State Of The Art Measuring and Modelling Techniques to Asses Behavioral Adaptation – a Literature Review

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ME2510-7 Literature Report

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“Automation does not simply supplant human activity but rather changes it, often in ways unintended and unanticipated by the designers of automation”

(Parasuraman et al. 2000)

List of abbreviations

BA = Behavioral Adaptation

ADAS = Advanced Driver Assistance System

ACC = Adaptive Cruise Control

SA = Situation Awareness

DSM = Driver State Monitoring

LKAS = Lane Keeping Assistance System

HMI = Human Machine Interaction

Important definitions

Behavioral Adaptation: "Those behaviors which may occur following the introduction of changes to the road-vehicle-user system and which were not intended by the initiators of the change" (OECD 1990).

Situation Awareness: "The perception of the elements of the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status near future" (Endsley 1988)

Introduction

Highly automated vehicles are a trending topic since Google introduced the first fully autonomous driving vehicle in 2009[1]. One of the many arguments for autonomous driving is that over 90% of all traffic accidents are caused by human errors (Treat et al. 1979; Green and Senders 2013). The implementation of autonomous driving vehicles can still take decennia due to technical limitations (e.g. bad sensor accuracy in heavy weather conditions, need for highly detailed maps, communications problems with other road users, etc. (Ghose, 2015)) and legislation problems (e.g. ethical questions like: "who is responsible for an accident if no human is in the loop?"). Until most of these issues are resolved, it has to be accepted that humans are in control of the vehicle, either performing a supervisory task (e.g. monitoring the environment) or operational (e.g. actual controlling the vehicle). Therefore new systems are developed to keep the human in the loop but still obtain some of the benefits of automation.

In literature these systems are called Advanced Driver Assistance Systems (ADASs). The benefits of these systems depends on the working principle, for instance, some systems reduce the braking distance significantly (e.g. Anti-Lock Braking System (ABS) and Autonomous Emergency Braking System (AEB)), assists the driver in lateral or longitudinal control (e.g. Lane Keeping Assistance (LKA), Adaptive Cruise Control (ACC)) or assist the driver on a strategic level (e.g. Navigation software). In order to work properly with these systems people need to adapt. Although adapting and compensating for changing circumstances is critical in driving situations, people sometimes adapt in such a way that the gained safety benefits, caused by the ADAS, degrades. For instance, Sagberg et al. (1996) showed that taxi drivers equipped with ABS, drive with a shorter headway time compared to drivers without. In other words, the drivers misuses the fact that ABS shorten their braking distance and use it to drive closer to the next vehicle. Another well-documented BA example is given by Bekiaris et al. (2001). They showed that people driving with an ACC system use their spare capacity caused by this system to perform other in-vehicle tasks, resulting in a significant lower Situation Awareness. In literature such an unintended negative adaption to a novel introduced ADAS is called Behavioral Adaptation (BA). In short-term and in long-term BA can mitigate the safety benefits of a novel ADAS or even completely negate them.

These examples emphasize the importance of taking BA into account in the design of a novel ADAS system. An example of a current developed ADAS is Haptic Shared Control (HSC). This system assist the human driver by adjusting the stiffness of the steering wheel and/or pedals, resulting in higher performances (in terms of steering and braking) and lower workload (Abbink et al. 2011; Petermeijer & Abbink 2015). A HSC System is intuitive to use (i.e. drivers quickly adapt) and, if designed well, is not experienced as intrusive. Some researchers found results that indicate BA in a HSC vehicle, for example Petermeijer et al. (2014) showed significant worse driving performance in case of an automation failure or a decreased Situation Awareness (observed in a lower reaction time) (Petermeijer & Abbink 2015). Whereas, Mars et al. (2015) found no BA effect in the steering guidance of a HSC system. These examples show that the real effect of BA in a HSC vehicle is still unclear. Therefore new research has to be conducted that measure and model BA in novel ADASs (like HSC). Once there are models that understands the human driver this could help in designing countermeasures that limit BA, resulting in higher safety benefits. To assist ADAS developers to design ADAS that limit BA the following research question need to be answered:

[1] "Google Self-Driving Car Project". Retrieved 02-09-2015 from: http://www.google.com/selfdrivingcar/

What are promising ways to predict behavioral adaptation in Advanced Driver Assistance Systems?

This research question will be answered by means of a literature survey. This literature research gives a comprehensive insight in measuring and modelling techniques in assessing BA. In order to do so, this report is divided into two parts:

(1) Theories about why BA occurs: Overview of well-cited motivations and triggers that could explain or cause BA. In addition, examples of potential changes will be given. (Chapter 2)
(2) Overview of techniques to measure and model BA: In order to understand these models it is important to know what kind of techniques are applicable to measure and model BA. (Chapter 3)

1 What is behavioral adaptation?

In literature Behavioral Adaptation (BA) is used in contrary ways. In Psychology BA is defined as “the whole set of behavior changes that are designed to ensure a balance in relations between the (human) organism and his surroundings, and at the same time the mechanisms and processes that underlie this phenomenon” - Grand Dictionnaire de la Psychologie. In road safety literature BA is often used in a more negative way as is defined by the OECD (1990):

“Those behaviors which may occur following the introduction of changes to the road-vehicle-user system and which were not intended by the initiators of the change” (OECD, 1990).

In this report the definition provided by the OECD group is used since this definition is commonly used in driver BA studies. Although this definition is convenient and used often in literature it still leaves room for own interpretation. For example what is an “unintended behavioral change”? In this report an unintended behavioral change will be defined as a change that reduces the safety benefits of the Advanced Driver Assistant System (ADAS).

1.1 Direct and indirect behavioral effects.

Behavioral Adaptation can be discern into direct and indirect effects. The direct effects are in literature called the *engineering effects*. Engineering effects are effects intended by the designer. For instance, in case of the Anti-Lock Braking System (ABS) the specifications are: “A braking system in which a sensor recognizes that a wheel is about to lock up. The sensor sends a message to a computer, which starts releasing and applying the brake, stopping the lock up and allowing the driver to maintain control or drive around an obstacle instead of sliding towards it” Hence, the ABS direct effects (intendent effects) is a shorter braking distance as well as maintaining control while braking. However, Sagberg et al. (1996) showed that car drivers equipped with ABS, drive with a shorter headway time compared to drivers without. This effect is not intended by the designer and thus an indirect behavioral effect. The definition Behavioral Adaption is equivalent to indirect behavioral effects, given that BA focus on the negative indirect behavioral effects. Of course, not all behavioral adaptations are negative. For instance, the Foundation for Traffic Safety (Mehler et al. 2014) showed an increased use of turn-signal among drivers with Lane Departure Warning Systems (LDWS), especially if they drove often on highways. Please notice that positive behavioral adaptations are not considered as a Behavioral Adaptation in this report since it is not a BA according to the definition given above.

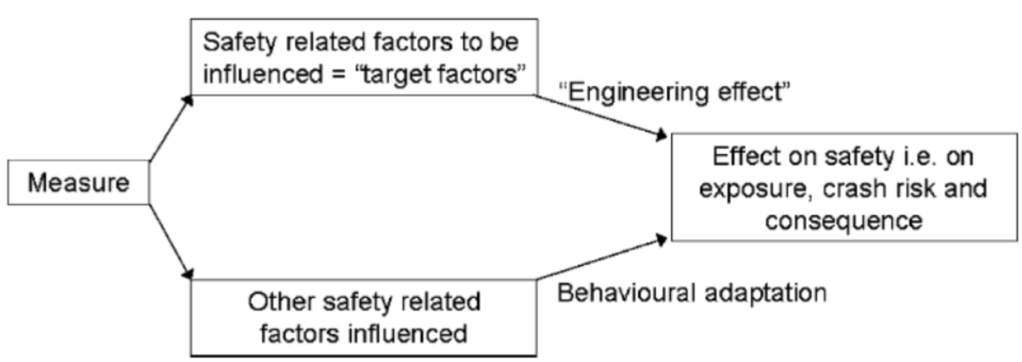

Figure 1: Schematic presentation of safety effects due to behavioral adaptation
Source: Khorasani et al. (2013*)*

Besides direct and indirect behavioral changes there is a third category: "*system misuse*". Although this category is not often used in literature, it is an important aspect of unintended behavior. Drivers are always extremely creative in exploring the limitations given by the ADAS designers. Often this leads to misuse of the system, e.g. current commercial cars are equipped with full range adaptive cruise control in combination with Lane Assistance Systems allowing hands-free driving. However, due to legislation, drivers are still obligate to maintain hands on the steering wheel. Current systems require that the driver keeps hands on the wheel every 10 to 20 seconds otherwise an alarm goes off. The driver can simply circumvent this safety measure by hanging a bottle on the steering wheel (see figure 2). This is also a clear example of "adapting" to an ADAS unintended by the designer of the system. However, in this report this category is not considered as a BA but rather as cheating the system.

Figure 2: Placing a bottle on the steering wheel to circumvent the hands-free warning. Source: Adopted from https://www.youtube.com/watch?v=qi2oIRMwmZY

2 Driver Behavior Theories

Although BA is a widely acknowledged phenomenon, the motivations and factors that trigger these kind of BA are not clearly established and are debated often. This chapter gives an overview of in literature mentioned factors likely to explain the processes underlying BA. If the reason why people adapt their behavior is known, ADAS designers could design novel ADASs more effectively in terms of safety (e.g. systems that not suffer from BA). The question that will be answered in this chapter is: What are theories behind a BA and what are common BA triggers argued in these theories?

2.1 Michon's adapted hierarchical control model

Many of the theories discussed later use the hierarchical task distinction given by Michon (1985). According to Michon (1985) a driver tasks can be divided into three levels: *Strategic*, *Maneuvering* and *Control* level. "The strategic level of a tasks defines the general planning stage of a trip, including the determination of trip goals, route and modal choice, plus an evaluation of the costs and risks involved. At the Maneuvering level drivers exercise maneuver control allowing them to negotiate the directly prevailing circumstances."(Michon 1985). The ground level is the control level. This level is equivalent to the "skill based behavior" defined by Rasmussen (1983): "It represents sensory-motor performance during acts or activities which, following a statement of an intention, take place without conscious control as smooth, automated, and highly integrated patterns of behavior". This level is basically on operational level and governs how the driver operates the vehicle.

Panou et al. (2007) stated that Michon hierarchical model needed to be adapted with an additional *behavioral level* because personal motives are crucial factors for driver behavior. Examples of personal motives are for example subjective risk. Subjective risk is the risk people are willing to take during driving (will be elaborated further later in this chapter). As the revised hierarchical structure in figure 3 shows, that behavior is at the top of the hierarchical structure and influence all three levels.

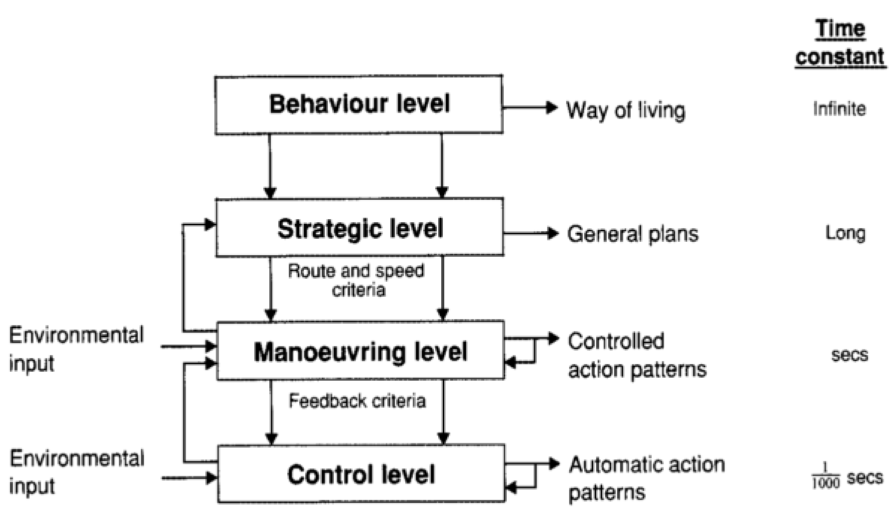

Figure 3: The hierarchical structure of the driving task (adapted from Michon, 1985)
Source: Panou et al. (2007)

2.2 Adaptation Triggers

Why would a driver adapt their behavior in general or how can we assure desired behavior? Many researchers have probed this, from child raising to appropriate work behavior development (World Bank 2010). Drivers behavior can differ a lot (e.g. from a slow driving grandfather towards a young male driving a Volkswagen Golf), though, this does not mean that responses towards certain behavioral triggers will also differ that much. *It is important to understand that adaptation triggers cannot change a person, but by shaping the environment they function within, the way people behave can be influenced.*

2.2.1 Motivational Triggers

The underlying motivation is very important in explaining BA. Many motivational theories try to explain BA and which triggers are important in inducing these adaptations. Some well-cited motivational theories are based on the following triggers:

- *Subjective risk assessment*.
  Risk can be divided into three basic terms: objective risk, subjective risk estimate and the feeling of risk. Objective risk has also been referred to as 'statistical risk' ((Grayson et al., 2003), it is the objective probability of being involved in an accident. The objective risk is determined post hoc from analysis of accident data. "Subjective risk estimate refers to the driver's own estimate of the (objective) probability of collision. Such estimates of risk represent the output of a cognitive process, while the feeling of risk represents an emotional response to a threat, a distinction previously clarified" (Fuller 2005). Many BA theories are based on Subjective Risk. Either by stating that people tend to maintain a certain subjective risk level (Wilde 1998)) or the tendency to keep the subjective risk below a certain risk threshold (Näätänen & Summala 1974). Nevertheless, subjective risk is stated as an important motivation to adapt behavior.
- Fuller's (2005) *Task-Capability Interface (TCI)*.
  Fuller's TCI describes the interaction between the determinants of task demand and driver capability. "The task demand is determined by factors such as the environment, other road users and speed, with capability being determined by training, education and experience. Task difficulty homeostasis is proposed as a key sub goal in driving, and the choice of speed is argued to be the main solution to the problem of keeping task difficulty within driver-preferred bounds" (de Winter & Happee 2010).
- *Trade-Off between Performance and Effort (TOPE).*
  People will tend to make a trade-off between performance and effort. If people are rewarded with higher performance at the cost of a bit more effort, the chance of performing this is action is high. Same logic, if a little performance increase is gained with a huge effort, the chance of adapting is limited (e.g. Speed/Accuracy Trade-Off (Fitts 1954))
- Utility Maximization Model from (O'Neill 1977): Panou et al. (2007) summarized the Utility Maximization model as follows: "The utility maximization model proposed by O'Neill (1977) assumes that the driver has certain stable goals and makes decisions to maximize the expected value of these goals. Some of these goals are achievable more effectively through risk-taking behavior, for example, speeding to save time or gain social status. These motivating factors are counteracted by the desire to avoid accidents as well as by fear of other penalties such as speeding tickets. Balancing goals with the desire to avoid accidents therefore derives driving behavior choice. O'Neill claims that the balance, which affects the decision made, is shifted when a safety measure is introduced. An assumption made by the theory, which has been

questioned (OECD 1990), is that the driver is 'rational'. In other words, the driver is an accurate judge of the accident probability resulting from each mode of behavior."

Wilde's Risk Homeostasis and Fuller's TCI model are both well-cited and also often criticized motivational theories, therefore both will be elaborated further in the remaining part of this section.

Wilde's Risk Homeostasis Theory (RHT)

Wilde's Risk homeostasis posits that: "People at any moment of time compare the amount of risk they perceive with their target level of risk and will adjust their behavior in an attempt to eliminate any discrepancies between the two" (Wilde 1998). It is argued that a change in system (e.g. by introducing an ADAS) influence the perceived level of risk resulting in an adjustment action (see figure 4). For example, by introducing light poles drivers are able to see more when driving in the night resulting in a lower perceived level of risk. Wilde's Risk Homeostasis theory suggest that drivers will compensate for this effect by, for instance, drive faster in order to reach the target level of risk. So basically, by introducing light poles behavioral adaptation occurs. Although this sounds like a quite feasible argument, this model is often argued as "too vague" (Michon 1985). The entities are not clearly defined and therefore impossible to observe and impossible to measure, simply because these processes happen unconsciously. Similar statements were made by Elvik & Vaa (2004) and Ranney (1994) who both stated that it is impossible to generate testable hypothesis for this theory due to the lack of real quantified aspects in this model. In addition, de Winter & Happee (2010) argued that in Wilde's Risk model contrary behavioral adaptations could easily be defended with subjective arguments like: "the familiarization period (getting used to the ADAS) was too short to observe an effect" without stating what the familiarization should be instead. Even though the RHT seems unable to develop testable hypothesizes, this doesn't mean that perceived risk is not an important BA trigger. The urge to survive is in the human nature, whether this is to stay away from a lion in Africa or driving a car safely on a narrow road. If the result of a certain act is undesirably in terms of safety, it is highly likely to act differently next time. In other words, if an ADAS system is perceived as a system that increases/decreases safety, it is likely that BA occurs.

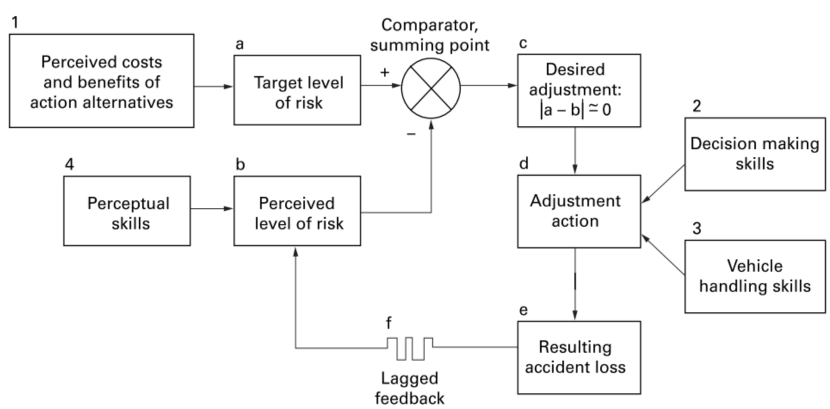

Figure 4: Homeostatic risk mechanism
Source: Wilde (1998)

Important note regarding subjective risk by Saad et al. (2004): "Most of the results obtained came from simulator studies or closed track experiments, where by definition, such critical events can be studied without real danger for the participants, However, and for the same reason, we should keep in mind that driver risk-taking in this context may be quite different from that observed in real driving situations. This is a paradox that we usually have to deal with in traffic safety research."

Fuller's Task-Capability Interface (TCI)

Another well-cited motivational model is Fuller's Task-Capability interface (TCI) (Fuller 2005). The reason that TCI is often cited is, besides its plausible theory, it also gives a great overview of factors/triggers influencing driving behavior. TCI model describes the interaction between the determinants of task demand and driver capability (figure 5). If the task demands exceed the capability this leads to loss of control which could result in a collision or, if lucky, an escape. Similar to Wilde's RHT, subjective risk influences this model, however the model lays more emphasis on task homeostasis instead of risk homeostasis. Task homeostasis means that people tend to keep the difficulty to perform a task constant. According to Fuller: "Drivers appear to be able to make judgements of task difficulty easily and to behave in such a way as to keep the level of task difficulty within target boundaries." Although many researches have substantiate this theory, it is directly opposed to the "Trade-Off between Performance and Effort theory" (TOPE). The TOPE stated that people will always balance performance with effort. An example of the contradictory aspect between the two models: by introducing a LKAS (Lane Keeping Assistance System), a lane keeping task should become easier in terms of workload and higher performance (Petermeijer & Abbink 2015). According to the TCI theory, this decrease in task difficulty needs to be compensate, which could be done by for example a higher speed. Contrary, TOPE theory could suggest that due to the negligible increase in performance benefits no BA will occur. Moreover this example emphasized the subjectivity of motivational models, which make them unable to use as predictive tool.

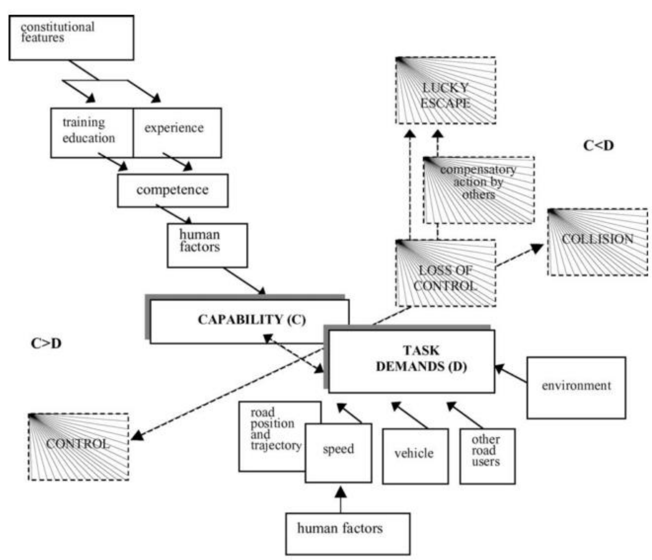

Figure 5: The task-capability interface model
Source: Fuller (2005)

2.2.2 Attitude towards ADAS

Peoples' attitude can also explain the variation in responses towards ADAS. According to Saad et al. (2004) the attitude towards an ADAS can roughly be divided into two groups. On the one hand drivers can use ADAS as a *reference tool* meaning that if a change at maneuvering level occurs the aim of the driver will always try to understand the system and to avoid any unwanted effects due to their perceptual limitations (Shinar & Schechtman 2002)). On the other hand, drivers can use ADAS as a slave system which offers them a chance to extent their own driving limits or even allocate attention to a secondary task. Saad et al. (2004) captured these strategic distinctions with relation to the maneuvering level in Table 1. It shows that the goal of "reference tool" drivers is to limit the (subjective) safety risk. All decision are done with this goal in mind, e.g. in case of a warning they will try to understand "why" they occur and "how" these warnings can be used to driver safer. The ADAS can assist the driver in achieving their safety goals. Drivers using ADAS as a slave system will have a tendency to misuse the system. It is hypothesized that younger males are more often in this category. Saad et al. (2004) stated that drivers using the ADAS system as slave system are generally "capable" drivers or "Sensation Seekers". Sensation Seeking is defined by Zuckerman (1994): "a trait defined by the seeking of varied, novel, complex, and intense sensations and experiences and the willingness to take physical, social, legal, and financial risks for the sake of such experiences. Central to this trait is "the optimistic tendency to approach novel stimuli and explore the environment" (Saad et al. 2004). These "capable" drivers and sensation seekers try to maximize the sensation of pleasure which limit the safety benefits of the ADAS.

In Table 1 it can be seen that both levels (reference and slave) consider a positive attitude towards the ADAS. Whether the ADAS increases the safety benefits or allows driving to the limit. However, this table could be extended by drivers that consider the ADAS as punishment rather than support. Hjälmdahl & Várhelyi (2004) showed that in a haptic advisory system (haptic gas pedal) was less effective for drivers with a negative attitude towards the system. In addition he found that drivers with a negative attitude towards the system generally experienced more stress while driving. This indicates that it is important to show drivers the benefits of a novel ADAS in order to obtain a positive attitude.

Table 1: Four different levels of behavioral change to an ADAS system
Source: Saad et al. (2004*)*

Changes at maneuvering level		Changes at strategic level	
		ADAS as a reference tool	*ADAS as a "slave" system*
Unsafe acts under Critical traffic situations	High	• Learning to comply with warnings	• Allocating attention to secondary tasks
	Low	• Learning to make better distance estimations	• Driving to the limit

2.2.3 Design of BA triggers

If behavior is triggered in the wrong way it can be perceived as annoying or as punishment rather than support. Although BA triggers can be a useful tool to reduce BA, if a trigger is designed badly (such that it is perceived as annoying or punishment) unintended adaptation could occur. For instance, Parasuraman & Riley (1997) showed that drivers may turn off the system when they consider a certain warning signal to be intrusive or annoying. One of the challenging design aspects of a trigger (for example a warning system) is the activation threshold. If an activation threshold is set too low this will result in high falls alarm rate and finally in a distrust of the system (in literature called cry-wolf effect). An interesting AIDE project tried to develop an adaptive forward collision warning systems, with one type of adaptation being to observe driver reaction time, so that drivers who habitually reacted quickly got later and hence less irritating warnings (Carsten 2007).

Similar to a warning system the design of a guidance system can evoke different behavioral responses. If the guidance force is designed in the wrong way this could, in long term, cause after-effects (Petermeijer et al. 2014). Another example of opposed behavioral effect due to incorrect design is if driver intention and systems intention deviate. Griffiths & Gillespie (2005) showed that these differences in intension can lead to collisions with obstacles in the middle of the road since drivers were not able to overcome the system in order to avoid the obstacle.

2.3 Potential Changes

In literature many examples of behavioral changes are given (Table 2). In this literature report the distinction will be made between *performance changes* and *driver state changes*. The same distinction will be used in chapter 3 (overview of measuring techniques and modelling driver state changes). Many different Performance changes can occur. Draskoczy et al. (1998) showed that BA may appear in changes of speed, following distance, way and frequency of overtaking, way and frequency of lane changing, late braking, change of level of attention etc. (Figure 6). Performance changes can in long-term also result in a shift in locus of control. Locus of control is the individual's assumptions regarding responsibility for the outcome of events. Driver state changes are even more diverse than performance changes. Novel ADAS systems are designed to increase performance but the response on driver state is not often accounted for. For instance, a LKAS assist the driver while steering, therefore steering becomes easier so less steering deviation is expected. Maybe in addition increase in speed is observed but it is highly unlike that the complete other side of the scope occurs (decrease of speed and higher speed deviation). In driver state monitoring this great variation can occur. Let's consider the same LKAS, it can be interpret as useful and trustworthy leading to decrease in workload and increase of situation awareness (SA). The opposite can also occur, if the LKAS is distrusted an increase of workload can occur in combination with a decrease of SA (Stanton and Young, 2002). This example shows the wide variety in BA responses which is one of the reasons that makes BA research so complicated. Changes in behavior can also occur outside the two distinction made in this report. Martens & Jenssen (2012) showed a generation of extra mobility (e.g. taking the car instead of the train) or road use by "less qualified" drivers due to introduction of an ADAS. These changes are not taken into account since they do not fall within our definition of BA (i.e. do not reduce safety). Some potential changes often shown in literature can be seen in Figure 6. Table 2 shows different direct and indirect effects for several ADASs.

Which change will occur and in what degree depends on the working principle and design of the ADAS but also highly depends over time (Table 3). Let's consider the ACC system. Bekiaris et al. (2001) made a comprehensive review of driver behavior issues related to time. The behavioral changes differ a lot, especially over time. Therefore, difference between short and long term is discussed in the next section.

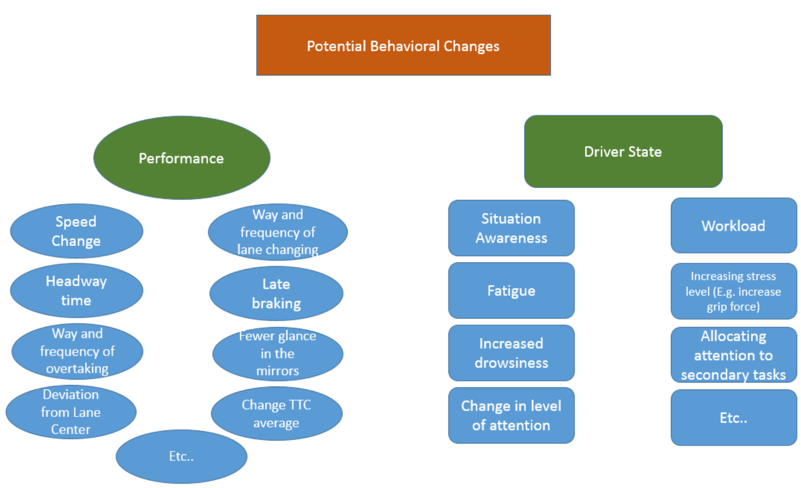

Figure 6: Potential behavioral changes found in literature. Separated in terms of performance and Driver State changes

Table 2: ADASs and their potential effects on driving performance
Source: Östlund et al. (2005)

Function	**Supported control layer**	**Direct (intended) effects on driving performance**	**Examples of potential indirect effects on driving performance**
ABS	Tracking	Enhanced longitudinal (braking) control	Reduced headway/increased speed
Lane departure warning	Regulating	Enhanced lateral control	Over-reliance -> reduced control when system malfunctions
Speed alert	Monitoring	Better speed keeping	Over-reliance -> reduced control when system malfunctions Visual distraction -> reduced lateral and longitudinal control, reduced event detection performance
Navigation support	Monitoring	Improved route finding	Over-reliance -> get lost when the system gives errant guidance Visual distraction -> reduced lateral and longitudinal tracking control, reduced event detection performance
Phone	Non-driving related	As small as possible	Dialling -> visual distraction -> reduced lateral and longitudinal tracking control, reduced event detection performance Conversation -> cognitive distraction -> More focused tracking control, reduced event detection performance
Action scheduling (AIDE metafunction)	N/A	Improvements on all layers	Indirect effects have not been studied – difficult to predict.

Table 3: Driver behavior issues when introducing ACC
Source: Bekiaris et al. (2001)

Short term	Long term
Mistrust: distrusting the ACC system	Spare capacity: using spare capacity for other in-vehicle tasks
Over-reliance: relying too much on the ACC system	
Brake pedal forces: increasing brake pedal forces Imitation: unequipped vehicles imitate equipped vehicles Reliance on vehicle in front: vehicle in front might have poor driving behaviour	Fatigue: ACC could take over too many driving tasks causing fatigue Quick approach to vehicle in front: the development of new behaviour Time-headway: driving with smaller time-headways Indication for overtaking: use ACC as an indication of when to overtake
Overtaking: difficulties with overtaking and being overtaken	

2.4 Short-term vs Long-term adaptation

BA responses highly depend on time. The different BA responses between short-term and long-term can be quite contradictory. Mistrust is a common short-term effect whereas, allocating attention to secondary task (indication of over-trust in system) is a common long-term effect. This variety shows the importance of taking time into account when performing a BA research. The question that need to be addresses is: (1) how much time is sufficient to observe BA. (2) When can an effect be considered as long-term (or short-term)?

Time is considered as the main factor to short- or long-term adaptation. The definition for short-term is given by “Covering or applying to a relatively short period of time” – English dictionary[2]. The term relatively is of course very subjective, normally this is not that important but in BA research it is (due to variety in responses). Typically, a response is called short-term if the driver has driven an ADAS shorter than 1 week. The term long-term is used already from 1 week (Marchal-Crespo et al. 2010). A bias is involved in the definition of short-term and long-term. A common used example to indicate this bias is given by an experiment performed by Neisser (1976). Neisser (1976) studied a student for one day each week over a period of six months. The objective was to simultaneously read and write down one text. After six months she was able to perform this task with a performance (in terms of error) were equally good. Saad et al. (2004) comment about this experiment: “But the period of the six months was not a matter of choice, it was simply a matter of coincidence. In other words, if the above mentioned effect would not be evident in six months but earlier (e.g. in four months) or later (e.g. in eight months), the process would have stopped in the fourth month in the first case or it would have continued for another two months in the second case. But performance improvement could not be interpreted differently but as a long-term-effect in either case.” Regarding this example Saad et al. (2004) stated that: “we can never be certain that our interpretation is not biased, since the influence of other intervening variables is largely unknown and possibly it will never be unveiled.”

A BA effect may not appear immediately when the ADAS is introduced, but usually appears after a familiarization period (Draskoczy et al. 1998). Draskóczy et al. (1998) argued that BA studies should

[2] www.dictionairy.com

conduct experiments at three different time frames: (1) just before system activation, (2) immediately (within a month) after system activation, and (3) after 6 months of system use. Only then the real safety effects can be studied and insight in BA can be gained. Martens & Jenssen (2012) summarized these characteristics of the learning phase and the typical problems a specific time frame in response to ADAS in table 4. The table is supported by experiences from longer-term studies of Jenssen 2010, Carstens 2008, and Rudin-Brown et al. 2009. The first encounter or familiarization period is usually within 1-6 hours. Typical problems during this phase are HMI related distraction or distrust in the system. This is also what Bekiaris et al. (2001) found in Table 3. The second phase is the Learning phase, usually has a duration of 3-4 weeks but the duration of the phase can vary to some extent depending on the type of ADAS studied. The durations used in this table are just to give a certain indication of general durations of certain phases that are applicable on the studies referred to above. Intuitive and continues systems will have shorter learning durations than systems that only apply during a specific time frame. For instance, an intuitive continues haptic gas pedal (Abbink et al. 2011 and Abbink et al. 2008) will have a shorter familiarization period compared to an ACC system that only works in case the speed is set. Therefore ACC will take longer time to learn simple because the user works more often with the haptic gas pedal. From phase 3 the drivers' behavior reaches a sort of stability (Martens & Jenssen 2012). The driver gains a certain trust in the system and a shift in locus of control often occurs. A common problem during this phase is overreliance and drowsiness. Phase 4 and 5 are the phases that the driver learns to deal with malfunctions. During this phase loss of manual control skills can occur.

Table 4: Characteristics of five learning phases in the behavioral adaptation to ADAS
Source: Martens & Jenssen (2012)

Learning phase	Level of experience	Behavior	Duration	Scenario experience	Typical learning	Typical problems
1. First encounter	Tabula rasa	Exploratory	First day <50 km 1–6 h	Limited	Interface use	HMI related – distraction – distrust
2. Learning	Novice	Unstable	3–4 weeks $<1{,}000$ km 10–40 h	Most urban, rural road/ traffic conditions including day/night driving	Controllability	HMI related distraction System limitations
3. Trust	Relatively experienced	Relatively Stable	1–6 months	Most urban, rural road types including day/night driving and many weather conditions	Trust Shift in locus of control	Passive monitoring Overreliance Drowsiness
4. Adjustment	Experienced	Stable	6–12 months	All urban rural road types most summer winter conditions	Functional limitations Malfunction	Resentment
5. Readjustment	Expert	Very stable	>1–2 years	All relevant road traffic conditions	Rarely occurring hazard events System limitations and Malfunction	Mistrust Resentment Loss of manual control skills

2.5 Conclusion

This chapter gives answer to the question: What are theories behind a BA and what are common BA triggers argued in these theories?

Based on the theories discussed, the conclusion can be made that:

- Subjective Risk and Task difficulty are the most common used triggers in many BA theories (Wilde 1998; Näätänen & Summala 1974; Fuller 2005). Many researchers have criticized that these motivational theories cannot generate testable hypothesis and thus tend to be unfalsifiable (Ranney 1994; Elvik & Vaa 2004; de Winter & Happee 2010), however, the influence of these factors can still be argued.
- Drivers' attitude towards the ADAS highly influence what kind of BA occurs: Drivers can see the system as slave or reference tool. Drivers seeing the system as slave tool have the tendency to misuse the system, whereas reference tool drivers use the system to drive as safe as possible.
- Behavioral changes occur in: Driver State changes and Performance changes.
- BA can be observed in all levels of task defined by Michon (1985): At strategic level: e.g. navigation is taken over by the automation resulting in over-reliance (people get lost when the system gives errant guidance). At Maneuvering level: e.g. caused by ABS, where people drive with a reduced headway time (Sagberg et al. 1996) and at control level: e.g. caused by Lane Departed Assistance resulting in reduced control when system malfunctions (Burns 2001).
- BA is time dependent: A BA effect may not appear immediately when the ADAS is introduced but appears after a familiarization period (Draskoczy et al. 1998). This has to be taken into account when performing a BA research. Furthermore, the type of BA can be quite contradictory between short-term and long-term. Common short-term effect is Mistrust, whereas a common long-term effect is more related to over-trust like, for instance, allocating attention to a secondary task.
- Finally, the design of a BA trigger is important. A bad design can lead to increased BA or even to turning off the ADAS (Parasuraman & Riley 1997). Unfortunately, the distinction between a "good" or "bad" design is not well-described in literature and need to be investigated further. Table 5 summarizes the most common BA triggers used in BA theories.

Conclusion chapter 2

Most well-cited BA theories include BA triggers based on: driver's subjective risk assessment, task/utility management and driver's attitude towards the novel introduced ADAS. Although these theories are well-cited they are also well-criticized. Most of these theories (i.e. Wilde's RHS and Fuller's TCI theory) are argued to lack the ability to generate testable hypothesizes resulting in the fact that contradictory theories are both still seen in current literature. Furthermore, it can be concluded that BA occurs on all hierarchical levels as is defined by Michon (1985) (i.e. Operational, Maneuvering and Strategic level) and is highly time depended.

Table 5: Behavioral Adaptation Triggers

Triggers/Key element to a behavioral change	Definition	Effect	Some Examples of Trigger used in literature
Subjective Risk	“Subjective risk estimate refers to the driver’s own estimate of the (objective) probability of collision. Such estimates of risk represent the output of a cognitive process, while the feeling of risk represents an emotional response to a threat, a distinction previously clarified” (Fuller, 2005)	If a change in Subjective Risk is perceived this can lead to a behavioral change. Several models use subjective risk as major trigger. Either stating that drivers tend to maintain the level of risk constant (Wilde's risk homeostasis (Wilde, 1998) or tend to keep risk below a certain threshold (Näätänen and Summala, 1974)	Wilde's Risk Homeostasis theory (Wilde 1998), Risk Threshold model (Näätänen and Summala 1974)
Task difficulty	"Drivers appear to be able to make judgements of task difficulty easily and to behave in such a way as to keep the level of task difficulty within target boundaries" (Fuller, 2005)	"Driving task difficulty is inversely related to the difference between driver capability and driving task demand."(Fuller, 2005). If task demand change people will change behavior such to keep the task difficulty equal.	Fullers Task-Capability interface theory (Fuller 2005)
Trade-off between performance and effort	People tend to trade-off between performance and effort.	People will tend to make a trade-off between performance and effort. If people are rewarded with higher performance at the cost of a bit more effort, the chance of performing this is action is high. Same logic, if a little performance increase is gained with a huge effort, the chance of adapting is limited	Speed/accurate trade off (also known as Fitts Law) (Fitts 1954)
Attitude towards ADAS	"An individual's plans to carry out the recommended response" (World Bank, 2010)	According to Saad 2004: Drivers can see the new introduced ADAS as "Slave" system or as "Reference tool". Drivers that use the system as slave system can lead to risky driving behavior or allocating attention to secondary task. If change in attitude towards the system occurs this will directly lead to different driving behavior.	Slave-Reference tool theory (Saad et al. 2004)
Trust in system	The individuals trust in the system	Distrusting the system can lead to high workload and even stress resulting in low driving performance. High trust in the system can cause shift in locus of control and allocation to secondary task. Mistrust is often a short-term effect, whereas overtrust is often a long-term effect. (Panou et al. 2007)	Effect of trust towards ADAS (Hjälmdahl & Várhelyi 2004)
Competence	Driving skills	Competent drivers make less unpredictable maneuvers and adapt in a different way than incompetent drivers. E.g. competence drivers are more often Sensation Seekers	Sensation Seeking' (Zuckerman 1994)
Fear	"Emotional arousal caused by perceiving a significant and personally relevant threat" - World Bank	"Fear can powerfully influence behavior and, if it is channeled in the appropriate way, can motivate people to seek information, but it can also cause people to deny they are at-risk" - World Bank	The threat-avoidance model' (Fuller 1984)
Self-efficacy	"An individual's perception of or confidence in their ability to perform a recommended response" - World Bank	"Raise individuals' confidence that they can perform response and help ensure they can avert the threat" - World Bank	Driving as a self-paced task governed by tension/anxiety' (Taylor 1964)
Intentions	"An individual plans to carry out the recommended response" - World Bank	Intention is one of the most important variable in predicting behavior change, suggesting that behaviors are often linked with one's personal motivation.	Ajzens Theory of Planned Behavior (Ajzen 1991)
Utility Maximization	"The utility maximization model assumes that the driver has certain stable goals and makes decisions to maximize the expected value of these goals" (Panou et al. 2007)	"Some of these goals are achievable more effectively through risk-taking behavior for example, speeding to save time or gain social status. These motivating factors are counteracted by the desire to avoid accidents as well as by fear of other penalties such as speeding tickets. Balancing goals with the desire to avoid accidents therefore derives driving behavior choice" - Panou et al.	O'Neill (1977), Blomquist (1986)
Subjective Norm	"What an individual thinks other people think they should do" - World Bank	External influences or subjective norm is very important in developing behavior. People’s behavior highly depends on what the society depicts as "normal"	

3 Overview of Techniques to Measure and Model Driver Adaptation for different applications

In order to develop a comprehensive driver adaptation model it is important to gain insight in current behavioral measuring techniques. This section will give an extensive overview of state of the art measuring techniques to assess and model BA by answering the following question:

What methods are applicable to measure and model BA?

As described in section 2.3, behavioral changes can be divided into Performance and Driver State changes. Combined they can be used to comprehensively describe driving behavior. A model that understands and describes the human driver, can help designing ADASs that overcome the negative adaptations of the human driver. Carsten (2007) stated that “if there is a model that understands the driver, the potential of this system would be huge: it could give feedback to novices, assist elderly drivers in difficult situations, inform a driver when he or she is fatigued and adapt the operation of the vehicle to the needs of each individual driver”. In addition de Winter & Happee (2010) stated “based on the real-time monitoring of driver state and performance, it could give feedback and assistance to the driver and adapt the operation of the vehicle according to the driver’s needs in order to improve road safety”. To achieve such a BA model comprehensive measurements and assessing techniques to assess performance and driver state are needed. Before discussing the measuring techniques, first Michons’ BA classification scheme will be explained to give an overview of what kind of models are available.

3.1 Types of driver behavior models

Many different BA models can be found in literature from simple motivational models like Wilde’s risk homeostasis to extremely detailed mechanistic models (e.g. Boer et al. 2005 (Figure 7)). Michon (1985) proposed a simple classification scheme to distinguish between different driver behavioral models (table 6). In one dimension it distinguished between input-output based models (Behavioral models) and internal state based models (Psychological orientated models). In the other dimension between taxonomic models and functional models. “Taxonomic models is essentially an inventory of facts. The pertinent relations that, in such a model, hold between these facts are those of sets: super- and subordination, identify, sequential relations (before, while, after) and measures on sets: proportions, likelihood or generalized distances.” (Michon 1985). According to Michon (1985) a serious limitation of taxonomic model is the inability to express dynamical relations between elements. Functional models (i.e. motivational models and mechanistic models) have limitations too. Motivational models are often too vague and tend to be unfalsifiable (OECD (1990), Michon (1985), de Winter & Happee (2010)). Ranney (1994) argues that motivational models have not fully been specified (let alone tested), and thus most of them remain as constructs rather than as entities leading to the generation of rules and mathematical relationships. On contrary Mechanistic models are sometimes too specific, fitting random patterns, and tend to over parameterized resulting in lack of predictive power (de Winter & Happee (2010)). Despite these limitations, mechanistic models are objective and can easily be falsify and, if designed well, can predict. An example of a well-designed mechanistic model is given by Boer et al. (2005). Boer et al. (2005) developed a driver vehicle car following model with lead vehicle speed as input. His model consist of an extremely detailed driver and vehicle model that accurately captures the relationship between pedal depressions and speed fluctuations. With this model he was able to show different control strategies with respect to the easy measureable metric THW (Time headway). Boer et al. emphasized that metrics used in driver behavior studies must always be shown in context. E.g. that a lower THW metric is not necessarily a sign of degraded control performance but simply the result of a lower effort control strategy rather than a sign of greater struggle (Boer et al. 2005). In order to develop a good model it is important to have well-chosen measurements techniques and metrics which can be used as input for BA models. This will be discussed in the next sections.

Table 6: Summary of driver behavior model types
Source: Michon (1985)

	Taxonomic	Functional
Input-Output (Behavioral)	Task Analyses	Mechanistic Models Adaptive Control Models - Servo-Control - Information Flow Control
Internal State (Psychological)	Trait Models	Motivational Models Cognitive (Process) Models

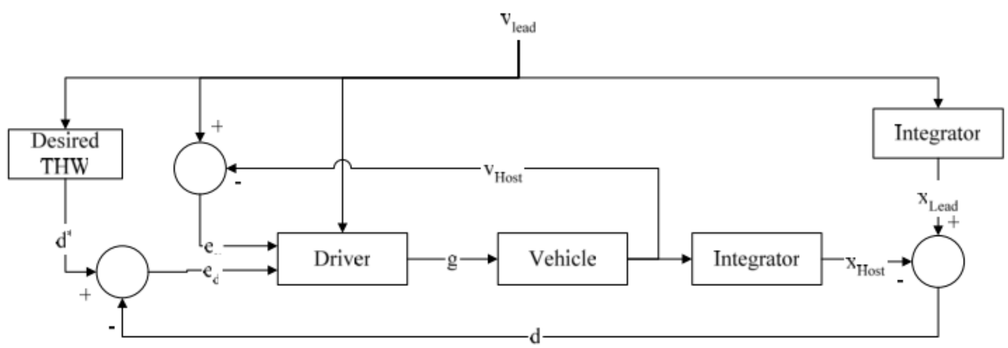

Figure 7: Driver vehicle car following model with lead vehicle speed as input
Source: Boer et al. (2005)

3.2 Driver State Monitoring techniques (DSM)

Since behavioral changes can occur in terms of Performance or Driver State, Measurement techniques should also be discerned into Driver State monitoring techniques and Performance Based measurements. In current literature many different metrics and measurement techniques are used to measure the same quantity. For instance, Situation Awareness can be measured by Eye movements, reaction time, questionnaires, speed variation etc. These metrics all state to give an objective measure of the subjective quantity Situation Awareness. This section will give an overview of common used DSM techniques and which quantity they measure. Most of the given information is based on reviews written by Hou et al. (2015), Johansson et al. (2004) and Saad et al. (2004).

3.2.1 What is DSM

“Driver state describes the general condition of a human operator interacting with a system. The concept includes behavioral activity, physiological patterns and psychological states, and is strongly context dependent” (Pleydell-Pearce et al., 1999). Simply said DSM are the Eyes, Brains and Hands of the system. Eyes: to watch, see and observe the driver. Brains: to interpret, classify, label and asses driver states. Hands: to execute action of regulation/control (e.g. transition of control from driver to automation if the DSM notice that the driver is in a fatigue state). This section will not take the latter into account but mainly focus on observing and assessing driver states. The development of DSM techniques are essential to provide appropriate services for various driving situations. If the system is able to robustly recognize dangerous driver states this could prevent many accidents. Nowadays drowsiness/fatigue and distraction/attention are measured in commercial cars (Volvo 2007 “Driver alert control” (Figure 8), Ford-Lincoln 2013 “Driver alert system”). If detected, the car can interfere to get the driver in a different state (e.g. by sounding an alarm, or just to inform the driver about his current state). According to Hou et al. (2015) a well-designed adaptive systems should be able to monitor the operator and use this information to enable flexible task allocation between the operator and the machine to reduce operator workload and fatigue.

Another new development in driver state measurement techniques is not only to warn the driver but also give additional information about his state. For example, it is found extremely useful to not only warn a fatigued driver but also give additional information about the magnitude. Barr et al. (2009) argued that “drivers underestimate the likelihood of actually falling asleep, the magnitude of sleepiness and its effect on impairment”. Current DSM techniques are not able to quantify such a state extensively, however, in near future this could be of great value. Even more important is the fact that driver state information can help in explaining why certain BA occur.

Figure 8: Driver alert control, Volvo
Source: http://blog.truecar.com/2010/12/22/spotlight-on-safety-drowsy-driving-just-as-risky-as-drunk-driving/

3.2.2 DSM approaches and technologies that can be implemented into ADASs.

Fatigue, stressed, fearful, distraction, situation awareness, increased workload are all words that describes a human's overall mode or state. These state have a significant impact on human ability to efficiently complete task when interacting with an ADASs (Hou et al. 2015). For instance, Hou et al (2015) stated that fatigued operators are more likely to perform at lower performance levels then fully alert operators. Additionally he mentioned that overworked and stressed operators are more prone to errors, and operators who are content are more likely to exhibit higher productivity then those who are fearful or distracted. Hou et al. (2015) classifies approaches that elicit data and draw conclusions about driver state into one of four categories with the following definitions:

- *Behavioral-based monitoring*: Monitoring and making inferences from what the driver is doing
- *Psychophysiological-based monitoring*: Monitoring and making inferences from the driver's state of body and mind
- *Contextual-based monitoring*: Monitoring and making inferences from the driver's surroundings or working environment
- *Subjective*-based monitoring: Monitoring and making inferences from what the driver communicates about his or her own state.

To obtain a full or accurate picture of a driver state it is important to combine multiple categories simultaneously. Only then it can be assured that the driver state is correct and accurate measured. This is illustrated in figure 9. Next each type of DSM category will be discussed shortly.

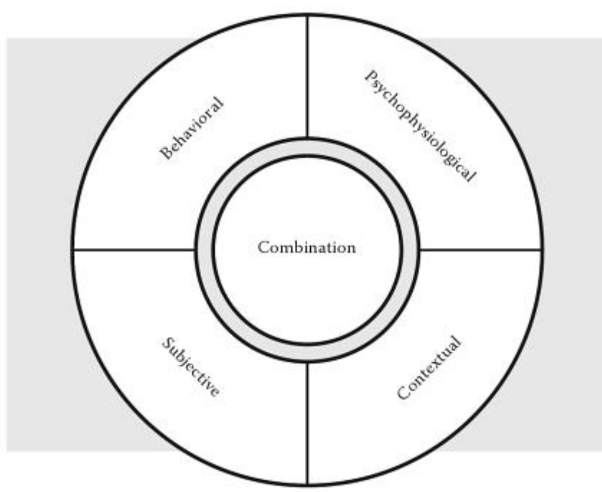

Figure 9: Visual relationship of the four primary types of driver state monitoring techniques. Combination-based monitoring draws on multiple subtypes.
Source: Hou et al. 2015, "Intelligent adaptive systems", Chapter 6

Behavioral-based monitoring
"Behavioral-based monitoring refers to inference of operator state by observation of operator actions in response to tasks, the working environment, or other stimuli (Wood 2004). Operator actions can be conscious, subconscious, voluntary, or involuntary; all actions have the potential to provide meaningful data that can assist in accurately determining operator state." (Hou et al. 2015). Behavioral-Based monitoring tries to capture the behavior of the driver. As we have seen in chapter 2, many factors can influence the drivers behavior (e.g. attitude towards an ADAS or fear etc. (see overview BA triggers in table 7). One of the methods is to look at the performance of the driver (discussed later in this chapter) but not always a behavioral change results into a performance change. An important behavioral-based monitoring technique that provides clues to determine operator state is *Operator-control Interaction.* More relevant behavioral-based driver state monitoring approaches (according to Hou et al. (2015)) are summarized in table 7. A benefit of behavioral monitoring techniques is that they are easy to measure. However, these measurements cannot be relied on too much due to the high variation in driver responses (e.g. maybe a driver increase grip force because it hands become slippery (sweaty hands due to heat in car) instead of an increased stress level indicator. So to obtain a complete assessment it is better to combine these measurements with psychophysiological-based monitoring techniques.

Table 7: Summary of Relevant Behavioral-Based Driver State Monitoring Approaches
Source: Hou et al. (2015), Chapter 6

Behavioral Feedback Approach	Summary	Examples of Current Uses
Eye tracking	• Monitors the operator's visual attention and cognitive activity	• Fatigue monitoring systems in vehicle operation • Advertisement design and evaluation
Operator–control interaction monitoring	• Monitors how the operator is interacting with the controls available • Key measurements include reaction time, haptic pressure, and input frequency	• E-commerce sites that monitor purchasing habits to present items that they may be interested in
Voice recognition and auditory analysis	• Monitors auditory cues that might provide information on operator state • Key measurements include frequency (pitch), tone, and timbre	• Voice recognition software

Psychophysiological-Based Monitoring (PBM)

Psychophysiological as: "Psychophysiology examines interactions between the mind and the body by recording how the body is currently functioning and relating the data to previously recorded behavior. The field is based on the premise that changes in the human body are related to changes in behavior, affect, and motivational state" (Hou et al. 2015)

Currently in literature a surge is going into PBM techniques. The techniques are becoming more and more reliable and less obtrusive which enables car manufactures to use psychophysiological monitoring techniques to obtain information about operator state. It is often argued that emotional and behavioral states are easier to identify than operator state related to task performance (Hou et al. 2015). In driving research PBM techniques are often used to define cognitive state, specifically mental workload, both qualitatively and quantitatively. Mental workload is conventionally determined using subjective questionnaires like the NASA-TLX (NASA Task Load Index), SWAT (Subjective Workload Assessment Techniques) or the simple OW (Overall Workload). However, PBM techniques like Cardiovascular (e.g. heart rate, ECG), Electroencephalogram (EEG to measure brain activity), Eye Measurements (Eye tracking or Pupil Dilation), Respiratory Measurements , Electro Dermal Response (EDR, skin conductivity) or Steering Entropy (level of disorder further discussed in section 3.3.2) can be used to assist these questionnaires to get a more objective indication of the subjective measurement workload.

A comprehensive overview of relevant PBM techniques and examples of their current use is given in table 8. Some PBM techniques that deserve to be highlighted because they are either often used in literature or considered as promising PBM techniques to use in the future.

Electroencephalogram: EEG records brain activity. It detects electrical activity in the brain using electrodes attached to the scalp. The number of electrodes attached can vary from 12 (clinical settings) to 256 (research settings). The systems measures activation of groups of neurons (brainwaves) on a time scale. Karamouzis (2006) showed that these measured brainwaves can be correlated to a specific stimulus (e.g., a specific sensory, cognitive, or motor event) to determine event-related potential (ERP). ERP is basically the understanding of what electrical activation takes place to a specific stimuli. Some of the great benefits of EEG research is that it is noninvasive, and have a high temporal resolution. What makes EEG so interesting for driving studies is that the workload level, high-order cognition and image processing all have unique patterns that can easily be detected by EEG brain scans. Downside of EEG records is that the signal-to-noise ratio is really bad (Gaillard and Kramer 2000) and it can be found obtrusive (Figure 10) (More benefits and limitations of current PBM techniques are argued in the discussion)

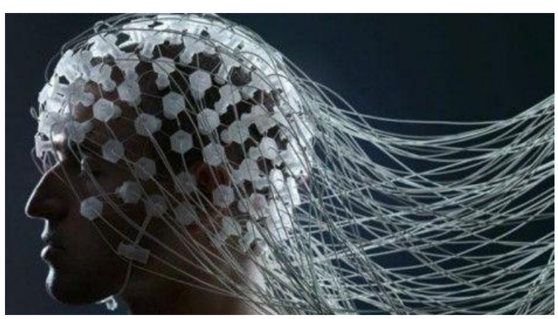

Figure 10: Obtrusiveness of EEG Measurement techniques (in research setting)
Source: Retrieved 01-09-2015 from: https://www.psychologytoday.com/blog/talking-about-trauma/201409/new-eeg-technology-makes-better-brain-reading

Electro dermal response (EDR): EDR is also known as galvanic skin response and measures the conductivity of the skin (or skin's impedance). Several studies have shown that EDR is an indicator of mental effort, arousal and vigilance level (Sharpe et al. 1995; Kapoor et al. 2007). In other words, if people are mentally or emotionally aroused a response is triggered in the skin. The different impedance is mostly affected by sweat. EDR metrics used are skin conductance level and skin conductance variation (root mean square of the skin conductance signal). Some benefits of the EDR technique is that EDR is less sensitive to environmental noise compared to other PBM techniques and is unobtrusive (can be implemented in the steering wheel). A big downside of this techniques is that it has a poor temporal resolution, high latency between stimulus and response and qualitative and emotion aspects of affect are not reflected in EDR. The latter is the reason that EDR is never used as single measurement in driving related research.

Cardiovascular Measurements: Cardiovascular is the most commonly used index to asses cognitive workload but they also have shown to be good indicators of cognitive effort, compensatory effort and positive or negative valence of emotion (e.g. attractiveness) (Hou et al. (2015)). Often used cardiovascular measurements are: electrocardiogram (electrical activity of the heart over time), heart rate and heart rate variability (HRV). These three measurements give a good indication of cognitive demands and attention. Cardiovascular measurements are often used in literature due to their unobtrusiveness, high reliability and considered as easy to use and interpret. A downside is that the accuracy of heart rate measurements is affected by respiration, physical work and emotional strains, which could make measurements inaccurate if not used in combination with other measurements (Cain 2007).

From the information provided in the section can be concluded that PBM techniques provide an objective and noninvasive way to quantify indexes like workload and SA. Hou et al. (2015) named 3 general benefits of PBM techniques:

- Objective outcomes,
- Unobtrusive sensor apparatus,
- Immediate and continuous results.

PBM techniques still suffer from some issues that limit the use of PBM in current research. Examples of limitations given by Hou et al. (2015) are:

- Inherently noisy sensor data,
- Need for specialized equipment that are often expensive,
- Data acquisitions issues: "Filters and artifact removal strategies for PBM technologies are neither standardized nor easily understood. Issues such as latency and recovery time must also be addressed further" (Hou et al. 2015)
- Data processing issues: "The large amounts of data collected from PBM technologies require computing technology capable of real-time processing to provide meaningful results for systems adaptation" (Hou et al. 2015).

A more comprehensive summary of limitations and benefits of each specific PBM techniques can be found in the discussion.

Table 8: Summary of Relevant Psychophysiological Monitoring Techniques
Source: Hou et al. (2015), Chapter 6

	Psychophysiological Monitoring Technology	Summary	Examples of Current Uses
Central Nervous System	Electroencephalogram (EEG)	• Electrode sensors placed on the scalp monitor electrical activity in the brain	• Clinically used to diagnose and research seizures
	Near-infrared spectroscopy (NIRS)	• Near-infrared light monitors blood oxygenation levels in the brain	• Clinically used to determine brain areas that are associated with information processing
Peripheral Nervous System	Electrodermal response (EDR)	• Electrical conductivity of the skin is measured to determine sweat levels	• Polygraphs
	Cardiovascular (electrocardiogram (ECG), heart rate variation (HRV), heart rate)	• Electrode sensors monitor heart activity	• Clinical or field assessment of stress
	Eye tracking	• Monitors the operator's visual attention and cognitive activity	• Fatigue monitoring systems in vehicle operation • Advertisement design and evaluation
	Respiration measurements	• Monitors breathing rate	• Polygraphs
	Skin temperature measurements	• Thermocouples monitor skin temperature for variations	• Polygraphs
	Electromyogram (EMG)	• Electrodes placed in or on specific muscles determine muscle activity	• Physiotherapy diagnostic tool

Contextual-Based and Subjective-Based Monitoring

Information about the environment is essential in understanding driving behavior. A well-known example that shows the importance of contextual information is the “ant on the beach” example by Simon (1981). Simon argued that “the ant's path is irregular, complex, hard to describe. But its complexity is really a complexity in the surface of the beach, not a complexity in the ant" (Simon, 1981). The context of a situations can give additional information in explaining the operator state. For example, higher stress/workload is expected while driving in an urban area than while driving on a rural road. This additional information can help in accurately estimate a current state. The driver perceptions of the environment is measured using the metric Situation Awareness. The most used technique to assess SA is the self-reported measure SAGAT (Situation Awareness General Assessment Technique). SAGAT is done in simulator studies where the simulation is frozen and displays are blanked. Subjects are then queried to describe their perception of the situation at that moment. Eye tracking can also be used to asses SA by making the assumption that if one is fixating on an object this object is also comprehends.

Subjective-base monitoring is the last approach that can help define operator state. “Subjective-based monitoring refers to approaches that elicit data about operator state by asking the operator. Subjective techniques can only be based on what the operator remembers and their interpretation of their experience (Cain 2007).” (Hou et al. 2015). Subjective input can help the system in deciding which state the driver currently is.

None of the 4 monitoring techniques is suited to accurately measure driver’s state. Even with the combination-based approach it is difficult to obtain 100% correctness. A reason could be that some indexes, like for example workload, do not have a general used definition and thus leave room for own interpretation. Nevertheless, the four DSM techniques combined are essential in order to fully understand and model BA.

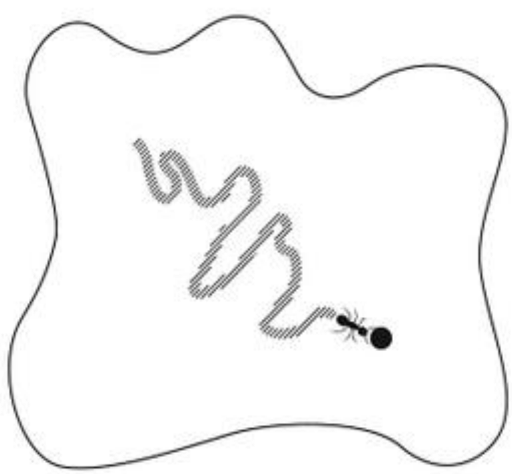

Figure 11: Simon (1981) Parable about an ant on the beach.
Source: Vicente (1999)

3.3 Performance-Based Monitoring Techniques

Driver's performance deals with the driver's ability to control the vehicle in both lateral as longitudinal direction. This section will summarize common used metrics to asses driving performance. Most of the information is based on the comprehensive metric reviews of Östlund et al. (2005), Johansson et al. (2004), Saad et al. (2004).

Performance-Based Monitoring Techniques are in general easy to measure and compute, which make them highly suited in online driving behavior research. Saad et al. (2004) summarized the 46 most used metrics from 105 driving researches (figure 12). These metrics are of course highly context depended but can still be used as indication of often used performance metrics. The most important metrics will discussed in terms of Accident risk, Controllability and Control Effort in section 3.3.1 and 3.3.2, because these factors are in chapter 2 concluded as important BA triggers (e.g. Subjective Risk, Competence and Performance-Accuracy Trade-Off theory).

Lateral control
Number of major lane deviation
Variance of steering wheel angle
Standard deviation of steering wheel angle
Standard deviation of lateral position
Steering entropy
Steering reversal rate (SRR)
Vehicle angular speed
Time to line crossing (TLC)
Longitudinal control
Mean speed
Speed Variance
Visual scene management
Glance duration on in-vehicle road information
Glance duration on driving information
Glance duration to any other areas
Visual demand (glance duration distribution among areas)
Decrease of rear-mirror glances frequency
Interactions with other vehicles
Time headway
Relative distance
Following distance
Duration of short inter-distance (<2sec)
Number of lane changing

Situation awareness
Reaction time
Braking reaction time
Reaction time and number of missing in PDT (peripheral detection task)
Speed of accelerator position variation
Number of emergency braking
Speed variation
Actions on pedal
Compatibility and suitability with driving
Number of actions on the system
Number of responses from the system
Dwell time (fixations + saccades) in an area
Number of fixations in an area
Lane occupation time
Glance duration
Glance frequency
Fixation duration
Task duration
Number of failures
Auditive Reading Time
Action time
System response time
Number of braking actions
Number of errors on braking
Number of actions on accelerator
Frequency of accelerator-foot-covering action

Figure 12: List of commonly used driving performance metrics
Source: Saad et al. (2004)

3.3.1 Driving Performance Metrics related to Accident Risk

How a performance metric actually correlates to accident risk is difficult to proof. Östlund et al. (2005) stated that this is due to a lack of sufficiently detailed behavioral data in existing accident databases as well as the lack of a basic understanding of the behavioral factors that cause accidents. Yet, the basic assumption is that driver performance metrics are directly related to accident risk.

BA is defined as unintended changes caused by the introduction of an ADAS. These unintended changes are defined as changes that reduces the safety benefits of the ADAS. Hence, to proof behavioral adaptation it is important to have metrics that are accepted in literature as indicators of accident risk. Examples of such indicators are:

- Time to Lane Crossing (TLC): TLC is defined by Godthelp and Konings (1981): "TLC is defined as the time to reach the lane marking assuming fixed heading angle and constant speed." Johansson et al. (2004) argued that in driving the TLC metric could be regarded as a reflection of the driving strategy, or to be more precise, the time-based lateral safety margins adopted by the driver.
- Time To Collision (TTC): "TTC represents the time until collision with an object (e.g. a lead vehicle) given the current trajectories and velocities of the own vehicle and the object" (Johansson et al. 2004). TTC is often defined as the distance between two cars (from bumper to bumper) divided by the speed difference to the lead vehicle. Sometimes in literature Headway Time is used instead of TTC, which is very similar to TTC (see figure 13). Varieties of the TTC metrics are: Minimum TTC, Mean of TTC local minima or Time Exposed TTC (TET). TET measures the proportion of time of which the TTC is less than X seconds (used by Östlund et al. (2005)). Van der Horst and Godthelp (1989) suggested that only TTC values below 1.5 seconds should be regarded as critical.
- Velocity: Speed is the most used metrics in BA research. Theories like Wilde's risk homeostasis or Fullers task capability model all use speed as BA indicators. Speed is directly related to accident risk as is proven many studies. Small speed level changes result in significant changes in the number of accidents (see e.g. Salusjärvi, 1981; Finch et al. 1994; Nilsson, 2004). In addition, higher speed variance is correlated with more accidents. Brehmer (2011) argued that accident probability is lowest for cars driving with an average speed, but increases for drivers who deviate more from the average speed. This suggest that lower and more even velocities mitigate accident risk. Speed metrics that take this into account are: Mean velocity, Variance of Velocity (standard deviation of the velocity), Maximum Velocity.

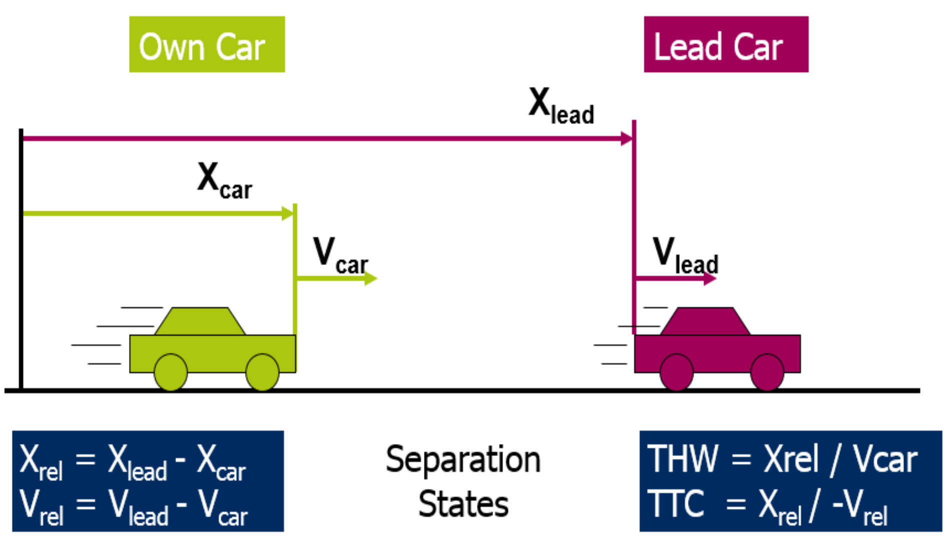

Figure 13: Time to Collision (TTC) and Headway Time (THW)
Source: Adopted from lecture 1, Human Controller course, http://ocw.tudelft.nl/ocw/

3.3.2 Driving Performance Metrics related to Controllability and Control Effort

Although one could argue whether controllability and effort directly influence safety (and therefore directly related to BA), they do increases the likelihood of an accident. Controllability is defined as the ability to control the car. Controllability can be expressed in lateral (steering-based metrics) and longitudinal (velocity-based) control. Control efforts metrics can be used to indicate whether a conflict arises between the ADAS and the driver (which could cause BA). Driving performance metrics related to controllability and control effort are:

Steering Reversal Rate (SRR): "The metric represents the number of times that the steering wheel is reversed by a magnitude larger than a specific angel, or gap" (Johansson et al. 2004). The threshold or gap is in literature often between 0.5 to 10 degrees. In some cases velocity is used as threshold rather than position. The metric is then called Steering wheel Action Rate (SAR) and is very similar to SRR. SRR and SAR are common used as a driving performance metric due to its simple computation. SRR and SAR reflects drivers control effort. Many steering reversals are interpreted as high effort without significant performance gain. In other words, a high SRR or SAR is often considered as inefficient steering behavior.

High frequency component (HFC) of steering wheel angle: Spectral analysis can be used to asses driving performance. HFC analysis which frequency bands are affected by different factors. A high HFC means more power on the higher frequencies, which can be interpret as more steering reversals. As discussed at SRR, many steering reversals (high HFC) reflects a higher control effort. In practice SRR is more often used than HFC since SRR is easier and faster to compute than HFC.

Steering grip force: Steering grip force is often used as metric to asses steering control efforts. The assumption is made that steering grip force reflects drivers' efforts put into steering control. Östlund et al. (2005) argued that "measuring steering grip pressure gives good opportunities to directly assess steering control efforts early in the chain of driver-vehicle reactions. Behind this statement lies the assumption that steering grip force reflects driver's efforts put into steering control. Both hands on the steering wheel could indicate that the driver is better prepared to cope with an unexpected event. Also a firmer grip or more active grip on the steering wheel could be an indication of the driver surge to be in better control of the steering".

Steering Entropy: Boer 2000, described steering entropy as a promising way to assess workload and controllability. A high steering entropy is associated with high workload and low performance (Boer 2005). It uses the assumption that a low workload driver does not deviate much from a predictable baseline trajectory. The entropy is calculated based on the error between the prediction and the current steering behavior. The prediction in Boer (2000) was obtained using an averaging filter. This prediction signal is used to calculate the 90th percentile α. This α is used to divide the signal in *i* bins, where the bin edges are chosen as ± (0, 0.5α, α, 2.5α, 5α). The measure of disorder or entropy is then calculated with the formula:

$$h = \sum_i p_i{}^I \log p_i$$

Where *I* is the number of bins and p_i stands for the proportion of the ith bin and is calculated from the experimental data.

<u>Pedal movement/force</u>: Similar to steering grip, pedal dynamics can be used to asses control efforts. Frequent pedal movement often reflects drivers' effort needed to control the speed. Similar to SRR, frequent pedal movement are considered as inefficient driving.

3.4 Behavioral Adaptation Models for different applications

The first part of this chapter showed different measuring techniques and metrics. Apart from measuring BA there have also been made attempts to develop predictive BA models, but what does such a model really need to contain? The objective of such a model is clear, to make predictions of the negative safety reducing actions of the driver in order to be able to counteract this. In other words, a model that can predict risky behavioral adaptations or actions. Possible solutions that mitigate BA will not be treated in this literature report but would really interesting for future research.

Model needs to be Hierarchical (i.e. applies on Operational, Tactical and Strategical level)

Most driver behavior models found in literature are based on quantitative modelling of stabilized behavior (i.e. don't take into account behavioral adaptation). One famous example of quantitative modelling is McRuer's steering model (Figure 14). He modelled a driver's steering behavior based on lateral position errors and heading angle errors. McRuer's model explicitly quantify relations between entities which makes this model easier to validate compared to the motivational models described in chapter 2. In McRuer's model the assumption is made that a driver behaves like an optimizer that minimizes the steering and heading error. However, this statement does not always hold since drivers tend to keep the car within safety boundaries rather than truly minimizing the error (e.g. drivers may swerve during driving without considering this driving behavior as bad performance (see also Performance-Accuracy trade off theory in Chapter 2)). Furthermore, McRuer's model only applies on only operational level (e.g. takes only lateral control into account and does not model longitudinal control or higher levels such as maneuvering). Winsum (1996) suggested that driving models that apply on only one level may produce meaningless results when behavior on another level is excluded from examination. "For instance, if the effect of a road measure on speed is examined it should also examine the effects on operational performance at the same time. Of course practical problems may prevent this and this is one of the reasons why simulators may be useful." Same conclusion was also drawn in chapter 2, where the author argued that BA occurs on all levels of driver task defined by Michon (1985) (i.e. on operational, maneuverable and strategical level).

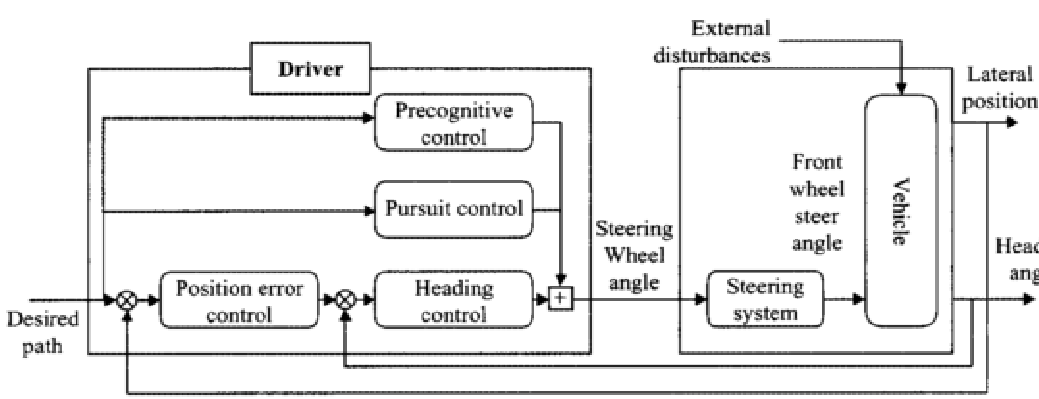

Figure 14: Compensatory model of driver steering
Source: McRuer et al. (1977)

Model needs to consist of quantitative values

A simple qualitative model that does include these three levels of operation is given by Rudin-Brown and Noy (2002) in Figure 15. This model uses many important components (triggers) some of them are also mentioned in chapter 2 like Trust, Competence and Personality (Locus of Control). Martens & Jenssen (2012) argued that this model does not describe relevant feedback on the impact of the control loop, which may differ depending on vehicle characteristics (e.g. ADAS). “For example, when an ADAS like ACC is activated the driver is out of the loop in terms of acceleration and deceleration control actions. The driver is only in the loop if he or she monitors the process and decides to intervene (some may use the spare capacity ACC system assistance offers to send text messages, glance at incoming mail etc.). The ACC sensors take over the driver detection of headway and have a direct impact on headway distance with a feed forward loop to the traffic situation as the movement of the ACC equipped car can be observed by other road users. This feedback loop to other road users is based on characteristics of system function, not on driver actions.” (Martens & Jenssen 2012). Rudin-Brown’s model is useful in terms of describing important factors of BA and their influence on all three driving task levels but is way too simple to make actual predictions. An already more detailed model that predicts BA and its associated effect on situation awareness and workload is given by Weller and Schlag (2004) (Figure 16). This model uses changes in vehicle (implementing an ADAS) or environment as input and three basic questions to determine whether BA will occur. This model basically combines two motivational models namely Wilde’s risk homeostasis model (Wilde 1998) and the utility model defined by O’Neill (1977) (both models described in chapter 2). Although similar models are often used in literature, they are impossible to use as prediction tool due to their vagueness and lack of qualitative results (e.g. do not explicitly explained what kind of behavioral change will occur and to what degree). These models often fail in generating testable hypotheses (Ranney 1994).

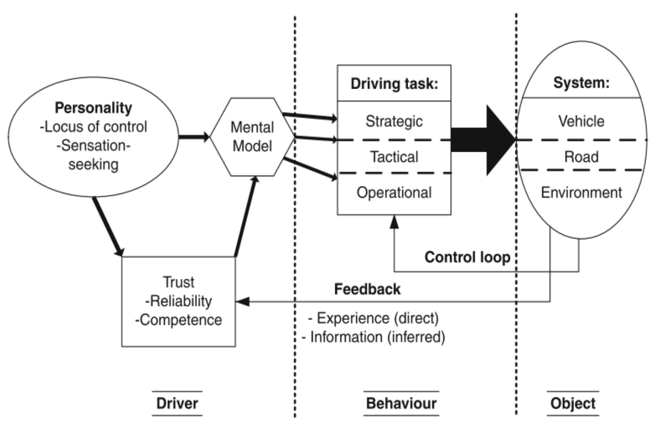

Figure 15: Qualitative model of BA
Source: Rudin-Brown & Noy (2002)

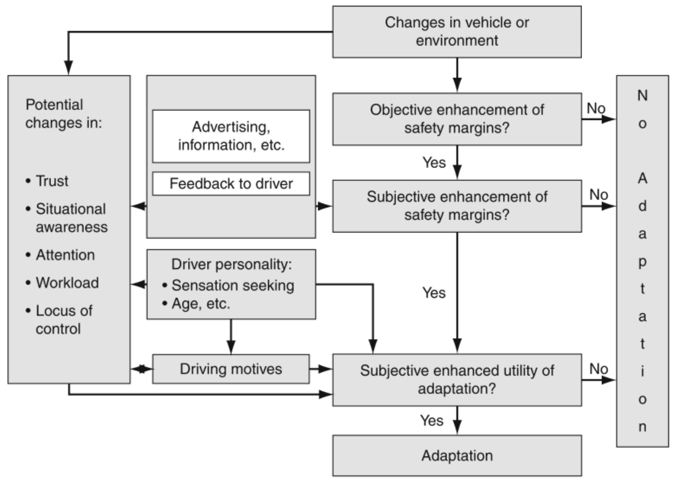

Figure 16: Process model of behavioral adaptation
Source: Weller & Schlag (2004)

As discussed in the beginning of this chapter, Michon (1985) categorized models into different categories. So far, each discussed model is considered as a mechanistic models, however the working principle of these models is still quite diverse. Therefore, Michon (1985) made an additional distinction within mechanistic models: the servo-control models and the information-flow models. Servo-control models describe signals that are continuous in time (e.g. McRuer's model), while information flow models involves discrete decisions (e.g. Weller and Schlag). Unfortunately, both types of models are often not considered as suited prediction tools due to either over-parameterizing (de Winter & Happee 2010) or lack of quantification (e.g. in the Weller and Schlag BA model: How can subjective enhancement of safety margins be quantified?). So what are models that can predict BA or predict driving behavior in a hierarchical quantitative way? A method that recent years is becoming more and more popular as human behavior prediction tool are the stochastic models.

BA Model as probabilistic tool

Carsten (2007) argued that the only possibility to model driver behavior is using a stochastic model. He stated: "Rather than predicting precisely and reliably what a driver will do at any moment - an endeavor almost certainly doomed to failure because of the variability of human response both between and within individuals - a model should attempt to predict the probability of error or failure and thus current and future risk". This conclusion is strengthened by Evans (1985) who compared the expected safety effects with actual safety changes in 26 studies and concluded that no behavioral model was available to predict effects of changes in the road-vehicle-driver system. Current models have still not proven to be able to predict these changes. The probabilistic modeling approach assumes that drivers tend to driver in a reproducible manner (Campbell et al. (2013)). The same assumption is used by Boer (2000) in the Steering Entropy metric. Many researchers agree that the probabilistic prediction approach is a promising driver behavior modelling technique (Angkititrakul et al. 2011; Campbell et al. 2013; Gindele et al. 2015; Kumagai & Akamatsu 2004; Kishimoto & Oguri 2008; Kumagai et al. 2003; Pentland & Liu 1999; Sadigh et al. 2013). Probabilistic driver behavior models have shown to be able to correctly predict quantitative information about driver behavior depending on state (Sadigh et al. 2013). However, these models suffer from the same problem as deterministic models, they have only been validated for specific and limited aspects of the driving task (e.g. apply on one task level such as McRuer's steering model). For instance, Kumagai et al. (2003) successfully predicted the stopping behavior at an intersection using a Bayesian network but this only works at an intersection where no maneuver can be performed. Recently, Gindele et al. (2015) published a novel driver decision making and planning prediction approach using a hierarchical Dynamic Bayesian model. This stochastic approach significant improves estimation and prediction accuracy of the learning approach, in addition they argued that this stochastic approach can cope better with noisy sensors and uphold a valid estimation, even if traffic participants are occluded for longer periods of time. Despite these promising results current stochastic models all predict stabilized behavior instead of predicting adaptation.

BA Model as Risk Compensation Prediction
As discussed in chapter 2, risk is one of the most important reasons for BA. The definitions of BA ("unintended behavioral change that limit the safety benefits") is directly related to risk, since lower safety benefits is a higher risk. In other words, predicting BA is equivalent to predicting risk. Unfortunately, the models that involve subjective risk tend to be impossible to validate and thus impossible to use as predictive tool. However, subjective risk could be divided into entities that can be quantitative measured. Carsten (2007) argued five major categories of driver capability, performance and behavior that are related to risk:

1. Attitudes/personality
2. Experience
3. Driver state (impairment level)
4. Task demand (workload)
5. Situation awareness

These five categories and their relationship to one another can be seen in figure 17. Winsum (1996) agreed that this model captured the most important factors that are related to risk. He emphasized the importance of adding experience (skills) and level of performance to the equation: "The line of reasoning makes clear that the concept of risk becomes more meaningful if skills and level of performance are added to the equation. This is to say that a certain speed may not be as risky for one person as for the other if they differ in certain required perceptual-motor skills, from the same

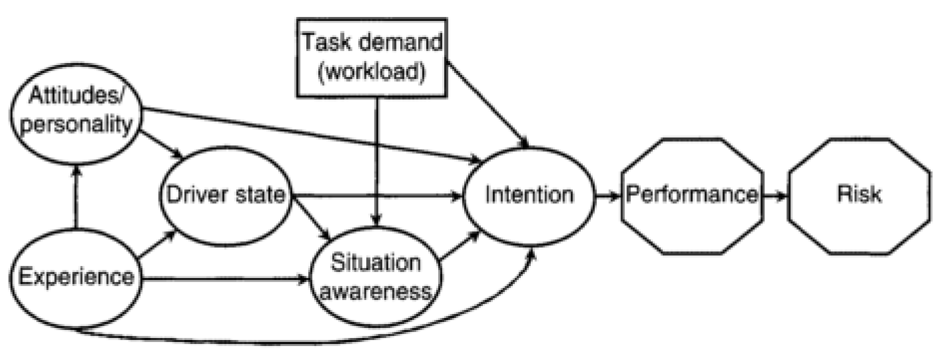

Figure 17: Relationship between categories of driver factors and risk
Source: Carsten (2007)

perspective as the fact that flying an F16 fighter plane is considerably more risky for the author of this thesis than for an experienced pilot”.
Although Carsten clearly explained why each factor is related to risk he didn’t clearly stated the correlations between factors and the way they can be measured. The same problem occurs with motivational models, without clearly describing correlations and quantifications this model leaves room for own interpretation. A great advantage of this model is that most of the categories objectively can be measured. Driver State, Workload and Situation Awareness can measured using the techniques described in the beginning of this chapter. The factors not explicitly explained can also be measured objectively. For example, Jamson (1999) argued that driving experience can be measured by looking at drivers steering behavior. He argued that novice drivers use a reactive steering behavior, whereas experience drivers use a more feed-forward (i.e. anticipating) strategy. Attitudes/Personality, is difficult to measure real-time but can be measured using questionnaires. According to Carsten the last chain towards risk is performance. Performance based metrics like Speed, Speed variability, Lane Keeping performance (TLC) and Time to collision (TTC) are related and validated by several models to accident risk (See also section 3.3). As already discussed above, one of Carstens model major drawback is the lack of quantitative relations between the different categories which makes this model currently impossible to use as predictive tool.

3.5 Conclusion

This chapter summarizes the most common measure and modelling techniques used in BA studies. The question that this chapter aims to answer is:

What methods are applicable to measure and model BA?

In literature several measuring techniques are used to measure the same quantity. In the discussion the best suited metrics and measurements techniques to use in a BA research will be discussed. Behavioral monitoring techniques can basically be divided in Driver State Monitoring Techniques (DSM) and Performance Based Metrics. This distinction is needed since a behavioral change is not always observable in terms of performance (e.g. a stressed driver may still drive with the same performance, but the stress signs were observable in terms of driver state indicators like: higher heart rate, higher grip force, sweaty hands etc.). DSM approaches that elicit data and draw conclusions about operator state can be categories into four categories: behavioral-based monitoring (e.g. operator-control interaction), psychophysiological-based monitoring (e.g. heart monitoring, eye tracking and electro dermal response measurements), contextual-based monitoring (e.g. using road information) and subjective-based monitoring (e.g. using drivers subjective input). To obtain the best and accurate picture of the driver's state all four categories should be considered simultaneously (Hou et al. 2015). Performance-Based Monitoring techniques (PBM) monitors driver's ability to control the vehicle in both lateral as longitudinal direction. Compared to other DSM techniques, PBM techniques are in general easier and faster to obtain which make them better suited (and therefore often used) for online driving behavior research.

The performance metrics were discussed in relation to Accident Risk, Controllability and Control effort since these factors are in chapter 2 concluded as important triggers to risk (e.g. Subjective Risk, Competence and Performance-Accuracy trade-off theory). Currently, only fatigue and drowsiness are actually measured and used in commercial vehicles due to the complexity and cost of many of the other techniques. Some often cited BA models were treated. From these models it could be argued that a well-designed BA model consist of the following criteria:

- <u>Hierarchical structure:</u> A BA model needs to have a Hierarchical structure as defined by Michon (1984) (e.g. apply on operational, maneuverable and strategical level). Winsum (1996) argued that one-level model predictions may be meaningless when behavior on another level is excluded from examination.
- <u>Consist of Quantitative Parameters:</u> Prediction models need to deal with quantitative values in order to make the results directly useful in the design of ADASs. Models that lack of quantitative values (e.g. motivational models) often fail in generating testable hypotheses (Ranney 1994).
- <u>Predict Future Risk Taking Behavior (preferably in a stochastic way)</u>: Instead of predicting behavior in general, a BA predictive model needs to predict future risk or the chance of changing behavior in a risky manner. This chapter argued that the subjective term risk can be divided into 5 quantitative categories: Attitudes/personality, Experience, Driver State (Impairment level), Task demand (workload), Situation Awareness. Where these categories can be used in a BA model instead of only the term "risk". Furthermore, this predicting is preferably done in a stochastic way. Rather than to predict what a driver will do at any moment at any time (which is almost doomed to fail due to the variability in human responses) a model should predict the probability that a certain behavioral change will occur. Probabilistic modelling use the

assumption that driver tend to drive in a reproducible manner (which is validated by Campbell et al. (2013)).

Conclusion chapter 3:
Currently no BA model was found that meet the criteria's of being: Hierarchical, Consist of Quantitative Parameters and Predict Future Risk Taking Behavior. The conclusion can be drawn that no suitable predictive BA model is available at this moment.

4 Discussion

It is essential to have well-defined metric and measurement techniques in order to be able to obtain quantitative parameters that can be used in models that predict BA effects to novel ADASs (for example a Haptic Shared Control System, as discussed in the introduction). This report described several models and measuring techniques that could be used to asses and predict BA. In order to distinguish between these models and measurement techniques table 9 to 11 summarizes the benefits and limitations of each model and technique.

Table 9 shows that current BA models are limited by either working in only one hierarchical level (e.g. McReur's Steering Compensatory model) to not using quantitative parameters (Rudin-Brown's Qualitative BA model and Weller and Schlag's Process model of BA). Without having quantitative parameters it is impossible to make quantitative predictions of BA and to generate testable hypotheses (Ranney 1994). For ADAS designers (i.e. car manufactures) it is not only interesting whether a BA will occur but in what degree as well. Moreover, as stated in chapter 3, instead of predicting what driver will do at any moment at any time it could be better to predict the chance of a BA in order to cope with the variability in driver responses to an ADAS. Stochastic models have shown to be able to predict stabilized behavior (Angkititrakul et al. 2011; Campbell et al. 2013; Gindele et al. 2015; Kumagai & Akamatsu 2004; Kishimoto & Oguri 2008; Kumagai et al. 2003; Pentland & Liu 1999; Sadigh et al. 2013). Unfortunately, no BA models can be found in literature that predicts BA in a stochastic way. This is recommended to try in future researches. Another problem that many models suffer is the use of the quantity "subjective risk". Models that contain this quantity are often argued as untestable due to their lack of quantitative parameters (See conclusion chapter 2). A solution to this problem is given by Carsten's risk model (Carsten 2007), who separated "risk" into 6 quantifiable categories: Attitudes/personality, Experience, Driver State (Impairment level), Task demand (workload), Situation Awareness, Performance. These categories could be used in a BA model instead of the term subjective risk resulting in a model that uses the term risk without being untestable.

As discussed in chapter 3, techniques to measure BA can be divided into Driver-State Monitoring (DSM) and Performance-Based Monitoring techniques. In table 10 & 11 the benefits and limitations of the in this report considered measuring techniques are summarized. Based on these two tables the conclusion can be drawn that Performance-Based Monitoring techniques are in general easier to measure and compute but cannot be used as reliable measurement tools for the assessment of SA and Workload. DSM techniques are stated to be good Workload estimators, especially if used in conjunction with other DSM techniques. As conclude in chapter 3, a model that can predict and asses BA would be a model that predicts risk taking behavior. Risk can be divided into 6 quantitative categories. So the question raises: which of the in Table 10 and 11 described DSM and Performance Metrics are best suited to quantify one of these categories?

<u>Driver state (Impairment level)</u>: Impairment levels are currently measured in commercial vehicles by use of Eye-Tracking techniques. The number of blinks and fixations (i.e. eye gaze strategy) can be used to determine impairment level. Other techniques that can assess impairment level are: EEG and Heart Rate Monitoring techniques, however, as table 10 argues these techniques either require expensive equipment (EEG) or the measurement accuracy is highly affected by other physical and cognitive factors (Heart Rate Monitoring). Therefore, Eye-Tracking in combination with Heart Rate Monitoring is argued as best suited to assess impairment level.

Performance: Performance metrics that asses BA are the metrics that are relate to risk taking behavior. TLC, TTC and Speed metrics are directly related to accident risk, which make them initially all three useful to use in a BA model. However, Östlund et al. (2005) argued that if the lane markings do not represent the safe travel path as perceived by the driver, either very large TLC values will be found, or there will be several line crossings, resulting in unreliable TLC metrics which are very difficult to interpret. Despite that, TLC, TTC and speed metrics capture most common BA changes argued in chapter 2 (e.g. closer headway time, higher speed. Late braking, frequency of overtaking, etc. (see figure 6 section 2.3)). Therefore TTC, TLC and Speed metrics are recommended by the author as one of the most important metrics in BA studies/models.

Task demand (Workload): Workload is conventionally determined using subjective questionnaires (e.g. NASA-TLC). Downside is that it cannot be used as online measurement technique. Alternatives, that can be used online, are the DSM technique EEG, Eye-Tracking or Entropy metric. EEG can identify unique brain scan patterns for different level of workload, however, the specialized equipment is expensive and subjects can become stressed due to the sensors placed on the scalp, resulting in a biased result (e.g. higher workload due to obtrusive sensors). A non-obtrusive technique is Eye-tracking. It is argued that pupil dilation is correlated to Workload in several studies (Pomplun & Sunkara 2003), however, the accuracy of this method is highly affected by lighting conditions and is not often used in current driving related studies. Another promising technique to asses Workload is the level of Entropy. Boer (2000) showed that the Entropy metric is very sensitive to cognitive modes. Downside of this technique is the need for baseline data, which cannot be used for statistical comparison. Due to the downsides of the alternatives the conclusion has to be made that the conventional questionnaires are best suited to asses Workload (if no online workload results are needed).

Situation Awareness: As stated in chapter 3, SA can be measured by means of the SAGAT technique. Downside of this technique is that it can only be used in driving simulator studies and it abruptly interrupts the driving task. Less interrupting SA technique is Eye tracking. Eye tracking can be used online. It makes the assumption that if a person fixates on a certain object, this subject really comprehends this object as well. The correctness of this statement can be argued and need to be investigated further. Regarding this statement, Damböck (2013) showed that drivers with eyes on the road were not always able to prevent an accident (due to late responses). This suggest that fixating on an object does not evidently mean they also comprehends it.

Experience: Experience can also be obtained using questionnaires (ask the driver how often they drive in a month etc.). An alternative is looking at drivers steering/pedal behavior. Jamson (1999) argued that novice drivers have a more reactive steering behavior, whereas experience drivers use a more feed-forward (i.e. anticipating) strategy. This result suggests that steering performance metrics like SRR and Grip Force can be used to indicate experience but this needs to be investigated further as well.

Finally Attitudes/Personality, is more difficult to quantitatively assess. Campbell et al. (2013) showed that people tend to drive in a reproducible manner, which could indicate that performance metrics TLC and TTC can also be used as quantified measure to value personality. However, much more research needs to be conducted in Attitude and Personality assessment. Especially, since chapter 2 concluded that the way drivers adapt their behavior highly dependents on the driver’s attitude towards the system (e.g. using the system as Slave, turning off the system etc.).

Table 9: Benefit and Limitation of some BA models

Models	Beneftis	Limitation
McRuer's Steering Compensatory model (McRuer et al. 1977)	\+ Highly detailed, \+ Uses quantitative parameters, \+ Can be used real-time	\- Models stabilized behavior (instead of BA), \- Only works in one dimension (i.e. on operational level), \- Assumes driver as optimize controller, which does not always hold
Rudin-Brown's Qualitative BA Model (Rudin-Brown & Noy 2002)	\+ Describes effect on all three driving task dimensions, \+ Describes effect of common BA triggers	\- No quantitative output/input parameters, \- Does not describe relevant feedback on the impact of the control loop (Martens et al. 2012)
Weller and Schlag's Process model of BA (Weller & Schlag 2004)	\+ Uses specific questions to determine whether BA occurs. \+ Describes potential changes	\- Does not use quantitative parameters, \- Basically combination of motivational models, and therefore fails in generating testable hypotheses.
Stochastic Models (e.g. Kumagai et al. 2003; Sadigh et al. 2013; Gindele et al. 2015)	\+ Proven to work as multi-dimensional predictive behavior model \+ Stochastic models have shown to be able to predict stabilized behavior	\- Currently no stochastic BA model available, \- Only applies on stabilized behavior
Carsten's Risk Model (Carsten 2007)	\+ Describes risk in a quantitative categories	\- Does not describe BA, \- Does not specify relations between risk categories.
Motivation Models (e.g. Wilde's Risk Homeostasis theory (Wilde 1998), Fuller's Task-Capability model (Fuller 2005) etc.)	\+ Well-cited, \+ Often used as foundation to explain BA	\- Fail in generating testable hypothesis due to lack of quantitative parameters (Ranney 1994; Elvik & Vaa 2004; Winter & Happee 2010)

Table 10: Benefit and Limitations of important DSM techniques;
Note: Most information is based on the comprehensive review of Hou et al. (2015)

DSM techniques (+ key reference)	Working Principle	Benefits	Limitations
Electroencephalogram (EEG) (Niedermeyer and Lopes da Silva 1999)	Electrode sensors placed on the scalp monitoring electrical activity in the brain	\+ Noninvasive, \+ Portable and field-ready EEG is currently available, \+ High temporal resolution, \+ Unique patterns for workload level, high-order cognition, verbal processing, and image processing observable in brain scans	\- Requires expensive and sophisticated signal-processing equipment, \- Low signal-to-noise ratios, \- Individual brains may differ in their organization, providing distinct patterns of EEG activity \- Can be considered as obtrusive
Eye Tracking (Victor et al. 2005; Bednarik 2005)	Monitors the operator's visual attention and cognitive activity	\+ Blinks and eye gaze can discern task demand and fatigue \+ Eye-tracking measurements are correlated with mental workload, \+ Can be used as tool to asses SA, \+ Already used in commercial vehicles	\- Lighting conditions may affect accuracy, \- Eye-tracking technologies do not take into account the fact that fixation patterns will differ depending on the environment (Hou et al., 2015)
Electrodermal Response (EDR) (Sharpe et al., 1995; Kapoor et al., 2007)	Measures electrical conductivity of the skin to determine sweat level	\+ Can indicate states of emotional arousal, \+ Less sensitive to environmental noise compared to other PBM techniques	\- Poor temporal resolution, \- High latency between stimulus and response as compared with other psychophysiological measurements, \- Qualitative and emotional aspects of affect are not reflected in EDR signal.
Cardiovascular (ECG, Heart Rate, Heart Rate Variation) (Chen and Vertegaal 2004)	Electrode sensors monitoring heart activity	\+ Heart rate measurements are unobtrusive, reliable, and easy to use and interpret, \+ Sensitive to cognitive demands and attention, \+ Relatively cheap, \+ HRV can provide measurements of both cognitive effort and compensatory effort, depending on the application (Byrne and Parasuraman, 1996)	\- Accuracy of heart rate measurement is affected by respiration, physical work, and emotional strain, which may make measurement inaccurate, \- Also sensitive to factors other than workload
Electromyogram (EMG) (Trejo et al. 2007;	Electrodes placed in or on specific muscles determine muscle activity	\+ EMG measurements correlate with state variables such as drowsiness and fatigue \+ EMG measurements related to the control of devices can be mapped in real time	\- Intramuscular EMG's require specialized technicians and can cause pain and undue stress to the operator, \- Need for expensive specialized tools
Near-Infrared Spectroscopy (NIRS) (Izzegtoglu et al. 2007; Keebler et al. 2009)	Near-infrared light monitors blood oxygenation levels in the brain	\+ Can measure changes using only light that previously required expensive apparatus, +\ High temporal resolution [ms]	\- NIRS is an emergent technology and analysis software is not mature

Table 11: Benefits and Limitations of well-cited Performance metrics

Performance-Based Metrics	Benefits	Limitations
Time-to-Line Crossing (TLC) (Godthelp and Konings 1981)	\+ Related to accident risk, \+ TLC is related to visual or cognitive distraction, \+ Often used in driving behavior studies, \+ TLC reflects the time-based lateral safety margins adopted by the driver (Godthelp, Milgram & Blaauw 1984)	\- Lane markers do not always represent the safe travel path as perceived by the driver, resulting in unreliable TLC metrics which are very difficult to interpret (Östlund et al. 2005)
Time-to-Collision (TTC) (van der Horst and Godthelp 1989)	\+ Takes speed difference between vehicles into account, which is a safety related factor, \+ directly related to accident risk, \+ Can be regarded as longitudinal time-based safety margin \+ More sensitive and reliable than distance headway in HASTE project (Östlund et al. 2005) \+ Often used in Driving behavior studies	\- TTC measures vary more than headway measures, resulting in less statistical power. (Östlund et al. 2005)
Velocity (speed, speed variation, maximum speed)	\+ Speed and speed variation are directly related to accident risk (Brehmer 2011), \+ Simple to measure and to compute, \+ BA is often observed in speed changes	\- Effect on mental workload and distraction are not easily interpreted, \- Speed metrics are influenced by data duration, therefore it is advised to always use same time window (Östlund et al. 2005)
Steering Reversal Rate (SRR) (McLean and Hoffman 1975; Östlund et al. 2005)	\+ Simpler computation than HFC, but gives almost same information, \+ Commonly used driving performance metric due to it straightforward interpretation and implementation (Östlund et al. 2005)	\- Unclear interpretation of the effects of cognitive load, \- SRR is not suited for use in built-up areas, due to the large variation induced by the road geometry, \- Sensitivity depends on chosen gap size, however not clear which gap size is best. (Östlund et al. 2005)
High frequency component (HFC) of steering wheel angle (McLean and Hoffman 1975)	\+ Contains more information than SRR, \+ Sensitive to both primary and secondary task load. (McLean & Hoffman 1975)	\- Difficult to compute, \- Unclear interpretation of the effects of cognitive load,
Steering Grip Force (Peters et al. 2005)	\+ Can assist DSM techniques, \+ Gives good opportunities to assess steering control efforts early in the chain of driver-vehicle reactions	\- Reliability of the measured steering grip force is not proven yet (Johansson et al. 2004)
Pedal dynamics (Wierwille et al., 1996)	\+ Related to longitudinal control (Johansson et al. 2004)	\- Safety relevance is unclear \- Not often used in behavioral studies, merely in accident studies
Steering Entropy (Nakayama et al. 1999; Boer 2000)	\+ Related to cognitive and visual/manual load (Boer 2000), \+ Correlated strongly with subjective workload ratings of drivers	\- Baseline data cannot be used for statistical comparison to experimental data since the data sets will then be dependent (Johansson et al. 2004)

5 Conclusions

This literature survey aims to answer the following research question:

What are promising ways to predict behavioral adaptation in Advanced Driver Assistance Systems?

In order to develop predictive BA models it is important to understand the motivation behind BA. The conclusion can be made that these BA motivations are often based on: driver's subjective risk assessment (Wilde 1998; Näätänen & Summala 1974), task difficulty/utility management (Fuller 2005; O'Neill 1977) and driver's attitude towards the novel introduced ADAS (Saad et al. 2004). Unfortunately, it can be concluded that these theories are not suited to use as base for a predictive model. They tend to fail in generating testable hypothesizes and sometimes give contradictory results (e.g. opposite results between Wilde's Risk homeostasis theory and Trade-Off between Performance and Effort model) which make them unreliable and impossible to generate quantitative BA predictions. Besides motivational models it can be concluded that currently no suitable predictive BA models exists. Current BA models are too simplistic and lack quantitative parameters. The limitations of the discussed models can be used as important pillars for the development of a future predictive BA model. It is argued that a well-designed predictive BA model needs to consist of:

- Hierarchical (i.e. applies on operational, maneuvering and strategic level): a model should be hierarchical since BA occurs on all these three levels, hence a predictive BA model should predict behavior on all these levels as well.
- Consist of Quantitative Parameters: by using quantitative parameters a BA model would be able to generate testable hypothesis and more important quantitative BA predictions.
- Predict Future Risk Taking Behavior (preferable in a stochastic way): Risk is directly related to BA. This report argues to use Carsten's Risk categories (e.g. Attitudes/personality, Experience, Driver State (Impairment level), Task demand (workload), Situation Awareness, Performance) to quantify Risk. After comparing the discussed metric and measurement techniques, the conclusion was made that for each category quantitative and objective measurement techniques are applicable that combined can assess risk, and thus BA.

Currently no models are available that make proper quantitative BA predictions. The models are often too vague and lack of quantitative parameters resulting in unreliable and unfalsifiable results. Therefore, more research need to be performed into the understanding and measuring of BA. Techniques to measure and asses BA are improving and getting less obtrusive which makes them better suited for car driving research.

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