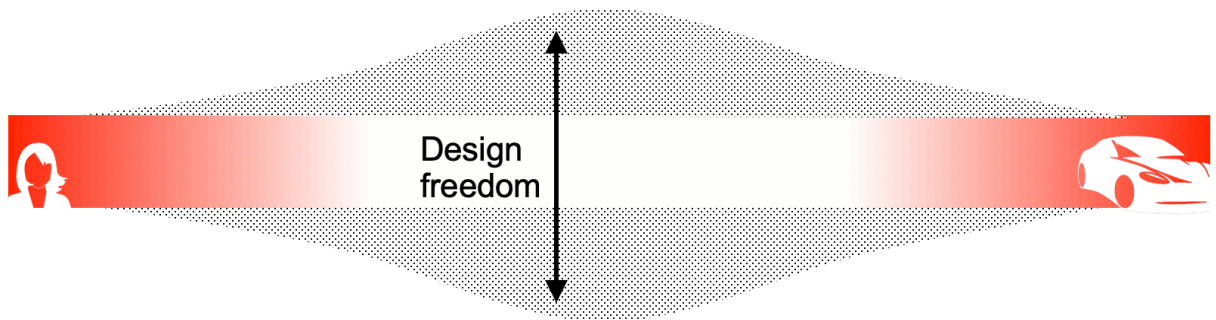


Figure 5.7 OEM design space for brand identity, crucial for industry acceptance.

5.4.4. Apply a generic ritual

The underlying principle for the design of HMI should be to elicit safe and sustainable behaviour of the driver in his/her interaction with the vehicle. The HMI should be tested and designed taking human capabilities into account. In the interaction between the mediator system and the driver, the information provided to the driver must be tailored to each transfer scenario, to evoke adequate driver fitness and actions within the available timeframe.

Timing of alerts is a major parameter in autonomous driving vehicles. It must be adapted to the emergency of the situation. Messages should be provided early enough for the driver to be able to react in the proper way. Timing is also essential in addressing the challenge of potential conflicts i.e. when driver and decision logic disagree on the preferred driving mode. This may occur because of mere driver preference or because the driver and the mediator system interpret the context differently.

Given that all interactions are constructed from the same components, similar to the standard model of human cognitive process, a standard sequence within control transfers between human and vehicle, either full or partial, serves as a template. Structural application and consistent visualization of the template in use cases, design processes and experimentation assures comparability, thus minimizes the risk of bias.



Figure 5.8 Generic control transfer ritual

While the template of this transfer ritual and its components are fixed, the values of each component vary. The transfer ritual consists of the following components (Figure 5.8):

- $S^1, S^2 \dots S^n$ are *signals* of the HMI to the driver. Signals may trigger different senses or a combination thereof, while intensity and intrusiveness are likely to be determined by the urgency of the situation, i.e. the driver's required response time. Components of each signal that must be designed (auditory, visual, vibration, ...) are their intensity and duration, and if and how they are combined (multimodal).
- $t^1, t^2 \dots t^n$ are *time intervals* from one signal to the next. Time intervals are being determined by the anticipated moment of the actual (partial) control transfer and the driver's response, i.e. changing state of alertness or driver fitness (measured cognitive process).

- *Transfer* is the actual control transfer of (partial) control from driver to vehicle or from vehicle to driver.

Figure 5.9 depicts these components within the Mediator system model.

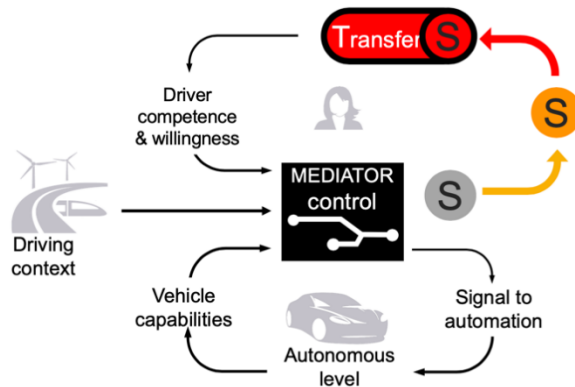


Figure 5.9 Generic control transfer ritual positioned in the Mediator system.

5.4.5. Design for learned affordances

Related to the earlier defined levels of information streams, we have to set the scope of what the HMI encompasses, and to which level of detail each must be included in research and design. The HMI must synthesize between conventional information and new information by the Mediator system. All HMI messages should be compatible with on board systems and their display priority should be managed jointly. HMIs should be designed in such a way that any licensed driver is able to effectively and safely use them in any vehicle. As a consequence of this, HMI functionalities for safety time-critical situations should be harmonised: pictograms' form, colours or positions, auditory warnings sounds, haptic warnings.

In contemporary cars, which will co-exist with autonomous vehicles for a few decades, drivers manually control the external user interface (blinker, break, reverse, horn). Only in emergency situations the system in a contemporary car will automatically initiate the break-warning and alarm lights and communicate with emergency services. Those signalling functions will (partially) remain to be controlled manually in partially autonomous driving modes. While the external user-interface design is not the focus of this project, controlling the external user-interface is an integrated task of the HMI, as well as providing feedback to the driver upon its operation. It is advised to acknowledge the likeliness of new future components of the external user interface, and address their control by either the driver or the automation, at least on a theoretical level.

To avoid unwarranted trust, a challenge for the HMI is to ensure that the driver is aware of the limitations of the system (i.e., the operational design domain), and acts accordingly. This entails monitoring the level of attention in the situations that arise from different driving scenarios, conveying the correct information to maintain and regain driver situation awareness when needed, and to develop and maintain the appropriate level of trust (not too much or too little) in the automated vehicle. Thereby it needs to be assured that the human is confident of what is going on, minimizing the likelihood of human errors or annoyance. The human and the automated vehicle system interaction shall be considered in level of automation and operational design domain, the human and the system have to act in synergy. This will help avoiding the trap complacency

phenomena (Parasuraman, & Manzey, 2010), that happens when a cognitive attention bias leads to errors of over-estimation or uncertainty in relation with automation.

Learning has been identified as a twofold challenge as in learning new skills in using the system, as well as unlearning conventional skills by frequent use of the system (Section 5.2.7). Both are also an identified challenge by the European Road Transport Research Advisory Council (ERTRAC) from the perspective of driver licences and how driver training handles the differences between the functionalities with which semi-automated cars are equipped.

The common denominator between the aforementioned issues, i.e. the complexity of information, controlling the external HMI, design for trust and design for learning, is that recognition of familiar affordances (standardisation) emerges as a design prerequisite. Given that the Mediator HMI will combine conventional driving skills with new driving skills, conventional automotive interior affordances may not always apply. In that case, affordances from other domains are likely sources for HMI design.

5.5. Learning from aerospace and maritime

Also in other transport modes, human-machine interface is an important issue. In the next two sections we look at aerospace (Section 5.5.1) and maritime (Section **Fout! Verwijzingsbron niet gevonden.**).

5.5.1. Learning from aerospace

The European Union Aviation Safety Agency (EASA) has established a set of *guidelines* (Acceptable Means of Compliance; AMC) for demonstrating compliance with the requirements (Certification Specifications; CS) applicable to turbine powered large aeroplanes. One specific part (as presented in AMC 25.1302 and CS 25.1302) addresses the design (and approval) of *installed equipment intended for flight-crew members' use in the operation of the aeroplane* from their normally seated positions on the flight deck. The AMC also provides recommendations of the design and evaluation of controls, presentation of information, system behaviour, and system integration, as well as design guidance for avoidance and management of flight crew error. Since flight crew errors will occur, even with a well-trained and proficient flight crew operating well-designed systems, the design must support management of those errors to avoid safety consequences. For example, the design should enable the flight crew to detect and/or recover from errors.

Following the requirements as addressed in CS 25.1302, flight deck controls and presentation of information (i.e. visual, auditory or tactile) intended for flight crew use must:

- Be presented in a clear and unambiguous form, at resolution and precision appropriate to the task.
- Be accessible and usable by the flight crew in a manner consistent with the urgency, frequency, and duration of their tasks, and
- Enable flight crew awareness, if awareness is required for safe operation, of the effects on the aeroplane or systems resulting from flight crew actions (i.e. provide adequate feedback).

Following the requirements as addressed in CS 25.1302, operationally-relevant behaviour of the installed equipment must be:

- Predictable and unambiguous, and
- Designed to enable the flight crew to intervene in a manner appropriate to the task.

Note that the set of guidelines (as presented in AMC) is not a complete set of rules that must be followed strictly. It is a mere design philosophy that could be adopted in order to be compliant with the requirements (as presented in CS). Real-world constraints have to be taken into account, trade-offs have to be made, interpretation is sometimes needed and deviations are justifiable as long as consistency is maintained.

5.5.2. Learning from maritime

5.5.2.1. Similarities and differences

There are similarities, but also differences between driving a car and manoeuvring a ship, flying an airplane or driving a train. The size and masses of the objects are very different from passenger cars and the consequences of personal injury and material damage can be significantly larger. The medium the objects travel on or in is also different and controlled and regulated differently. When manoeuvring a ship, avoiding grounding and collision is a major task, in addition to maintaining watertight integrity and keeping the ship ballasted.

Speed is another difference. Except for high-speed vessels most ships travel at a low speed compared to cars. Due to the mass and the medium water is, a ship cannot perform emergency braking like cars, but needs to turn to avoid grounding or collision.

5.5.2.2. Duration and fatigue

Vessel operators are trained professionals. On most ships the operation is a 24/7 activity where the navigation and manoeuvring task is shared between different watches. A normal arrangement on-board is 6 hours on and 6 hours off for 4 weeks, then 4 weeks off whereby the crew is replaced with a new one. Others work 4 hours and are off duty 8 hours, while others work 12 hours and rest for the next 12 hours. There are many other arrangements⁴, but fatigue can have a different dimension working on ships compared to driving a car. You cannot leave the ship when you are not on duty⁵. Driving a car manually requires full attention from the driver all the time, while manoeuvring a ship can be labour-intensive when sailing in harbours, narrow waters and in offshore operations, but less demanding in open seas.

5.5.2.3. Single driver position vs. multiple control positions

In passenger cars the driver position is fixed, and the seating position is similar on most vehicle types. Most of the input devices have a fixed position and the seat, steering wheel and mirrors are adjusted to get optimal reach and view. On a ship, there are typically two workstations used when sailing. This is how they are defined by the International Maritime Organization (IMO MSC/Circ. 982):

- Workstation for navigating and manoeuvring:
Main workstation for ship's handling conceived for working in seated/standing position with optimum visibility and integrated presentation of information and operating equipment to control and consider ship's movement. It should be possible from this place to operate the ship safely, in particular when a fast sequence of actions is required.
- Workstation for monitoring:
Workstation from which operating equipment and surrounding environment can be permanently observed in seated/standing position; when several crew members are

4. See for example Sjøfartsdirektoratet / Norwegian Maritime Authority - RSV 08-2015 - Working hours arrangements for minimum safe manning (July 2015).
5. Margartea Lützhöft, Michelle R. Grech, Thomas Porathe: Information Environment, Fatigue and Culture in the Maritime Domain. Research Article (August 2011).

working on the bridge it serves for relieving the navigator at the workstation for navigating and manoeuvring and/or for carrying out control and advisory functions by master and/or pilot.

Depending on the ship type and classification there might be a separate *Workstation for manual steering* placed in front or behind the two other workstations. Due to the size of ships additional steering positions are needed when docking or performing deck handling. *Workstations for docking* are placed on each of the bridge wings. Supply vessels and many construction vessels typically have an aft bridge with a *workstation for ship handling* and a *workstation for aft support*.

5.5.2.4. User input devices (UID) and visual display units (VDU)

A workstation consists of one or several consoles containing the needed input devices and visual display units for performing the given tasks. The workstation is operated standing and/or seated. There are restrictions of where the display units can be placed to not interfere with the view zones. The input devices should be placed within reach in given zones. General input devices are buttons, trackballs, trackpads, numerical keyboards. There are many special purpose devices such as joystick, heading wheel, mini wheel, thruster levers and rudder controls. Visual display units are divided into task, control, information and settings displays. Settings and control displays have touch control; task displays may have it. Gesture control is so far not used. Voice-control is difficult to use due to a lot of communication activity.

5.5.2.5. Route planning

Route planning is a task performed at harbour before the journey starts and changes are done during the journey. A *Workstation for planning and documentation* is used for this task.

5.5.2.6. Command control

It is possible to steer and control a vessel from different workstations. Due to this possibility a system is needed for transferring command between workstations and the HMI needs to clearly inform the operator which workstation has command over which system. In addition, the transfer between what the system controls and what the operator controls must be clearly indicated.

5.5.2.7. Some similarities with automated driving levels and the maritime industry

Automated driving is defined with 5 levels. In the maritime domain we can find similarities to automated driving, here are some examples from Kongsberg Maritime systems and products:

Level 1 – Track pilot (TP)

The Auto pilot system has different modes. In the simplest mode the system controls rudders or azimuth thrusters to maintain a given heading. Due to wind and current forces the ship can drift off the route. To follow the route Auto track is activated. The system will keep the ship on the given route. The speed of the vessel is controlled by the operator.

Level 2 – Track pilot (TP) / Speed pilot (SP)

This is comparable to adaptive cruise control and lane keeping assistance in cars where the system controls lateral and longitudinal motion. In a ship the system will follow the track and define the speed between waypoints and adjust it to keep the estimated time of arrival (ETA), maximum speed in zones, etc. In combination with an automatic radar plotting aid (ARPA), the operator can leave the workstations but needs to be on the bridge. If the ARPA detects any objects with risk for collision the officer will be alerted. With ARPA the system is closer to level 3.

Level 3 - Dynamic positioning (DP)

Kongsberg Maritime has delivered Dynamic Positioning systems since 1976. A seagoing vessel is subjected to forces from wind, waves and current as well as from forces generated by the propulsion system. The Dynamic Positioning systems automatically maintain the vessel's position and heading using its propellers and thrusters. The system can be used for keeping a vessel in a given position and heading. Or it can be used to follow a defined track for e.g. a pipelaying vessel. When fully activated the operator is relying on the system's ability to keep the vessel in the given position, but he is ready to take over at a short notice.



Figure 5.10 DP operator monitoring the DP system on a supply vessel delivering cargo to a drilling rig. The DP system controls, heading, sway and surge. (Photo: Stig Olav Skeie/Kongsberg Maritime).

Level 4 – Unmanned Machinery Space (UMC/E0) with Watch Call

On a ship classified with UMC/E0 the engineer on duty can periodically leave the engine control room and machine spaces provided he can be reached by the Watch Call alert signalling device. He can be asleep in the cabin during night and will be awoken by the sounding of the alert system if any alerts occur. The bridge officer will also be alerted. The bridge can periodically be manned with one officer, while the other is asleep or elsewhere on the ship. A Bridge Navigational Watch Alarm System (BNWAS) is then used. It monitors bridge activity and detects operator disability during one-man bridge operation. Optical or infrared cameras track movements on the bridge, use of input devices or the BNWAS reset button. If none such activity is registered in a given period, the system will wake up the 2nd officer on duty. If no response, the whole crew will be alerted.

Level 5 – Autonomous Underwater Vehicle (AUV)

Kongsberg's HUGIN autonomous underwater vehicles (**Fout! Verwijzingsbron niet gevonden.**) can function without tethers, cables, or remote control, they have a multitude of applications in oceanography, environmental monitoring, and underwater resource studies. HUGIN can dive down to 6000-meter depths, do various surveys and return to the point it was launched. It has up to 100h endurance.

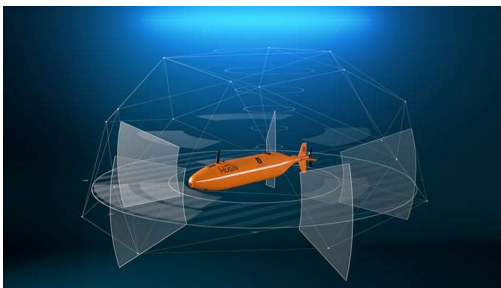


Figure 5.11 HUGIN is a free-swimming autonomous underwater vehicle (Illustration: Kongsberg Maritime).

5.6. Conclusions

The challenges raised in Section 5.2 have been addressed where possible in subsequent sections on design space (Section 5.3), recommendations (Section 5.4), and learning from other transport modalities (Section 5.5). However, some challenges are not yet solved and might need to be studied in dedicated experiments:

- A generic transfer ritual has been described at a conceptual level, but knowledge is missing on how to best operationalize this ritual into a concrete transfer protocol for the Mediator system.
- Shared control within an automation level has been described for the haptic modality. Note that drivers often complain about the functionality of existing lane keep assist systems (i.e., a haptic shared control task). There is little knowledge on establishing haptic shared control at a level that is acceptable for drivers. Moreover, knowledge in the automotive domain is missing on the relation between user acceptance and providing AI support through other modalities.
- Two approaches to prevent negative consequences of mode confusion have been presented: provide transparency on the automation mode (i.e., minimize mode confusion), or alternatively, inform the driver about the task(s) he/she is responsible for (i.e., modes are no longer relevant). A potential problem of the latter approach is that drivers will find it difficult to anticipate when task responsibilities are about to change. Thus, the question becomes: how can we enable the driver to form a mental model of the automation that facilitates anticipation, without burdening the driver with detailed mode information?
- For industry acceptance, design freedom for the Mediator system is expected in non-safety-critical situations. It is not yet determined which situations are indeed safety-critical, thus requiring harmonization of the information communication resulting from the Mediator system.
- Several studies have been described on which (combination of) modalities work best for certain interactions with automation (e.g., take-over request, increasing situation awareness). However, seeing that these studies made use of a limited set of stimuli, it is questionable whether a generalization to other modalities can be made. Also, it is questionable whether generalizations can be made towards all possible interactions with automation (e.g., probing questions on driver state), especially given that no standard testing protocol has been developed yet. Both aspects are subject for further exploration.

Knowledge has been presented to tackle most of the challenges individually, but there is a knowledge gap on dealing with multiple challenges simultaneously. In some cases, a solution for one challenge may even have negative side-effects with regard to dealing with other challenges (i.e., trade-offs).

- A recommendation to prevent overreliance is to inform the driver about the operational design domain of the automation (i.e., transparency). Care should be taken not to overload the driver with too much information. What is the optimal balance between transparency and information load?
- General recommendations have been given with regard to learning how to use the Mediator system and how to deal with mode confusion. Knowledge is missing, though, on if and how differences between users should be reflected in the chosen approach. For example, a skilled pilot may be able to interpret detailed information on the automation

mode, but may not desire to be subjected to such information (i.e., impact on user acceptance).

- User acceptance has been framed in terms of preferences with regard to who is in control: driver or automation. Conflicts may arise when the Mediator system tries to improve driver fitness (e.g., a wake-up call, direction attention to the road), or when the Mediator system enforces manual driving to prevent de-skilling while the driver prefers to delegate control to the vehicle. Knowledge is missing on how to predict the occurrence of such conflicts, and on how to resolve them.

Aforementioned knowledge gaps will be the starting point for subsequent experimentation within the MEDIATOR project.

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6. The decision making component

6.1. Introduction

This chapter deals with the central decision making component of the Mediator system, i.e. the central “Mediate Control” component. The basic goal of the decision making component is visualized in Figure 6.1 below, and can be summarized as follows: making mediation decisions between the human and the automation, based on information on the driving context, the human driver state and capabilities, and the automation state and capabilities.

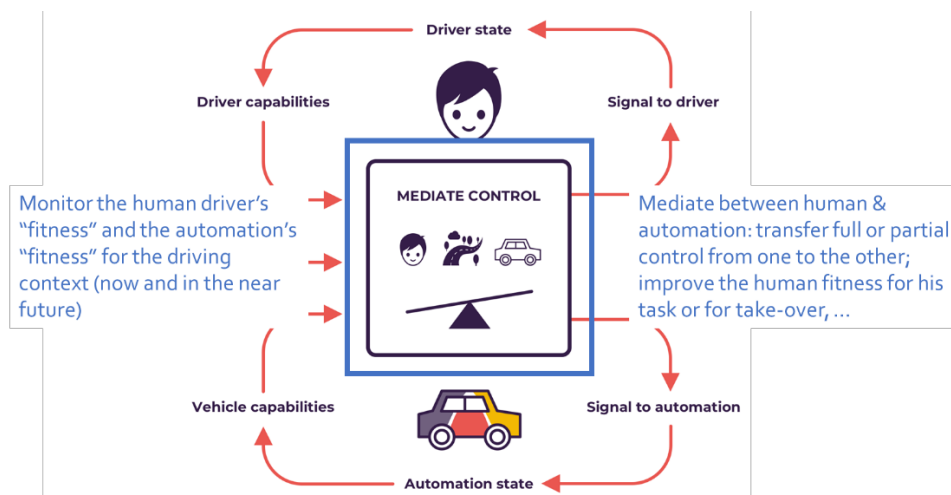


Figure 6.1 The central Mediate Control Decision Logic component and its goal visualized.

Such decisions may transfer full or partial control from one type of driver (either the human driver or the automated driving system) to the other. Full control transfer means the entire (lateral and longitudinal) control of the vehicle is passed to the other type of driver, such that the other type of driver does not have to be involved at all any more. Partial control means that only some parts of the control (e.g. only longitudinal control, accelerating and braking) is transferred, with other parts (e.g. lateral control, steering) remaining with the original type of driver. To what extent the full range of partial to full control transfer is possible and to what extent the driver can be completely out of the loop, i.e. not even for monitoring, depends on the level of automation.

In any case, the decision making needs to take into account that transfer of control takes some amount of time, if it is to be done safely. For example, when transferring from the automated driving system to the human driver, the human must have sufficient time to be brought fully back in the loop and resume control. The same holds for transfer to the automated driving system, but perhaps less so. This means that the decision logic must not only take the current situation into account, but also the *expected situation in the near future*. If for example the driving context becomes so complex or confusing to the automated driving system sensors and reasoning systems that they cannot safely handle it anymore, this must be estimated sufficiently far in advance, so that the hand-over to the human can be done safely, with sufficient time. Ideally, this *prediction* or *forecast* of the near future would potentially extend to longer than a few seconds,

perhaps minutes or longer, such that control transfers can be planned and announced via the vehicle's HMI in a more controlled manner than possible in just a few seconds (see Chapter 5).

The Mediate Control decision making component makes its decisions based on information on the driving context, the current human driver state and capabilities, and the current automation state and capabilities. This is discussed in more depth in the previous chapters, but in any case this means that this component needs input (through appropriate interfaces) about each of these elements from sensors and components capable of producing that information.

Besides the issue of whether to transfer control, the issue of full versus partial control transfer, and the issue of having to predict ahead of time when to transfer, there are several additional considerations for the decision making process. Figure 6.2 illustrates the various aspects of the decisions to be made by the Mediate Control decision making component.

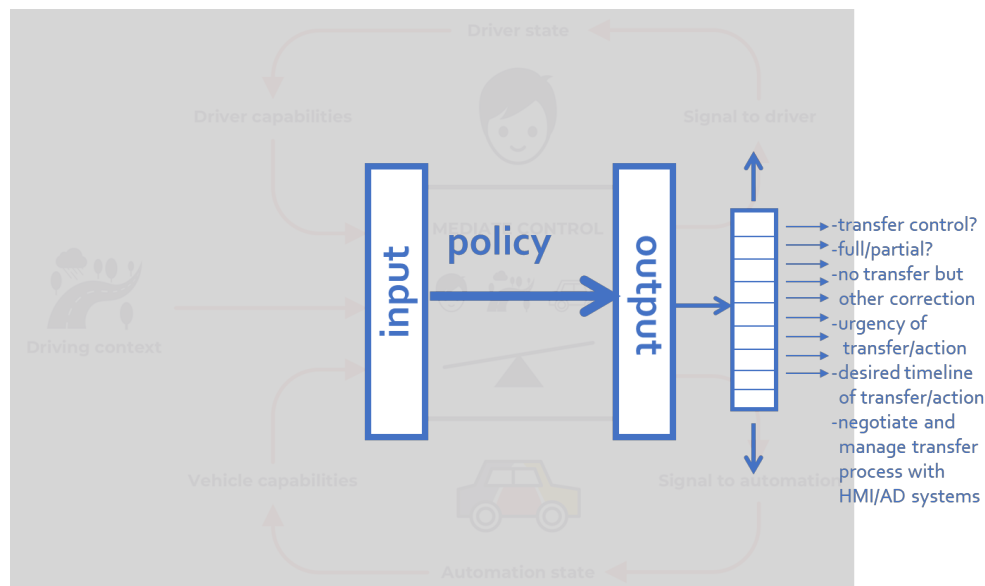


Figure 6.2 Illustration that the decision made by the Mediate Control decision logic actually entails many different aspects.

First of all, it may be that the decision should not entail a (full or partial) transfer of control but some other action. For example, it may be that the human driver is currently in control and should stay in control, but is deemed to be not sufficiently attentive—in which case he or she needs to be made attentive again.

Furthermore, a decision by the Mediate Control component to transfer control or do some other “corrective” action must probably be accompanied by an indication of the level of urgency, and the desired timeline of the action. Different levels of urgency and different desired timelines probably lead to different HMI interactions and possibly different hand-overs from and to automation as well. Different levels of urgency are also related to the issue of potentially *forced* control transfer versus *optional* control transfer. In a safety critical situation, control transfer may be forced. As an example, one may consider the case that a human driver who is in control of the vehicle falls asleep; or the case that a car equipped with a highway autopilot-type system is exiting the highway. In other cases, when both the human driver and the automated driving system are capable of driving, it is conceivable and even likely that control transfer is optional. Note that both forced control transfer and optional control transfer already exist, in limited forms. An example of forced control transfer is an Automatic Emergency Braking (AEB) system taking over from the

human driver when a collision appears imminent. An example of optional control transfer is the option available (at the time of writing) in certain luxury vehicles of highway pilot-type system that can be activated by human drivers.

Once a control transfer action has been decided, this process must be ‘negotiated’ or ‘managed’ with and by the interface to the human driver (HMI) and the automated driving system, leading to a controlled and safe and comfortable transfer. It seems likely that in that process, the human driver and/or the automated driving system must be monitored to check whether their responses are adequate with respect to the task of taking or relinquishing control. An example is the human driver who must soon take control now paying appropriate attention to the road, taking the steering wheel, etc.?

6.2. Solutions in other fields

In the field of helicopter transport, Ruf, & Stütz (2017) describe an adaptive, cognitive assistance system that provides situation-adapted support by continuous crew supervision with the aim of balancing crew workload. Suitable levels of automation are selected using an agent system that weighs the current user needs and the available technical capabilities. The main inputs to their model are the operator workload, which is a task model-based construct, and the automation trust worthiness, which is delivered by a reliability estimation process.

The related decision logic can choose between four levels of automation that they defined for their application of manned-unmanned teaming helicopter missions. The decision logic consists of an artificial agent system, which utilizes a Markov Decision Process (MDP). They substantiate this choice by explaining that the problem comprises full control ability about the state transition, in contrast to Markov Chain or Hidden Markov models, and that in their prototype completely observable states were assumed, in contrast to Partially Observable MDP.

Neogi (2016) investigated aviation safety requirements for effective task allocation between human and automation in the context of a critical situation during take-off. She first developed task models, i.e., logical descriptions of the activities or work to be performed in order for an agent to accomplish its goals. For this she used the Soar cognitive architecture (Laird, 2008). For the computation model she used a hybrid input output automata, which is a non-deterministic state machine that can possess an infinite number of states. Unlike Ruf, & Stütz (2017), Neogi did not use MDP for her application as MDPs do not traditionally admit the notion of continuous time. Considerations for choosing a specific computation model as described by Ruf, & Stütz (2017) and Neogi (2016) can help choosing an appropriate computational model for the Mediator decision logic.

Özyurt, Döring, & Flemisch (2013) describe the development of a cognitive assistance system (COGAS) for supporting the crew of navy ships, and especially the decision maker, of a combat information centre (CIC) during air target identification. While applied to a very different domain, the system, visualised in Figure 6.3, is similar to the intended Mediator system. The evaluation of COGAS using a human-in-the-loop experiment is described by Özyurt, Döring and Flemisch in 2014. These papers and other papers on COGAS provide not only useful information for the further development of the Mediator decision logic, but also for workload measurements, task model definitions, as well as the computational models and software that is used for implementation.

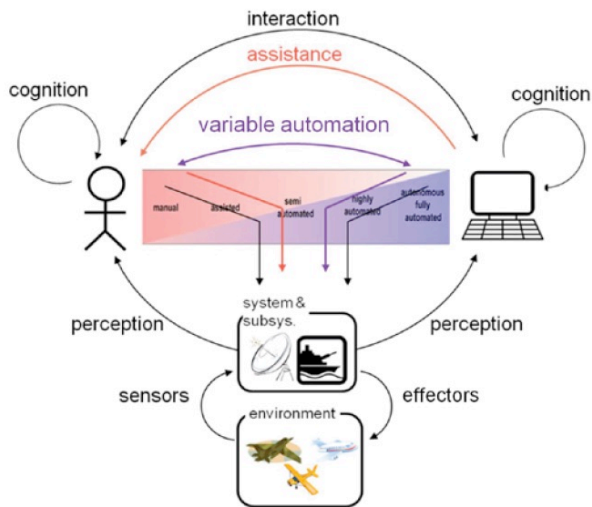


Figure 3. Assistance system with flexible automation

Figure 6.3 Description of a cognitive assistance system (COGAS) from (Özyurt et al., 2013).

Goodrich, & Boer (2003) evaluated an ACC system design based on consistency of the human mental models. They define a mental model as consisting of a set of perceived states, a set of decisions or actions, and a set of ordered consequences of these actions given the perceptual states, as is visualised in Figure 6.4.

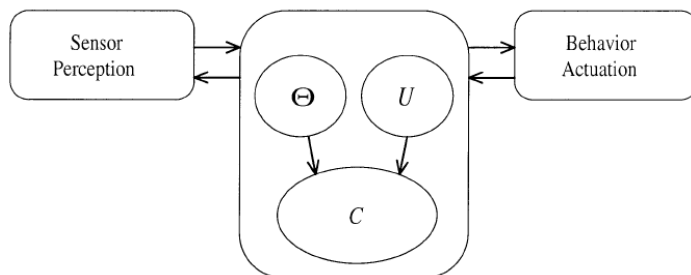


Figure 6.4 Mental model as defined by Goodrich and Boer (2003).

In the case of ACC design, they experimentally support the hypotheses 1) that the automation limits should correspond to the limits of a subset of the human operator skills and 2) if the human executes a skill correctly, the automation skill execution should mimic that of the human operator. These hypotheses are based on the idea that if the humans mental model of a task is similar to the automation task execution and limits, the human will understand the system, i.e., have transparency, and with that be better able to co-operate with it.

While this paper focusses on the automation design, rather than on the design of a system mediating between said automation and the human operator, some of the design principles proposed here also apply to the Mediator system. For example, the design principles can be applied to determine which ADAS systems should be turned on together, such that the resulting automation task resembles a task as described by a human mental model.

6.3. Decision Logic

In the next subsections we discuss the models and algorithms that will form the backbone behind the decision logic that is at the heart of the Mediator system.

6.3.1. Overview of Decision Models

The field of Artificial Intelligence spans the many areas of research that are required to build intelligent agents, such as the one at the core of the Mediator system. Typically, an agent can be characterized using a “sense-think-act” loop, which starts by interpreting incoming sensor data, take a decision what action is appropriate and finally execute the chosen action. All three components are present in the Mediator system, but here we limit ourselves to the decision-making process.

Many types of models have been proposed to capture the decision making of an agent, for instance as discussed by Russell, & Norvig (2009). One of the earliest approaches is to capture all knowledge of the agent in a database of logical facts, and then use techniques like theorem proving to infer behaviour. Classical planning extends these ideas by allowing for agents to reason over the effect of actions on state variables (instead of ground states). Finally, when non-deterministic environments are concerned, we can turn to techniques like contingent planning or the Markov Decision Process model.

Neogi (2016) studied the problem of task allocation in increasingly autonomous airplane cockpits. She focuses a first-order logic framework, which allows for formally verifying the safety properties that have been defined a priori. For instance, the system can detect potentially inconsistent information states between the human pilot and the intelligent agent. While valuable, the underlying model cannot reason over multiple outcomes, which means it is unsuitable for the dynamic and hard-to-predict environments the Mediator system operates in.

A key distinction between the different decision-making models is whether or not they account for non-deterministic environments. Often, the system we aim to control is simply not deterministic or cannot be modelled with sufficient accuracy for it to be deterministic. For instance, in the context of the MEDIATOR project, there is uncertainty about how a human driver will respond to a message that it should take control. A second type of uncertainty relates to the fact that often the agent does not have access to all the required knowledge. For instance, the level of fatigue of the driver is likely to be an important variable to take into account, but it is not known. Instead, it has to be deduced by interpreting sensor data. To be able to take decisions under these types of uncertainty, AI researchers have turned to the Markov Decision Process model, as detailed next.

6.3.2. Markov Decision Process

A Markov Decision Process (MDP) captures the interaction of an agent with an environment that is assumed to respond probabilistically to the actions the agent executes (Puterman, 1994). In particular, it defines a stochastic transition function that computes the probability of jumping from a particular state of the system to another one, given the action to be executed. It is important that the description of the state of the system captures all information required to compute such probabilities, without needing to rely on past information (the so-called Markov property). The state description can also be modelled by multiple state variables. For instance, there will be variables related to the driver state (e.g., tired or not), vehicle state (e.g., current speed) and driving context (e.g., other vehicles). We can distinguish between multiple types of variables, such as finite discrete ones or continuous ones.

There is an inherent trade-off between modelling the environment as accurately as possible and keeping a tractable model. Note that such a “curse of dimensionality” is present in any approach to decision making. A promising technique to combat a state explosion is to develop a divide-and-conquer technique such as a hierarchical model. In a hierarchical setup, the overall task is divided in sub-tasks, each with its own state variables and time scale (potentially). This allows the agent to solve several smaller decision-making problems instead of one large one.

Furthermore, when not all of these state variables are directly known to the agent, a Partially Observable MDP (POMDP) is an appropriate model (Spaan, 2012). This extends the MDP with an observation function, that relates sensor observations to states in a probabilistic manner. For instance, determining the driving context relies heavily on sensors that have limited accuracy and also only provide a local view.

A second component of an MDP or POMDP is its objective function, as discussed next.

6.3.3. Objective function

An intelligent agent is usually built for a certain purpose, which is encoded in its goals or objectives. In the MDP model, a reward function is defined that maps states (and potentially actions) to a real number, the so-called reward. It can be used to define certain goal states as well as states to avoid, as well as the cost of executing actions. While the agent receives a reward every time step, it optimizes for a long-term sequence of rewards. That way, it does not myopically pick the action that gives a reward now but balances it with the rewards it can get in the future. For instance, in terms of the Mediator system, if there is a high reward for switching control now, but we can foresee that in a couple of time steps we would need to switch back, not switching might be the better action to take. In a complicated system such as the Mediator one, there are often multiple objectives that one would like to achieve. In such a context Multi-Objective MDP models might need to be considered (Rojers, 2013). Furthermore, as safety is paramount, a choice could be to not encode safety in the reward function, but instead formulate it as a constraint. In that case, a Constrained (PO)MDP model would be appropriate (Walraven, & Soaan, 2018). Next, we discuss how, given a description of the MDP model, an agent can compute what action to take next.

6.3.4. Optimization algorithm

A solution to an MDP is called a policy, which maps states to actions. The quality of a policy can be quantified by its values: the long-term sum of rewards the agent expects to receive when executing the policy. A policy that achieves maximum value is called an optimal policy. In the literature, a large number of algorithms have been proposed to compute such (optimal or sub-optimal) policies. An important distinction is between offline and online algorithms. In the latter case, when the agent is in a certain state, it performs a search to compute the best action to take. In the former case, the agent has precomputed the best action in every state and only needs to look it up. While the response time of offline methods is desirable in the context of our Mediator system, depending on the problem size an accurate offline solution for the entire MDP might not be feasible. An elegant solution could be to couple a state evaluator that has been trained offline with a small amount of (time-bound) online search. Furthermore, as discussed before, the hierarchical nature of the problem can be exploited when solving the problem.

6.3.5. Learning component

Besides the distinction between offline and online decision making, it is key to consider whether the MDP model that has been defined is accurate. Typically, such models are defined by experts or learned from data. In both cases, it is possible that the model is not accurate enough in unexpected

circumstances: those not foreseen by the experts or never experienced before and hence not in the data set. The latter is a serious problem when validating the safety of autonomous vehicles in general, as certain key events might occur only very infrequently. In the Mediator context, we will develop methods that reason about the uncertainty of the model itself, in order to achieve robust solutions. For this to be feasible, the machine learning methods employed during model learning should have an uncertainty measure attached to them.

A specific issue that we can foresee for our Mediator system is how a human driver will respond to actions that aim to improve his or her fitness to drive. When interacting over time, we can adjust our model of how the response will be, but in any case, the response needs to be monitored closely. In fact, this is a key reason to focus on models that allow for uncertain outcomes, as the Mediator system needs to accurately trade off potential lack of positive effect on human driver fitness with the need to execute an emergency stop procedure, for instance.

6.4. State space

The Mediate Control decision making component makes its decisions based on information on the driving context, the current human driver state and capabilities, and the current automation state and capabilities. Together, these information sources make up the input space of the decision making component, or in the terminology of Markov Decision Processes (the currently selected most likely candidate for the formalized decision making framework to use), the *state space*. The integration of these input information sources into the state description to be used in the Mediate Control decision making component is visualized in Figure 6.5. We envision multiple markers or indicators for each category (driver state, automation state, driving context), as illustrated in the figure. We will go into more detail about each of the categories in the next three subsections.

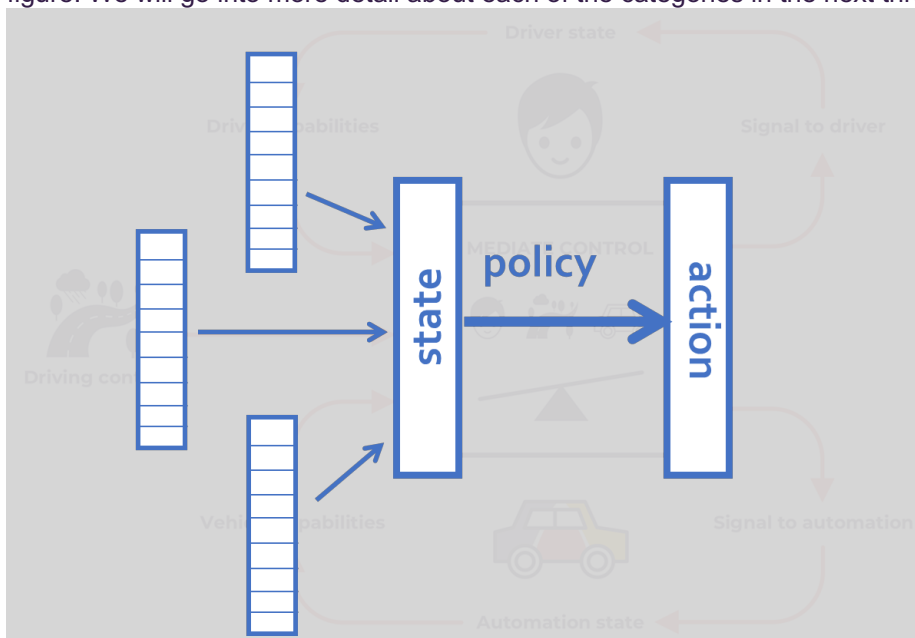


Figure 6.5 Illustration of the integration of the input information sources from driver state, automation state, and driving context into the state description to be used in the Mediate Control decision making component.

6.4.1. Driver States

For the driver state/capabilities, we envision indicators on the fatigue level, distraction level, the (longer-term) competence of the driver, perhaps indicators on cognitive overload or underload, and

perhaps indicators on personality, emotions, trust of the driver in the systems, and personal preferences. These are summarized in Figure 6.6. The extent to which each will be realized is yet to be decided. However, the set-up of the Mediator system and this component providing input to the Mediate Control decision making component should first of all be that it is extendible and adaptable to new and various indicators. Second, the driver state component must not provide relatively ‘raw’ indicators on fatigue, distraction, etc., but “summary” variables indicating the driver “fitness”, in such a way as to make that comparable to what the automation side will provide. Chapter 3 on the assessment of human fitness and Chapter 7 on the functional requirements provide more information on this.

Importantly, given the importance of *predictive information* for decision making as outlined in the introduction of this chapter (i.e. the decision making system must know well ahead of time if a control transfer must be made), the driver state indicator variables must also be accompanied by *forecasts* (for the next seconds, or minutes, if possible). Furthermore, *confidence* values should be provided as well, such that the decision making component can gauge how certain the driver monitoring system is about the human driver being very fatigued, for instance.

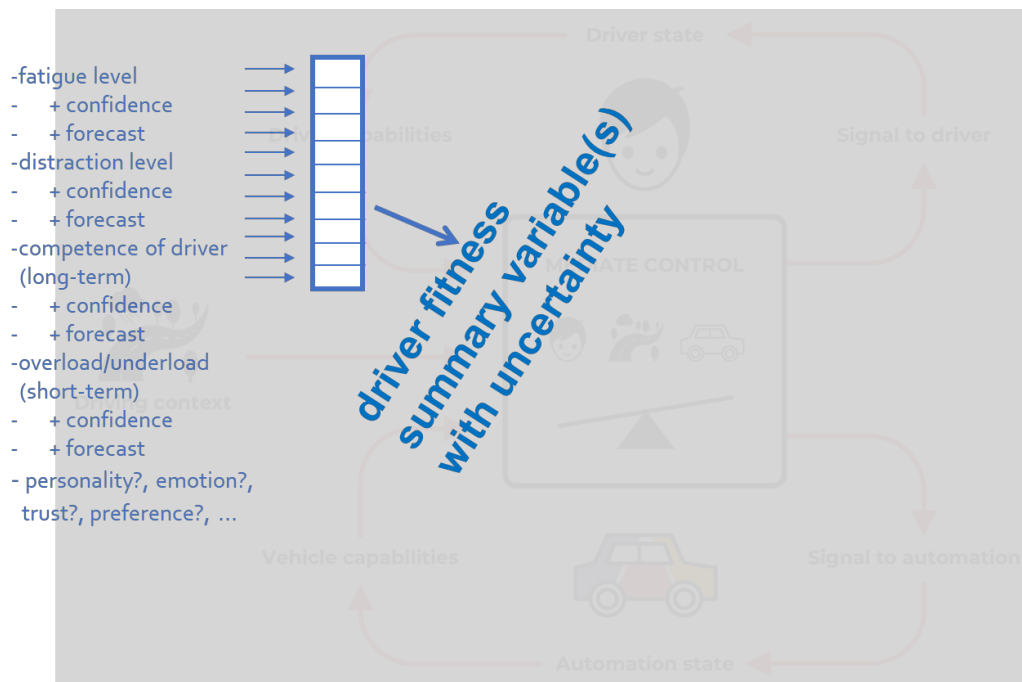


Figure 6.6: Possible driver state inputs to the Mediate Control decision making system.

6.4.2. Automation States

Similarly, for the automation state/capabilities input, we envision various indicators. These might be organised along the lines of the various levels of control used in the automated driving systems, as illustrated in Figure 6.7. These may include a (highest level) “navigation” level (taking care of the route planning); a “guidance” level (where information is collected regarding the currently estimated ‘world model’ and the trajectory plan for the next several seconds is computed); and a “stabilisation” level (responsible for real-time control of the actuators and keeping the vehicle stable at all times and speeds). Each such level can have its own relevant indicator variables. However, similar to what is described above for the driver state variables, the automation state component must not provide relatively ‘raw’ indicators which may be tied to internal automation levels or

measures, etc. Instead, “summary” variables indicating the overall automation “fitness” should be provided, in such a way as to make them comparable to what the driver state side will provide (see also Chapter **Fout! Verwijzingsbron niet gevonden.**).

Also, and similar to what is proposed for driver state variables, *forecasts* (for the next few seconds or even minutes) and *confidence* values will be required, so that the decision making system can gauge whether in the next few seconds or minutes a transfer of control is needed or possible.



Figure 6.7: Possible automation state inputs to the Mediate Control decision making system.

6.4.3. Context States

Both the human driver state indicator variables and the automation state indicator variables depend on the driving context, and must take the driving context into account in their own way, essentially giving the best input they can for answering the question: is the human driver, or the automated driving system, suitable for the current and predicted driving context? However, we envision that *in addition*, it may be good for the Mediate Control decision making component to have its own ‘view’ of the driving context. As illustrated in Figure 6.8, this may include indicators on the type of road the vehicle is currently on (and will be on soon), including perhaps availability of HD map information, an estimation of the current (and predicted) traffic complexity that is encountered, weather and time of day, the (perhaps related) visibility of relevant objects and infrastructure markings, etc. The idea behind this is that this may allow for a type of ‘taxonomy’ of driving contexts to be designed or learned, perhaps with associated rules or statistics on when and where either the human driver or the automated driving system can, or typically does, perform well or not. This will help the Mediate Control decision making component in its decisions. Again, the various indicators should be available in the form of “summary” variables that the decision component can relatively easily integrate into the overall input (or “state”) representation.

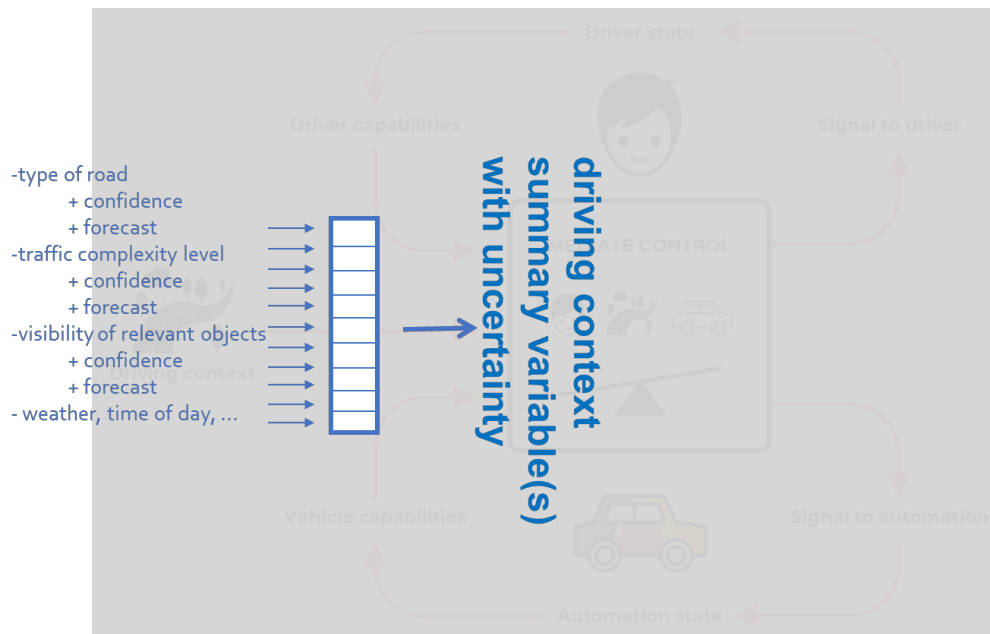


Figure 6.8: Possible driving context inputs to the Mediate Control decision making system.

6.5. Action Space

The action space of the decision making component refers to the set of actions which the decision logic requires from all other components and the corresponding information those components need from the decision logic to execute this action. For example, if the decision logic found a driving task transfer to be necessary, it will output a request for a driving task transfer action to the HMI and provide all necessary information needed to perform such an action. At this stage, four classes of actions, resulting in seven individual tasks, are identified and shown in Figure 6.9.

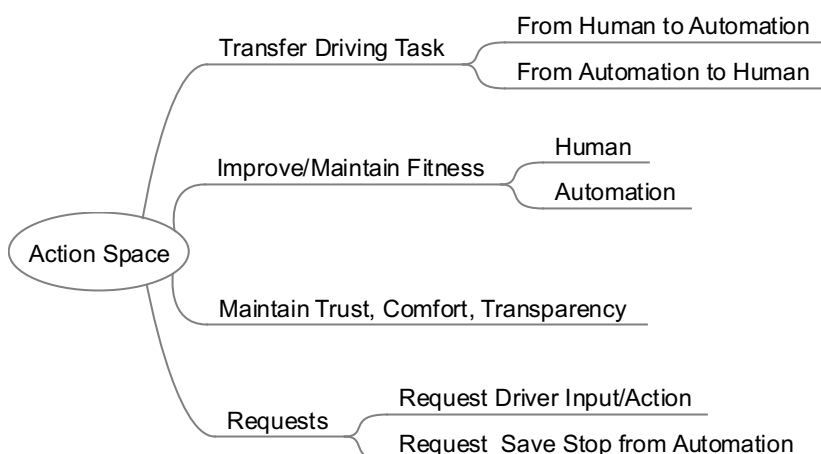


Figure 6.9: Action Space of the Mediator system

The main action of the Mediator system is to mediate the transfer of a driving task between automation and human. All other actions listed can be seen as sub actions of this initial action. For example, for a safe transfer of the driving task, the human fitness may need to be improved.

Hence, one option for the Mediator system is to develop a hierarchical division of actions, but in the next subsections all four classes of actions are described individually.

The information provided to the other Mediator components, i.e. information needed to be able to execute the action properly, should be selected with optimal human-automation teaming in mind. An important quality for the design of human-machine cooperative systems is that there is consistency between the four cornerstones authority, ability, responsibility and control (A2RC) (Flemisch et al., 2011), as well as consistency between the mental models of all actors (Flemisch et al., 2011; Goodrich, & Boer, 2003). Selecting the information provided to other models with each action request, should thus be done to optimize consistency between A2RC, as well as consistency between the mental models of all actors.

At this stage in the project it is still undecided for which exact sub-actions of the overall driving task the mediation will be designed. As also discussed in Section 4.2.2, human target-oriented behaviour, which includes the driving task, is often subdivided as skill, rule and knowledge based behaviour as defined by Rasmussen (1983). In automation, sub-tasks of the driving task are instead often categorized using the three-level hierarchy of the driving task, consisting of navigation, guidance and stabilisation, defined by Donges (2015). Donges (2015) combined both schemes to describe the human in a driving task. Both schemes can be useful to form definitions of driving sub-actions for which the Mediator system will mediate between human and automation.

In this section, next to the general definition of a sub-action, also the term *task type* is introduced. This term refers, for example, to actually controlling the vehicle or a request to monitor the automation controlling the vehicle. The task type can therefore be described using three of the four cornerstones of Flemish et al. (2011): authority, control and responsibility.

As mentioned, the following sections elaborate on the four identified classes of actions in the action space of the decision logic (Figure 6.9). Examples are given, where possible, to reduce the level of abstraction and further explore the type of information required for the proper execution of different actions by other Mediator components. For each action an initial list of information is presented. The lists contain quite some technical information, which might be logical for the developers, but might only confuse the actual drivers who are expected to understand such information. It is therefore important to ensure that only the information that is relevant to the driver is communicated in an intuitive and uncomplicated manner. In general, the purpose of these lists of information is to help to define the possible parameters of the action space needed for the actual development of the Mediator system. They should not be considered as definite parameters of the action space. The definite parameters will be defined based on the exact scope, architecture and terminology of the Mediator system.

6.5.1. Transfer Driving Task

One of the Mediator system's main goals is mediating a safe transfer of a driving (sub)task between human and automation. In order to transfer a driving task several characteristics of the transfer have to be defined and several preconditions have to be met. When defining these characteristics and preconditions all four cornerstones, authority, ability, responsibility and control, as well as consistency in mental models, should be taken into account.

6.5.1.1. Authority

It should be clear who currently has the control authority and to whom the control authority is being transferred. For example, on a highway the driver can desire the longitudinal vehicle control authority to be transferred to the automation, with the aim of reducing his/her workload.

It should also be clear who has the change authority, in which direction they have this authority (towards more automation or towards less automation), if this authority is (partially) transferred and to whom. For example, in an emergency situation, the automation might obtain change authority to change to a higher automation level, such as the authority to activate emergency braking.

6.5.1.2. Ability

The control ability of an actor refers to their fitness to execute a certain control task. Before each transfer of control it should be clear that the actor to whom the control is transferred has the ability to execute the corresponding control task. For example, a transfer of driving task to the human driver should not be initiated when the driver is too fatigued to drive safely. In this case, instead of a transfer of driving task request, the decision logic might send out a request to improve human fitness.

6.5.1.3. Responsibility

It should be clear to both actors who has the responsibility for which parts of the driving task. For example, while a Cooperative Adaptive Cruise Control (CACC) has the authority to change speed when another vehicle is approaching, the driver has the authority and responsibility to change the vehicle speed to avoid a crash.

6.5.1.4. Control

Especially if the control authority is shared, i.e., if both human and automation have authority to exert control for the performance of the same control task, it is necessary that both actors are aware of any controls being executed. For example, during lateral haptic shared control, the control actions of both driver and automation are communicated via haptic feedback, as both automation and human exert control forces on the same steering wheel. Any changes in the control strategy of either actor should also be communicated, such that the other actor can adapt. For example, during a transfer of control authority, the stiffness with which the automation exerts control forces can be gradually reduced until no forces are exerted and the human has full control. In haptic shared control, such change in stiffness is again communicated via haptic feedback.

6.5.1.5. Mental Models

Understanding state changes or reasons behind driving task transfers can help in developing accurate mental models, but also can increase trust in the system and driver comfort. For example, the driver can be informed that the driving task is transferred to the automation due to driver inattention. With this information the driver can predict when such a transfer of driving task is initiated in similar future scenarios, but also understand how to avoid such scenarios if desired.

When requesting a transfer of driving task, the decision logic should provide the HMI and other Mediator components with enough information to ensure consistency of A2RC and the actor's mental models. At this stage, the following initial list of driving task transfer information is proposed:

- Task type (e.g., defining authority/control/responsibility);
- Sub-tasks (e.g., lateral/longitudinal control);
- Direction (automation to human or vice versa);
- Time available;
- Urgency;
- Necessity;
- Human or automation fitness sub-measure (e.g., fatigue for humans or lane marking reliability for automation);
- Transfer completion.

6.5.2. Improve/Maintain Fitness

A first sub action of the Mediator system relates to improving or maintaining fitness, either of the human driver or of the automation.

6.5.2.1. Human Fitness

Before a transfer of driving task to the human is requested, the decision logic will determine if the human is fit enough to drive. In case of sufficient fitness, the transfer of driving task request is sent out to the HMI. However, if the human is not sufficiently fit, a request to improve the human fitness is sent out. The HMI is then expected to try to improve the human fitness based on information sent out together with the request.

In order to improve human fitness the HMI first of all needs to know for which task the human fitness needs to be improved. For example, the decision logic needs the driver to take over lateral control, while the automation continues with the longitudinal control. In this case, the driver needs to be prepared both mentally, e.g., have sufficient situational awareness, and physically, e.g., have his hands on the steering wheel, to take over the steering wheel. The HMI can thus request that the driver puts his hands on the steering wheel, but does not need to request feet on the gas pedals, as this control task does not need to be performed.

It is also possible that the driver needs to be prepared to take over a driving task, but does not need to take control right at that moment. In that case, the driver regains control authority together with the automation, but does not resume actual control of the vehicle. Deciding if the human is sufficiently fit for this type of task could include a score regarding his situational awareness, but might not require him to have his hands on the steering wheel.

The decision logic should also convey information on why human fitness is currently insufficient. This can help the HMI to decide how to improve human fitness. Taking the first example, if the driver is unfit because he is drowsy, the HMI might use blue lighting to decrease drowsiness. However, if the driver is involved in a secondary task, a simple request to stop the secondary task might suffice.

As the HMI in this case takes actions with the goal of improving human fitness, it can be helpful if the HMI receives information on the corresponding change in human fitness. For example, a drowsy driver could first be subjected to blue light and if his fitness does not improve, the light strength can be increased, or other, possibly less preferred actions, such as alarming sounds, could be set in motion.

In summary, at this stage the following information is proposed to accompany an “improve human fitness” request:

- Task type (e.g., authority/control/responsibility);
- Sub-tasks for which to improve human fitness (e.g., lateral/longitudinal control);
- Human fitness sub-measure (e.g., fatigue, hands not on steering wheel, distraction);
- Change in corresponding fitness sub-measure.

6.5.2.2. Automation Fitness

Before a transfer of a driving task to the automation is requested, the decision logic will determine if the automation is fit enough to drive. It is possible that the automation is currently not fit to drive, but would be after a control action of the human. For example, if lane markings on the current lane

are unreliable, a request to change lanes to a lane with better markings can be made. If information on the desired vehicle trajectory over a longer period of time is known, one could predict when the vehicle is approaching a situation in which the automation is known to be unfit. Depending on the driver fitness/willingness to drive, it could be optimal to avoid the situation where the automation is known to be unfit, by changing the itinerary. In this case the human can be requested to approve the itinerary change, or, if the automation has itinerary change authority, the itinerary can be changed automatically to maintain sufficient automation fitness in the future.

At this stage, the following information is proposed to accompany an “improve automation fitness” request:

- Task type (e.g., authority/control/responsibility);
- Sub-tasks for which to improve automation fitness (e.g., lateral/longitudinal control);
- Automation fitness sub-measure (e.g., lane marking reliability, future road type such as highway/city roads);
- Action required from human (e.g., request to change lanes or approve new itinerary);
- Information that needs to be communicated to human (e.g., the itinerary has been changed).

6.5.3. Maintain Trust, Comfort, Transparency

Mental models are used to predict the behaviour of the other actor during the driving task. An important concept for the development of proper mental models is system transparency. Appropriate system transparency improves system performance and increases trust (Hoff, & Bashir, 2015).

Throughout the driving task both human and automation will update their mental models of the system. As mentioned before, these mental models need to be consistent for proper human-automation cooperation. One way of aiding in the development of consistent mental models is to provide the driver with information on the automation state. For example, drivers can be informed of the levels of uncertainty of the automation in order to reduce overreliance, such as was proposed by Beller, Heesen, & Vollrath (2013). Another option could be to inform the driver of the tasks currently assigned to the automation, to avoid mode confusion.

Both types of information could be provided continuously, or only provided when a probability is detected that overreliance or mode confusion is occurring. In the former case, such information might be outputted directly from the automation component to the HMI, while in the latter case the decision logic should decide if system transparency is indeed in jeopardy and a specific request to maintain system transparency should be sent out to the HMI.

The following information is proposed to be sent out in case of a request to maintain system transparency:

- Type of transparency issue that might occur (e.g., overreliance, mode confusion);
- Automation state needed to improve transparency (e.g., automation uncertainty levels, control tasks assigned to automation);
- Probability of transparency issue actually occurring.

6.5.4. Requests

The fourth and final class of actions in the Space Action has to do with requests. One request relates to initiating a save stop, another relates to asking the driver for specific input or action.

6.5.4.1. Request Save Stop from Automation

If the decision logic predicts an unsafe situation in the near future, without seeing a possibility to improve either human or automation fitness, it can decide to initiate a save stop manoeuvre. It depends on the actual vehicle whether such a manoeuvre will be performed by the automation, or a request will be sent to the human. If, for example, the vehicle is equipped with SAE level 3 automation or higher, a “save stop” feature will likely be implemented as part of the automation. In this case, the automation will be requested to initiate the save stop manoeuvre. If, on the other hand, the level is only equipped with SAE level 2 automation, such feature is likely not implemented. In this case, before the driver actually becomes unfit, the driver is requested to commence a save stop manoeuvre.

At this stage, the following information is proposed to accompany an “initiate save stop” request:

- Actor requested to perform a save stop;
- Human fitness sub-measure;
- Automation fitness sub-measure;
- Urgency;
- Time available before initiation;
- In case human is requested: save stopping opportunities nearby and/or other information to aid in performing the manoeuvre.

6.5.4.2. Request Driver Input/Action

In order to support decision making it is possible that human input is required at times. In this case the decision logic can send out a request to the HMI for user input. For example, if the human markers for fatigue have a high uncertainty, the driver can be asked to provide a rating of his level of fatigue. Also less direct ways to decrease the human marker uncertainty can be initiated. For example, the driver can be asked to perform some secondary task in order to test fatigue levels. Driver input can also be requested when the decision logic has identified multiple solutions. For example, the driver requests a transfer of a driving task because he needs to do a secondary task, while the automation is currently only marginally fit. In this case a transfer of the driving task could be made directly, but another solution is to delay the transfer until a safer transfer of the driving task can be organised. A request for user input could be sent to the HMI to determine which solution the human prefers.

At this stage, the following information is proposed to accompany a request for driver input/action:

- Required action and action specific information (e.g., reduce uncertainty in specific fitness sub-measure, choose preferred solution);
- Time available;
- Reason for request (e.g., fitness uncertainties, multiple solutions found).

In the structure presented here both the actions “Request Driver Input/Action”, e.g. a request for additional information to aid decision making, and the action “Improve Automation Fitness”, e.g., requesting to stop a using a mobile phone, can contain requests for driver actions. Due to their difference in origin, they are here described in different sections. For the implementation, however, it might be more logical to group all requests to the driver.

6.6. Conclusion

In this chapter the basic principles and components of the Mediator decision logic have been presented. From the work done so far, some key knowledge and development gaps can be identified.

- First of all, the interface between the human, automation and HMI components and the decision logic component will need to be defined in more detail. Using these detailed interface descriptions, a clear integrated framework of all components that form the basis of the Mediator system will need to be developed.
- Second, the decision logic will make use of an objective function to determine which action is preferred in terms of safety and comfort. How exactly safety and comfort will be defined and mapped onto measurable and comparable parameters that can be used in such an objective function is still to be investigated.
- Third, further complexities of the Mediator system are found in the validation of the system, as explained in Subsection 6.3.5. This is particularly challenging due to the limited availability of data for all possibly occurring situations. Suitable methods for the development of robust solutions should therefore be investigated.
- A fourth knowledge gap that needs to be addressed is the feasibility of adapting the decision logic to specific persons. This could be more static, e.g., in the form of predefined settings for driver types, or more dynamic, e.g., real-time adaptation based on driver behaviour using learning algorithms. The feasibility of such solutions should be investigated together with the expected benefit for safety and comfort.
- Finally, the feasibility of the Mediator logic from a legal and ethical perspective should be investigated. For example, can Mediator overrule the driver, and if yes, in which circumstances?

These knowledge and development gaps, focusing on integration, validation and feasibility, will be addressed as next steps in the project.

This chapter also described the initial ideas for the implementation of a decision logic. This process identified some additional knowledge and development gaps which are mainly relevant for the actual design and development of the system.

The core of the decision logic process will most likely be based on Markov Decision Processes (MDP). Due to the complexity of the Mediator system, however, likely multiple adjustments to the standard MDP are necessary. Section 6.3 described several adaptations such as, making use of a hierarchical structure to reduce problem complexity, using partially observable MDPs to deal with non-observable states and in particular the uncertainty surround assessments of the fitness of both the human driver and the automated driving systems, and multi-objective MDPs and constrained MDPs to deal with the several objectives that need to be optimized in the Mediator system. While these adaptations to the MDP are relatively well known, it is not yet evident how to combine all or some of these adaptations within the Mediator system.

Another choice that still needs to be investigated related to the use of offline or online optimization or some combination of both. While offline optimization would be most time-efficient regarding the required real time capability of the Mediator system, the complexity of the offline problem likely makes this unfeasible. In further steps in the project, online or hybrid solutions will be investigated.

Subsection 6.3.5 briefly touched upon the challenges to deal with complex procedures over time. For example, the high level task of improving human fitness can have a complex low level procedure associated with it to accomplish this, which needs to be monitored for expected outcome continuously. Similarly, the take-over procedure will consist of a relatively simple high level decision to switch control between automation and driver, combined with a complex low level procedure to achieve this smoothly.

For the state space, the main knowledge gaps relate to how exactly the state information will be defined. Currently, only a general idea exists of which information should serve as an input to the decision logic, as explained in Section 6.4. However, no exact definition of the data representations and parameters is defined yet. In the next steps in the project, such definitions will be developed taking account of the human factors and the features of the automation.

Similarly, an exact definition of the data representations and parameters in the action space will need to be developed based on knowledge on HMI, human factors and automation characteristics. Another knowledge gap in the action space is the implementation of a hierarchical structure combining high level actions with their low level procedures that realize the high level actions. These procedures will need to be accurately mapped out and communicated to the HMI, as well as monitored. In next steps in the project a priority list of all identified knowledge and developments gaps will be established, based on what is most relevant for the development of a first basic working example of the Mediator system.

In the next steps of the project these knowledge and development gaps will be addressed. After further investigation of these gaps, an outline of the quantified decision logic algorithms will be defined.

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7. Use cases and their functional requirements

7.1. Introduction

In order to limit the scope of the development of the Mediator system during the project a limited number of use cases have been identified which reflect the intended functioning of the Mediator system. Within the MEDIATOR project an operational Mediator system will be developed for these use cases, each with their own set of functional requirements.

This chapter describes the initial set of three main use cases (Section 7.2) and their relevant functional requirements (Section 7.3) and non-functional requirements (Section 7.4). In a later stage, each use case will be further narrowed down into more detailed sub-use cases. An example of the structure of such a sub-use case is provided in Section 7.5.

7.2. Preliminary use cases

Initially three use cases have been identified for the Mediator system. Since the main goal of the MEDIATOR project is to improve traffic safety in the transition towards automated driving, the three use cases represent each of the three middle levels of automation: SAE level 2, SAE level 3 and SAE level 4 (see Figure 5.5 for details). Each of these levels of automation put different requirements to the human driver and the automation, and, hence require different forms of mediation. The next three subsection describe the three preliminary use cases and their main safety challenges related to the human factors (Chapter 3), the automation (Chapter **Fout!** **Verwijzingsbron niet gevonden.**), the HMI (Chapter 5) and the decision logic (Chapter 6). In addition to the main challenges, a “special focus” has been identified for each use case. These special focus topics are not necessarily unique to a use case, but are specifically (safety) relevant, interesting or challenging in that particular case.

7.2.1. Use case A: Continuous mediation

The first use case focuses on the main challenges at SAE automation level 2. With level 2 automation, the driver is required to participate in the driving task continuously. The central idea of this use case is that there will be shared control between the automation and the human. While the automation systems do certain parts of the driving task, the human driver does other, complementary tasks in parallel. Adequate situational awareness needs to be maintained at all times. The main risks in level 2 automation are mode confusion and underload, which may have a negative impact on driving performance.

The main challenge in this use case is to determine the most optimal task load for the human driver to maintain situational awareness and adequate driving performance. For example: will the driving performance and related situational awareness maintain an acceptable level when the driver is only involved in the passive monitoring task? Or will driving performance only remain at a sufficient level when the control task is continuously shared between the human and the automation, and the driver is thus requested to continuously and actively provide input? Related challenges are then to

make drivers aware of the task they need to perform, help them to perform the task safely, and assess if they are adequately involved in the task.

As indicated, in a vehicle with level 2 automation, drivers are required to have constant situational and mode awareness, which is highly relevant for the interaction with vulnerable road users. Therefore, for this use case a special focus will be placed on the interaction with vulnerable road users. More specifically, can the Mediator system use vulnerable road user information from the automation to improve the drivers' situational awareness?

7.2.2. Use case B: Driver standby

The second use case focuses on the main challenges at SAE automation level 3. At level 3, the driver can hand over full control to the automation and be “out of the loop” for periods of time. Central in this use case is the question how to maintain accurate information about current and near-future human and automation fitness, in order to allow for these periods of automated driving in which the driver is out of the loop. This can only be the case under specific conditions when the automation system is confident it can function for the next moments. The driver should therefore be prepared to resume control on short notice at any time.

The main challenges in this use case are determining how long it takes to regain driver fitness, how long automation is fit to drive, and how these times should be balanced. The estimation of the time automation can drive safely without human supervision and the time the driver needs to take back control are paramount. Estimating these values with sufficient confidence is a major challenge. The HMI challenge is how and when to communicate this time budget to the driver, and how to mediate human take-over in a relatively short time.

The time it takes a driver to become sufficiently fit to take over from the automation does not only depend on context and dynamic driver states, but also on static characteristics of the driver, such as driving experience. In this use case a special focus is placed on adapting the Mediator to different driver characteristics.

7.2.3. Use case C: Time to sleep

The last use case focuses on the main challenges at SAE automation level 4. At level 4, the driver can refrain from the driving task for extended periods of time, on the order of several minutes to potentially several hours. The central idea of this use case is very similar to the level 3 use case, except that the periods of automation can span several minutes to hours. This allows the driver to do other completely immersive tasks for a long period, such as sleeping.

The main challenges in this use case are predicting the moment the take-over should take place with sufficient confidence, and bringing the driver back into the loop after a period of full absence due to sleeping or being completely immersed in another task. In such cases, it might be an extensive process to bring the driver back into the loop.

In this use case, the driver can be completely out of the loop for prolonged periods. A special focus is placed on bringing the driver back into the loop after a long period of full absence, as this might be the most challenging scenario in level 4 automation. Specific attention is devoted to determining if this process can be facilitated by presenting arousing stimuli or providing relevant context information and interactively checking whether the driver is coming back into the loop successfully.

7.2.4. Overview of challenges

In Table 7.1 below, for each use case, the main challenges for human factors/behaviour, automation, HMI, and decision logic are summarized. It should be noted that these are not the only challenges, but challenges that are most prominent for the use cases presented here. More general challenges relevant to all use cases are not shown in this table.

Table 7.1 Overview of use case challenges and special focus.

	Use case A	Use case B	Use case C
Human factor challenges	Continuous fitness assessment Mode awareness	Determine time to driver fitness Mode awareness	Determine time to driver fitness Mode awareness
Automation challenges	Sharing context knowledge Shared control	Determine time to automation unfitness (real-time sensor/AI based predictions)	Determine time to automation unfitness (map/zone based predictions)
HMI challenges	Avoid mode confusion Avoid overreliance Shared control Keep driver in the loop Maintain situational awareness	Avoid mode confusion Avoid overreliance Mediate short notice take-over	Mediate long absence take-over
Decision logic challenges	Maintain driver fitness	Determine time automation is fit Determine time to take over Ensure timely and suitable take-over procedure	Determine time to take over Suitable take-over procedure
Special focus	Interaction with vulnerable road users	Driver specific time to fitness (e.g. elderly drivers)	Long term unfitness (e.g. sleeping, being fully immersed in work etc.)

7.3. Related functional requirements

For each of the above-mentioned use cases, a list of higher-level functional requirements is made. These functional requirements describe the intended functions of the Mediator system. The functional requirements flow from the Mediator functions, and follow a layer system with requirements becoming more specific with each level. The Mediator system seeks to optimise safety between control for the human driver and the automation. Therefore, the ability to assess human and automation fitness is essential for the system to function. Additionally, the ability of the Mediator system to act on the fitness assessments is required. These three elements make up the high-level functional requirements of the system. An overview of the functional requirements structure is shown in Figure 7.1. The next subsections discuss the functional requirements related to human fitness, automation fitness, and Mediator actions in more detail.

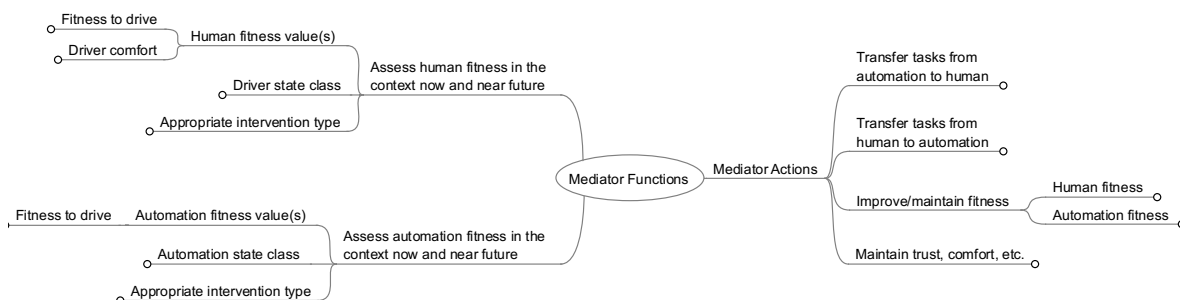


Figure 7.1 Functional requirements structure.

7.3.1. Assessment of human fitness

The first functional requirements related to the need to assess human fitness to drive. The human fitness values refer to the ability to control the vehicle and the comfort of the driver. A trade-off between safety and comfort is made, with safety having priority at all times. In order to ensure drivers use the Mediator system, optimisation for comfort is made when possible. The ability to distinguish between different classes of driver state allows for the prediction of future fitness values and can be used to determine the intervention type best suited.

Human fitness values

Measures that describe the ability of the human driver to control the vehicle. This is divided into two different sets of requirements:

- **Fitness to drive:** The ability to assess the level of driver fitness. This can for example be the time to driver fitness and time to driver unfitness. How fitness is determined depends on the use case. Use case A also requires determining the fitness for an active monitoring task or haptic shared control. These fitness assessments include a confidence level and a prediction of this fitness in the future.
- **Driver comfort:** The ability to assess driver comfort. This includes direct measures of comfort, but also indirect measures such as trust in the automation. A level of confidence and prediction of this comfort in the future are included in the assessments.

Driver state class

The ability to differentiate between classes of driver state, such as fatigued or distracted.

Appropriate intervention type

The ability to determine the intervention type best suited to improve human fitness now and in the near future, dependent on the current situation.

7.3.2. Assessment of automation fitness

The second set of functional requirements relate to the assessment of the automation systems' fitness to drive. Current and predicted ability to control the vehicle are represented in this group. The ability to distinguish between different classes of automation state is included here and assists the ability to decide on the appropriate type of intervention to improve fitness.

Automation fitness values

The ability to assess the level of automation system fitness can for example be the time to automation fitness and time to automation unfitness. These fitness assessments include a confidence level and a prediction of this fitness in the future. Fitness levels can be different for different automation systems, i.e., a level 3 system could be unfit, while a level 2 system is still fit to drive.

Automation state class

The ability to recognise, differentiate and predict classes of automation state. These classes refer to the reason for the current automation fitness and the current activation of the systems. Examples include roadworks or incidents that limit the automation fitness or the existence of an automation zone.

Appropriate intervention type

The ability to determine the intervention type best suited to improve automation fitness now and in the near future, dependent on the current situation. Examples of types of intervention include changing lanes or rerouting.

7.3.3. Mediator actions

The last set of functional requirements relate to the decision on an action and the required steps to complete the selected action. This includes the ability to decide on which actions are needed in order to complete a Mediator goal. The actions needed are guided by the intervention type most appropriate according to the assessment of human and automation fitness.

Transfer driving tasks to human

The ability to decide on, and carry out the actions needed to transfer driving tasks from the automation system to the human driver. Possible actions include the activation of specific HMI actions, followed by a take-over request and a take-over procedure.

Transfer driving tasks to automation

The ability to decide on, and carry out the actions needed to transfer driving tasks from the human driver to the automation system. Possible options include a forced take-over action when the driver is unfit for manual driving, or a voluntary take-over action when the driver activates the automation system.

Improve/maintain fitness

Functions that are used for implementing various interventions aimed at improving and maintaining driving fitness. This is divided into two different sets of requirements:

- **Improve and maintain human fitness:** The ability to decide on, and carry out, the actions needed to maintain or improve the current level of human fitness. Use case A includes the ability to realise a shared control task. This shared control task could be the creation of an active monitoring task to help keep driver attention, or a haptic shared control task to ensure driver participation.
- **Improve and maintain automation fitness:** The ability to decide on, and carry out, the actions needed to maintain or improve the current level of automation fitness. Possible actions include changing lanes or rerouting.

Maintain trust, comfort, etc.

The ability to decide on, and carry out, the actions needed to maintain or improve the current level of driver comfort, trust and related factors.

7.4. Non-functional requirements

Next to the functional requirements there are non-functional requirements for the Mediator system. The non-functional requirements help define what the Mediator system properties are like. These requirements are not directly related to what the system does, but relate to overall system qualities.

Non-functional requirements for the Mediator system include the following:

- The Mediator system shall be able to perform continuously and in real time. Without this feature the system does not have up-to-date information and, hence, will be unable to adequately mediate between automation and human driver.
- To ensure broad applicability of the Mediator system the system shall not be limited to one model of car.

- The system shall be trustworthy and transparent, facilitating acceptance and comfort for the user. This includes the requirement of only using non-intrusive measures for driver fitness. Should methods become less intrusive in the future, they could be added to the system.
- The Mediator system shall be secure, both cyberwise and physically.
- The Mediator system shall be easy to use, i.e., the time needed to learn how to use the system should be minimal for a broad range of driver types.
- The Mediator system shall be robust and resilient, i.e., have the ability to cope with errors in real time and always have sufficient performance. This includes retaining human driving skills and thus avoiding deskilling.
- Finally, the system shall be cost-effective.

The exact limit of the above mentioned requirements, e.g. number of car models, will be determined at a later stage.

7.5. Sub-use cases

In order to test the functionalities of the Mediator system, sub-use cases will be applied. The sub-use cases will be designed in such a way that specific functions of the system can be tested in varying settings, forming a test scenario. The functional elements concern the different types of action the Mediator system can take. These relate to transferring (part of) the driving task, assessing fitness and maintaining when necessary, and improving or maintaining trust and comfort. The definition of a sub-use case relates to the reason these actions are taken and the context they are taken in.

All sub-use cases will follow a structure that helps to specify what function is tested and what settings it is tested in. The functions that will be tested are discussed in Section 7.5.1 and the structuring of possible test settings in Section 7.5.2. The method used to select sub-use case elements is explained in Section 7.5.3 and an example is given in Section 7.5.4. The exact definition of the sub-use cases will take place in the next phase of the project.

7.5.1. Functional elements

A sub-use case will focus on testing a limited number of Mediator functions. These functions relate to assessment of driver and automation fitness, transition of the driving task between human and automation, and maintaining and improving of fitness, comfort and trust.

Table 7.2 below shows different functional elements of the Mediator system related to the transition of the driving task. Transition of the driving task can happen from human to automation or from automation to human. Different aspects of the Mediator system are involved, depending on the direction of the transfer, the initiation of the transfer and whether the transition is accepted by the driver and automation. The case in which the automation system is unable to function and switches off is considered “Mediator initiated”, but can never be denied.

Table 7.2 Overview of functional elements relating to task transition.

Transition to automation		Transition to human	
Accepted	Denied	Accepted	Denied
Human initiated			
Mediator initiated			

Further functional elements represent the need for the system to assess fitness level, and improve or maintain an adequate level of fitness, comfort and trust. These elements are shown in Table 7.3. Depending on the effectiveness of the action taken, different elements of the Mediator system are involved. Comfort and trust are not applicable to the automation system, and are thus not taken into account.

Table 7.3 Overview of functional elements relating assessment of, improving on and maintaining of fitness, comfort and trust.

Assess fitness		Improve and maintain fitness		Improve and maintain comfort, trust, etc.	
Accurate	Inaccurate	Effective	Ineffective	Effective	Ineffective
Human					
Automation					

7.5.2. Elements of the test setting

In order to test the Mediator system in different configurations, a selection of parameters can be made. These parameters can influence multiple factors of a sub use case and serve to validate the system in different settings. An overview of setting parameters is given in Figure 7.2. Short descriptions of possible different parameters are given below. It should be noted that this list is not exhaustive, and not all parameters might be present in later stages. Not all of these parameters are used within a single sub-use case. Parameters of no interest are not considered during a sub-use case and can be set to a “default” state where they have no influence on driver or system performance.

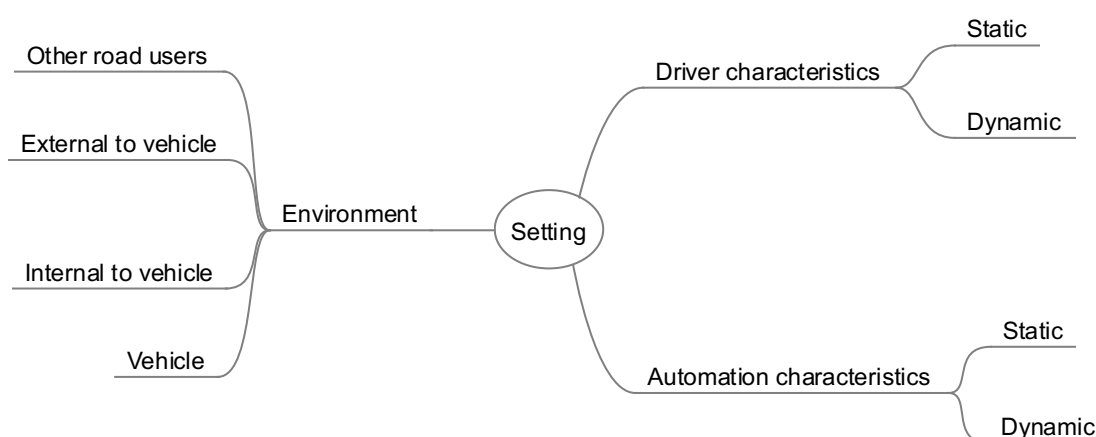


Figure 7.2 Overview of test setting parameters.

Environment

- **Other road users:** This includes type, number and behavioural characteristics (speed, location, direction, ...) of other road users.
- **External to the vehicle:** Parameters that influence the situation outside the vehicle. Road design, state, and type are included here. Vision condition and special events such as accidents or construction are also set here.
- **Internal to vehicle:** Parameters that influence the situation inside the vehicle. Temperature, ventilation, noise, inside lighting and possible distractions could be included here.
- **Vehicle:** Vehicle characteristics such as seating arrangement and ability to change seating style are included here.

Driver characteristics

- **Static characteristics:** Stable driver characteristics such as demographic, experience, driving style and attitude towards automation are included here.
- **Dynamic characteristics:** Dynamic characteristics are included here. These could be limb or seating position, sleep and distraction related factors, workload, and factors related to motion or health such as nausea.

Automation characteristics

- **Static characteristics:** Stable automation characteristics are included here. These could be automation level available, sensor characteristics and automation capabilities.
- **Dynamic characteristics:** Parameters that indicate the dynamic automation state class. This could be related to roadwork, bad lane markings or sensor failure. Automation settings such as time headway are also included here.

7.5.3. Selection of elements

A selection of functional elements and elements of the test setting will be made to create a sub-use case that tests a combination of elements that is relevant for the MEDIATOR project. What elements are selected depends on which part of the Mediator system is being tested in a sub-use case. The sub-use cases will be chosen in such a way that, if possible, they represent the more challenging situations. For example, this could mean that for distracted drivers a sub-use case of visual-spatial distraction by a phone is used, making additional sub-use cases with other forms of distraction redundant. A trade-off will be made between testing the Mediator system as broadly as possible, while maintaining as few distinct sub-use cases as manageable.

7.5.4. Example sub-use case

An example of a possible sub-use case is given below. In order to create this specific case, the functional elements and test settings chosen are listed below. Parameters not mentioned are of no particular interest for the current sub-use case, and are therefore considered to be either non-existent or set to a “default” state that has no impact on driver or system performance.

The functional elements are represented in Table 7.4 and

Table 7.5. A transition from automation to human driver is initiated by the automation system and accepted by the driver. Assessment of the human and automation fitness is accurate for the duration of the sub-use case.

Table 7.4 Overview of selected functional elements relating to task transition.

Transition to automation		Transition to human	
Accepted	Denied	Accepted	Denied
Human initiated			
Mediator initiated		Selected	

Table 7.5 Overview of selected function elements relating to assessment of, improving on and maintaining of fitness, comfort and trust.

	Assess fitness		Improve and maintain fitness		Improve and maintain comfort, trust, etc.	
	Accurate	Inaccurate	Effective	Ineffective	Effective	Ineffective
Human	Selected		Selected			
Automation	Selected					

Test setting elements:

- **Environment**
 - External to the vehicle
 - Road design: proximity to on-ramp
 - Road type: motorway
 - Other road users
 - Increase in number of other road users
- **Driver characteristics**
 - Dynamic characteristics
 - Limbs possibly away from controls
 - Distracted driver
- **Automation characteristics**
 - Static characteristics
 - Level 3 automation available
 - Dynamic characteristics
 - Level 3 automation system operational

Scenario description: Allowing the human driver to be “out of the loop” for short periods!

The driver uses level 3 automation on the motorway. The automation controls both the longitudinal and the lateral control tasks. The automation detects and tracks the surrounding vehicles. Mediator predicts the intentions of the vehicles and the time to automation fitness. The HMI communicates these data to the driver. The driver is commuting to work and is out of the loop for short periods of time because of reading mails on the laptop. Expected performance indicators of the monitoring and of the control tasks are used to determine the take-over time. The driver approaches a road section with dense traffic due to the proximity to an on-ramp. The driver continues to read his/her mails on the laptop. The automation predicts that certain vehicles might suddenly cut-in. Mediator estimates that the time to automation fitness decreases and becomes equal to the take-over time.

The HMI provides a take-over request to the driver. Mediator continues to support the driver during the take-over process and communicates the most safety relevant information to the driver. The driver resumes manual control safely. When the driver is fit and automation is available again, the HMI informs the driver. The driver can choose to activate automation or continue to driver manually.

The exact definition and selection of the sub-use cases, as well as the related research needs will take place in the next stage of the project.

8. Overall conclusions and next steps

The main goal of the Mediator system is to determine who is fittest to drive, human or automation, and consequently define preferred actions to be sent to the HMI or automation in order to ensure safety and comfort of the human driver. To this end, four components were defined: human state, automation state, HMI and decision logic. This deliverable described the state of the art knowledge and corresponding knowledge gaps related to these four components as well as a description of the high level (non) functional requirements and relevant use cases for the MEDIATOR project.

8.1. The (non)-functional requirements

Many of the knowledge and development gaps described directly relate to the (non) functional requirements. The human and automation state components need functions that can determine the corresponding fitness. How this fitness for the human and automation can be defined in such a way that they can be compared, and how the different levels of automation influence this definition is still to be investigated. Additionally, these components require functions that provide information on why the human or automation fitness is degraded and how to improve this fitness. Which information is available from sensors and how it can be used to improve driver state estimation and fitness will be investigated in the next steps of the project.

This sensor information can also be used to improve the design of the HMI. The HMI requires functions to perform take-overs between human and automation, improve human fitness and maintain appropriate levels of trust and comfort throughout the drive. Which in-vehicle and outside context information is required and how to best perform these actions should be investigated.

Determining which actions should be taken at any point in time to ensure safety and comfort is a required function of the decision logic. How to come to this decision and determining which information is needed and available from the other components will be a main focus of the research in the next steps.

Also, the non-functional requirements can be related to knowledge gaps. In particular, the system is required to satisfy the user and industry needs in terms of trustworthiness, user acceptance and comfort, and broad applicability of the system in a wide range of cars. How these requirements are met while taking into account the variability of the users and industry is to be investigated.

For each of the four components some more specific knowledge and development gaps were also identified. In the next subsections a short summary of the chapters corresponding to each component is given and the corresponding remaining knowledge and development gaps are summarized.

8.2. The human state component

The human state component chapter, Chapter 3, described the state of the art knowledge on human suitability to drive and driving comfort, i.e., the human fitness. Three performance measures were identified as being crucial to define suitability to drive: transfer of control performance, situation awareness and vehicle control performance. The influence of driver characteristics and

states on the performance and comfort measures, as well as how to measure them, were discussed.

While a considerable amount of literature is available on each aspect that influences the relevant driver performance measures, how to fuse them into one measure of suitability to drive for Mediator is still a considerable knowledge gap. This is in part due to the knowledge gaps related to predicting driver states and the corresponding driving performance in the near future. Also, knowledge gaps exist on how take-over time and regaining situation awareness is influenced by aspects such as driver characteristics, take-over experience, distraction and fatigue. Determining thresholds to indicate degraded performance is another knowledge gap that needs to be addressed.

Knowledge gaps also exist on how to measure driver states, such as comfort, trust, emotion and workload, continuously and in real time and how to make sure we are measuring the underlying construct that we expect to measure. Another knowledge gap concerns the effect of automation on driver states. So far, this aspect has not been investigated extensively, mainly because high levels of automation are not yet available on the market.

Finally, the different types of interventions that can be performed by the Mediator system to ensure safety and comfort for the driver are still to be determined and further investigated. For example, how can information underload or overload best be mitigated, how can the driver be kept in the loop when no control action is required, such as driving with SAE level 2 automation, how can deskilling be minimized, and how can Mediator actions be used to improve self-regulatory behaviour of the driver.

8.3. The automation state component

The automation component chapter, Chapter 4, provided relevant information about vehicle automation and the structure of the Mediator automation component which will bridge the gap between standard automation outputs and necessary information for the decision logic to determine the best course of action. Relevant literature was discussed and knowledge and development gaps were identified.

While some general key performance indicators (KPIs) of the automation directly address the relevant automation status, there is a knowledge gap on how to shape them such that they can easily be compared to human fitness measures by the decision logic, i.e., the required output of the automation state component.

Additionally, a knowledge gap exists on how to map the actual parameters from different levels of automation and different vehicles onto the same general KPIs.

Generally, the vehicle automation will have access to a large set of data on the driving context and vehicle state. Such information is needed for Mediator in two forms. First, the automation state component needs to provide information on why a certain subsystem cannot be used now or in the near future. For example, road blocks ahead prevent level 3 automation to be switched on. Secondly, some context and vehicle information can be relevant to determine the driver state. For example, in dense traffic human workload increases. A development gap exists on how such information available to the automation can be selected and shaped for these two purposes.

Additional knowledge gaps relate to improving the automation state. For level 3 automation the current state of the art systems can predict acceptable performance only about 5 seconds ahead. This is too short for most take-over procedures and a knowledge gap exists on how to increase this duration. Additionally, a complete overview on how to improve automation fitness to drive in real time, e.g., changing lanes to find better lane markings, is still missing.

8.4. The HMI component

In the HMI component chapter, Chapter 5, Mediator relevant state of the art knowledge on human machine interfaces is presented. HMI challenges were identified and corresponding relevant literature was discussed. The design space was described and possible output controls and modalities were discussed and compared. Using expert knowledge and input from other transport modalities recommendations for the HMI design were proposed and knowledge and development gaps were described.

One of the main HMI actions will be to transfer control between human and automation. While some recommendations on how to approach this transfer of control were given, the best way to operationalize this transfer, including choice and use of modalities, is still to be investigated.

Some level of transparency is needed for user acceptance and trust in the system, as well as to develop mental models to anticipate automation functioning and create appropriate reliance. Too much information, however, can cause confusion and information overload. How to elicit an optimal balance between this transparency and information load, however, is as yet unknown.

In particular for driving with SAE level 2 automation it is a challenge to keep the driver in the loop, while maintaining the benefit of workload reduction that this automation level brings about. There are still many knowledge and development gaps related to defining, designing, implementing and testing an appropriate way of keeping the driver in the loop.

While the aim of the Mediator system is to support the human needs in terms of safety and comfort, conflicts between the system and the human driver may occur. How to deal with such conflict situations in terms of ethical issues and user acceptability has to be investigated.

There is much design freedom for non-safety critical HMI design aspects. However, some aspects of the HMI should be standardized and follow existing standards to ensure safety. Which HMI aspects these are exactly, and how to integrate these in the overall HMI design is not yet clear.

More generally, the HMI should be designed as an intuitive system and minimize the time needed to learn how to use the system. The design should also be effective on the long term, taking into account human adaptive behaviour, and allow for skill maintenance, also when the automation can do most of the driving. Finally, the HMI design should take into account differences in user characteristics such as preferences and abilities. While some literature on these general design aspects exists, knowledge and development gaps exist on how to achieve these goals with the Mediator HMI design.

8.5. The decision logic component

In Chapter 6, the basic elements of the decision logic component were described. The decision logic will receive input from the human and automation state components including relevant context

information. Based on that input, it can decide on the most optimal action which in turn is outputted to the HMI and/or automation.

The role of the decision logic component at this stage is mainly focused on bringing the information from all components together in a coherent fashion. Currently, it is still unclear how the interface between these components will look like exactly. As a next step, a structure for these interfaces will need to be defined more clearly via an iterative process.

Specifically for the decision logic component, a knowledge gap exists on how to take into account safety and driver comfort in its objective function. Subsequently, a knowledge gap exists on how to validate the decision quality and robustness in the light of a lack of input data from the other components and the impossibility of testing for all possible situations.

Additionally, in the next steps, the feasibility of driver specific adaptation of the decision logic parameters should be investigated and its effect on overall safety and comfort. And finally, the feasibility of the Mediator logic from a legal and ethical perspective should be investigated.

8.6. Next steps

In summary, the MEDIATOR project is working towards a system that mediates, in real time, between the automated functions of a vehicle and the human driver ensuring that the one that is most fit for the task at hand is in control. In order to decide whether it is safer to have the driver or the automated system in control, the Mediator system has to assess the fitness of the driver and the fitness of the automation, set off against the requirements of the driving context.

As described in Chapter 2, mediating between the human and automation is a relatively new concept in the automotive industry. However, in the aviation and military domain research on this topic dates back to the nineties. Several early human assistance systems and more recent driver monitoring systems resemble (part of) what we intend to realise with our Mediator system. For the further development of our Mediator system we will build on the research and experiences with these Mediator-like systems. By using the design principles of the older and more general human-machine cooperative systems and by optimising and tailoring existing driver monitoring systems, our Mediator system aims to get the best out of the human and of the automation in order to improve safety without compromising driving comfort.

As the next step, a detailed design and work plan will be elaborated and, more or less in parallel, a series of studies will be help to bridge the most pressing knowledge and development gaps. For the identified use cases and test scenarios, a lab prototype of the complete Mediator system will be developed and relevant parts of the system will be implemented in in-vehicle prototypes. Each prototype will be evaluated extensively by means of computer simulations, driving simulators and on-road testing, focusing on functionality, reliability, and acceptability. By integrating the knowledge and experiences gained in the project, several guidelines, recommendations and protocols will be developed helping further development and dissemination of the Mediator system after the project has finished.

Appendix: Driver measurements based on inward-facing cameras

Various aspects regarding the “driver state” can be measured using real-time sensors and associated processing and computing devices and software. This Appendix focuses on the use of in-cabin, “inward facing” cameras for this purpose. General advantage of cameras are that:

- They are relatively inexpensive, compared to some other sensors such as special sensors built into the steering wheel or driver seat and/or based on physiological measures;
- They are relatively unobtrusive, compared to e.g. sensors attached to the face, head, or skin which typically measure physiological measures like EEG, EOG, and ECG;
- With one or just a few cameras one can measure a variety of driver state properties, as described in more detail below.

With a camera aimed at the face (together with an appropriate computing device and software) one can estimate, in real-time and with high frame-rates (20 fps and up), various aspects related to the eyes and the face. The positioning of the camera is not very important as long as a more or less frontal view of the face is obtained and a relatively good resolution (640x480 and up) and good framerate (30 Hz and up). Better performance can typically be obtained using a multi-camera set-up, e.g. to be able to see the eyes well from a larger range of angles, but at a substantial cost in terms of hardware and processing complexity.

First, **eye openings and closures** can be measured, which is relevant for measures like PERCLOS, which in turn is relevant for **fatigue/sleepiness** estimation. See Figure A.1 (left) for an illustration.

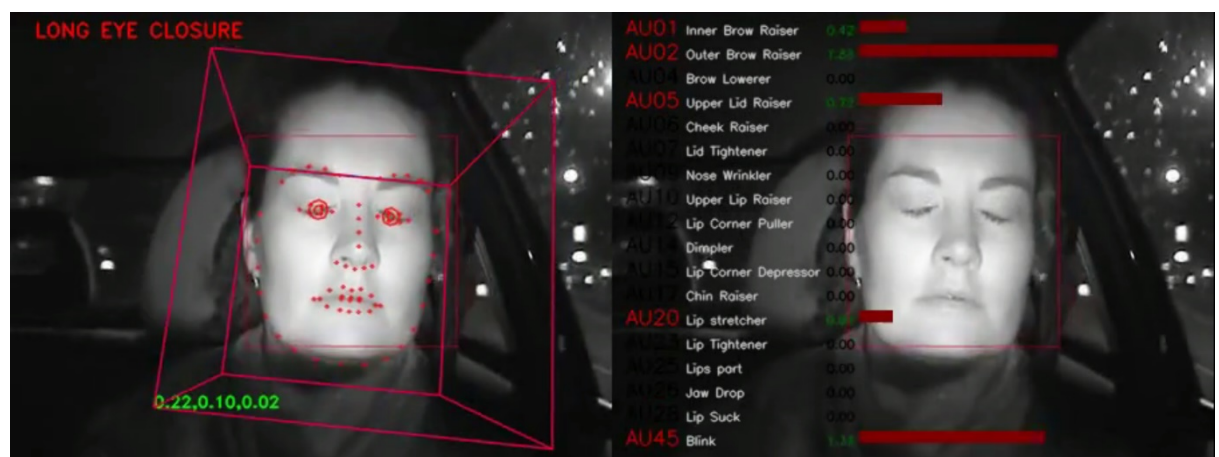


Figure A.1 Left: detection of eye closures, relevant in particular for fatigue. Right: extraction of facial features in the form of Action Units (AUs), relevant for fatigue and for emotion estimation.

Second, **eye gaze direction** can be estimated ('**eye tracking**'). This typically works best in combination with a (simple) calibration procedure in which drivers are asked (once) to look briefly at a number of pre-selected points (such as points outside the vehicle and/or points inside the cabin such as the instrument panel and rear view mirrors); such that the calibration program can

match those to the observed eye gaze patterns. Typically, this eye gaze direction estimation works best when not only the eyes are tracked, but the **head movements** are taken into account as well, especially when the eyes are not perfectly visible.

Using this type of eye tracking one can detect, first of all, **eyes on-road versus eyes off-road**, which is particularly relevant for assessing **distraction**. See Figure A.2 for an illustration. Furthermore, and going a bit further, using this technology one can estimate *where* the driver is looking; and in this way estimate (albeit imperfectly) whether he or she has seen certain relevant outside objects (e.g. certain road users coming from the right or from behind). In this way, one can assess, to some extent, his/her **situation awareness**. Figure A.3 illustrates this.

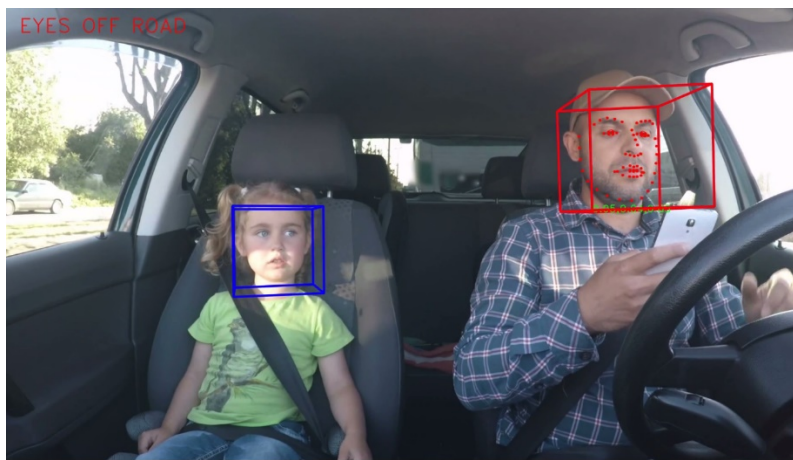


Figure A.2 Detection of eyes-off-road. Also illustrates detection of other (non-driving) people in the vehicle.

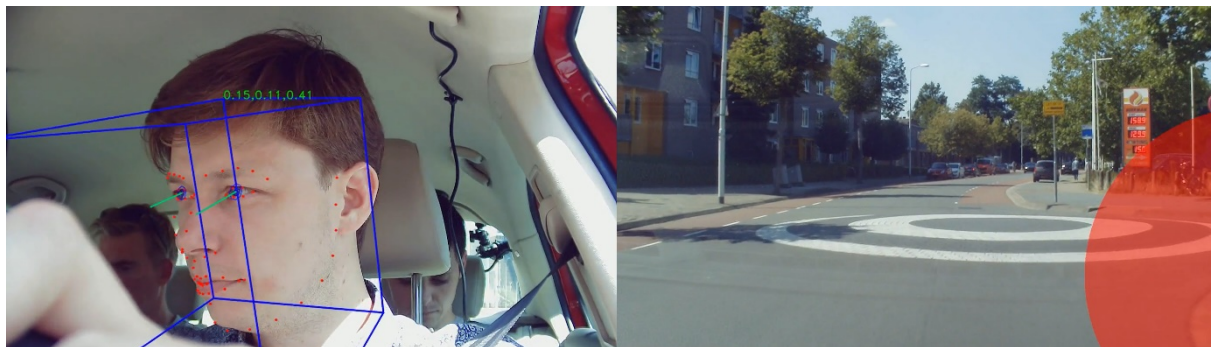


Figure A.3 Illustration of eye tracking (gaze estimation): the driver here glances at the right corner intersection, and is thus apparently aware that other road users might come from there, who have the right of way.

Third, more information can be extracted from face video on top of eye openings/closures and gaze direction. By extracting certain **facial features**, numerical data on facial expressions can be obtained which contains (imperfect yet usable) information on human **emotion**. Typically, the Facial Action Coding System (FACS) is used as the system to taxonomize the facial features (based on work by Hjortsjö, 1969; and Ekman, & Friesen, 1978). This uses so-called Action Units (AUs), which when combined can be classified into emotion categories. See the right side Figure A.1 for an illustration of this.

Examples of AUs are “Inner brow raiser”, “Nose wrinkler”, “Lip tightener”, etc. Certain combinations of values on those AUs are subsequently classified to indicate states like Happiness, Sadness,

Surprise, Fear, Anger, Disgust, Contempt. Thus, this may be used to assess dynamic driver states related to **mood, tension, comfort, motivation, and trust**. It may also perhaps be used to estimate **boredom** of the driver, and thus help in assessing **underload**. It should be noted, however, that the science and technology behind all this is imperfect; but it may still be possible to do something along these lines, especially when it comes to detecting relatively extreme cases, like expressions of shock/surprise or extreme anger or fear. Irrespective of emotion and boredom and the like, there are indications (and work in progress) that facial features, including (potentially reduced or different) facial expressiveness, as well as an increase in head and face movements related to yawning and a bobbing head, have predictive value with regard to **fatigue/sleepiness detection and prediction**.

With a (possibly additional) inward-facing camera which can see a larger part of the driver body and his/her hands, additional information can be extracted. Modern algorithms can automatically extract **hand and body pose information**. See Figure A.4 for an illustration. This can be used to assess **engagement by the driver with the steering wheel, other controls of the vehicle, or other objects such as a mobile phone**.



Figure A.4 Body pose information extracted from an inward-looking camera, allowing extraction of information on what the driver is doing with his hands.



Figure A.5 Object detection in the cabin: detecting mobile phone use.

Images from the same in-cabin inward-face camera can, in addition, be processed with more or less standard modern **object detection** algorithms, such that objects in view and manipulated by the driver can be detected and classified, such as a mobile phone, a sandwich, a coffee cup, a

booklet, etc., thus gaining even more information on what is happening in the cabin and what the driver is doing, including what the **type of secondary task** is, if the driver is engaged in such a secondary task. This is illustrated in Figure A.5, for the case of mobile phone use. The same type of object detection algorithms can also detect **other people in the vehicle**, which may be another source of distraction and lead to another type of secondary task, like conversation with passengers or disciplining children.

Driving context and driving performance measurements using outward-facing cameras

Outward (in particular forward) facing cameras can provide much valuable information on both the driving context by itself, and on the driver's driving performance. Similar to the in-cabin inward-facing case, compared to some other outward sensors (like radar and lidar) they have the advantage that they are relatively inexpensive and that from one camera's image stream a lot of diverse information can be obtained, given the right algorithms.

One type of information related to the driving context which can be obtained is based on the potential for detecting and tracking other road users from the outward-facing camera images. This gives, among other things, driving context information related to **traffic density and traffic complexity**. Furthermore, by assessing the relative position and speed of the lead vehicle, one can estimate safety-related variables like **time headway, time-to-collision, and post-encroachment time**; all of which may be indicative of **risk-taking tendencies** or **situation awareness** or both. Figure A.6 illustrates the detection and tracking of other road users in images and the potential of obtaining a 3-dimensional world view from that, from which the measures described above can be derived.

(It should however be noted that these estimates benefit greatly from data fusion with sensors that are better at (directly) measuring distances and speeds of outside objects, i.e. radar and/or lidar—which typically are also available in partially automated vehicles.)



Figure A.6 Detection and tracking of various road users using cameras (right), resulting in a 3-dimensional world view (left) that allows assessment of traffic density and complexity, relative distances and speeds, and derived measures.

Another important type of information that can be extracted from forward-facing cameras is **lane position and lane departure information**. See Figure A.7 for an illustration. This information is more indicative of the driver's driving performance than of the driving context per se. Lane departures are associated with **fatigue** (especially very high levels of fatigue, when the number of lane departures in driving simulator tasks tends to increase at apparently exponential rates). Lane departures are also associated with **distraction**, e.g. the well-known drifting off your lane when reading or writing a text message. And of course, lane departures are associated with safety,

because it is simply more likely to collide with another road user when departing from your lane, or drifting off the road in a one-sided accident.



Figure A.7 Illustration of lane position and lane departure information. Left: lane position within the acceptable limits; right: lane position outside the acceptable limits, i.e. a lane departure instance.

Other driving context-related information

Some other driving context-related information is also relatively easily obtainable, but is best obtained from other data sources than cameras. For example, **the type of environment** (residential, urban, rural, highway) is best assessed by making use of a **digital map**, using straightforward map matching based on the vehicle's GPS data. GPS data in combination with the digital map is also the best and easiest way to assess **speeding**.

Time of day, lighting, weather and temperature conditions and so on can be obtained using a combination of clock, calendar, and weather data provider data, possibly with the help of vehicle (CAN) data which typically includes inside and outside temperature, and often includes data from automatic precipitation detection or from windshield wiper use.

References

- Ekman, P., & Friesen, W. (1978). Facial Action Coding System: A Technique for the Measurement of Facial Movement. Palo Alto: Consulting Psychologists Press.
- Hjortsjö, C.H. (1969). Man's face and mimic language. free download: <http://diglib.uibk.ac.at/ulbtirol/content/titleinfo/782346>