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Human Factors of Transitions in Automated Driving: A General Framework and Literature Survey

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Abstract

The topic of transitions in automated driving is becoming important now that cars are automated to ever greater extents. This paper proposes a theoretical framework to support and align human factors research on transitions in automated driving. Driving states are defined based on the allocation of primary driving tasks (i.e., lateral control, longitudinal control, and monitoring) between the driver and the automation. A transition in automated driving is defined as the process during which the human-automation system changes from one driving state to another, with transitions of monitoring activity and transitions of control being among the possibilities. Based on 'Is the transition required?', 'Who initiates the transition?', and 'Who is in control after the transition?', we define six types of control transitions between the driver and automation: (1) Optional Driver-Initiated Driver-in-Control, (2) Mandatory Driver-Initiated Driver-in-Control, (3) Optional Driver-Initiated Automation-in-Control, (4) Mandatory Driver-Initiated Automation-in-Control, (5) Automation-Initiated Driver-in-Control, and (6) Automation-Initiated Automation-in-Control. Use cases per transition type are introduced. Finally, we interpret previous experimental studies on transitions using our framework and identify areas for future research. We conclude that our framework of driving states and transitions is an important complement to the levels of automation proposed by transportation agencies, because it describes what the driver and automation are doing, rather than should be doing, at a moment of time.

Keywords: human factors; automated driving; transitions; transition classification

1. Introduction

Car driving is becoming automated to an ever greater extent. Presently, most car manufacturers have released cars that are equipped with adaptive cruise control (ACC) and/or lane keeping assistance (LKA) systems, which are technologies that assist in the longitudinal and lateral driving tasks, respectively. In field operational tests, these driver assistance systems have been found to raise traffic efficiency and to reduce energy consumption (e.g., Alkim, Bootsma, & Hoogendoorn, 2007). Moreover, such systems may reduce the number of traffic accidents (Kuehn, Hummel, & Bende, 2009), most of which are currently attributed to human error (Brookhuis, De Waard, & Janssen, 2001; Dingus et al., 2006; Storie, 1977; Treat et al., 1979).

The existing driver assistance systems function as supportive automation and keep the driver in the loop by requiring the driver to monitor the environment and control part of the driving task. More advanced technologies that allow the driver to be out-of-the-loop for extended periods are now starting to be introduced. Three authorities, namely the German Federal Highway Research Institute (BASt; Gasser & Westhoff, 2012), the Society of Automotive Engineers (SAE, 2014), and the United States National Highway Traffic Safety Administration (NHTSA, 2013) have each formulated definitions that classify automated driving systems from driver assistance to full automation. In fully automated driving, the automation takes care of all monitoring and control activities, and a driver is not strictly needed anymore other than to set a destination. However, several problems, such as limitations of technology, divergent public acceptance, liability issues, and human-machine ethics, are yet to be solved before fully automated driving can become publicly available at a wide scale (e.g., Kyriakidis, Happee, & De Winter, 2015).

Previous human factors research indicates that automation resolves the imprecision and variability of human task performance, but also yields new types of safety concerns. It has been found that a high level of automation can cause out-of-the-loop problems such as complacency, skill degradation, mental underload (when the automation functions reliably), mental overload (when the operator suddenly needs to solve an automation-induced problem), and loss of situation awareness (Bainbridge, 1983; Bibby, Margulies, Rijnsdorp, & Withers, 1975; Endsley & Kiris, 1995; Hancock et al., 2013; Kaber & Endsley, 1997; Parasuraman & Riley, 1997; Vlakveld, 2015), which are issues that have also been implicated in the domain of automated driving (De Winter, Happee, Martens, & Stanton, 2014; Seppelt & Victor, 2016; Young & Stanton, 2002). Recently, a meta-analysis of 18 experiments on human-automation interaction found statistical support for the so-called lumberjack hypothesis, which postulates that as the degree of automation increases, the side effects of automation (e.g., performance impairment if the automation fails) increase as well (Onnasch, Wickens, Li, & Manzey, 2014). In the domain of automated driving, it has been argued that there is an 'uncanny valley' (Flemisch et al., 2016), whereby not the highest levels of automation, but intermediate levels in which the human is expected to monitor the automated driving system, may be particularly hazardous because humans are unable to remain vigilant for prolonged periods of time (Casner, Hutchins, & Norman, 2016; Norman, 2015). These studies make clear that due to the changes in the driver's role in automated vehicles compared to manually driven vehicles, human factors need to be carefully considered by researchers, designers, and policy makers (see also Kyriakidis et al., 2016; Merat & Lee, 2012).

Bainbridge (1983) argued that 'taking over control' is a primary task left for the human operator who supervises an automated system. Indeed, one cannot ignore the fact that automated driving systems will occasionally fail (Goodall, 2014), which implies that a driver has to resume control to avoid crashing. Moreover, automated driving systems of the near future will probably not be able to cover all traffic conditions, which implies that the driver has to take over control to avoid a collision or traffic violation. Empirical studies have confirmed that accidents and near-accidents are likely to occur in situations where drivers suddenly have to resume manual control from an automated driving system (e.g., De Waard, Van der Hulst, Hoedemaeker, & Brookhuis, 1999; Flemisch, Kelsch, Löper, Schieben, & Schindler, 2008; Jamson, Merat, Carsten, & Lai, 2013; Schermers, Malone, & Van Arem, 2004; Zeeb, Buchner, & Schrauf, 2015). The aforementioned out-of-the-loop problems exacerbate the inability of the driver taking back control from automation. Thus, it is important to investigate control transitions in automated driving, especially when considering that human factors studies have repeatedly demonstrated that humans are not good at supervisory tasks (Hancock, 2015; Mackworth, 1950).

One issue that occurs when interpreting the experimental literature on control transitions is that the results are much determined by the specific automation functions, traffic conditions, and task instructions (see De Winter et al., 2014 for a review). To be able to derive more general conclusions on driver behaviour across different automated driving systems and traffic situations, this paper proposes a framework that defines and classifies transitions focusing on changes of driving states. This framework is intended to build a dialogue among researchers who share common interests in understanding how drivers behave during transitions in automated driving. Our concept of driving states differs from the existing BASt, SAE, and NHTSA levels of automation because it formally outlines possible allocations of primary driving tasks and is descriptive rather than normative. That is, our framework describes what the driver and automation are doing at a given moment of time (descriptive approach) rather than what they should be doing according to design criteria/standards of conduct (normative approach).

This paper is organised as follows. Section 2 defines transitions between driving states. We explain that the driving states represent how the primary driving tasks of longitudinal control, lateral control, and monitoring are distributed between the automation and the driver, and that transitions are defined as a change from one driving state to another. Section 3 introduces a classification tree that categorizes different types of control transitions. In Section 4, we review experimental studies that are concerned with transitions in automated driving, and interpret the findings using our transitions framework. Finally, Sections 5 and 6 present research gaps and draw conclusions arising from this review and applications of the new framework.

2. Definition of transitions in automated driving

Most studies on transitions in automated driving have defined a 'transition' as either an activation or a deactivation of a function (Gold, Damböck, Lorenz, & Bengler, 2013; Miller, Sun, & Ju, 2014; Nilsson, Falcone, & Vinter, 2015; Pauwelussen & Feenstra, 2010; Toffetti et al., 2009), or a change from one level of automation to another (Merat, Jamson, Lai, Daly, & Carsten, 2014; Varotto, Hoogendoorn, Van Arem, & Hoogendoorn, 2015; Willemsen, Stuiver, Hogema, Kroon, & Sukumar, 2014). Similarly, Merriam-Webster defines a 'transition' as 'a change from one state or condition to another', whereas Flemisch et al. (2012) stated that a transition is the period between two different states. In summary, it can be argued that determining the 'states' based on driving tasks is a prerequisite for defining a 'transition' in automated driving.

2.1. Driving tasks

Car driving is a highly complex task that can be modelled at different levels of control with different levels of temporal granularity (e.g., Michon, 1985). We parsimoniously consider the following three primary driving tasks: (1) lateral control, (2) longitudinal control, and (3) monitoring, which are also present in the BASt, SAE, and NHTSA definitions of levels of automated driving. Our distinction between longitudinal and lateral control is also congruent with many models of vehicle control (e.g., Rajamani, Tan, Law, & Zhang, 2000) and driver performance (e.g., Nash, Cole, & Bigler, 2016), and with well-known taxonomies of driving tasks that distinguish between longitudinal (starting, accelerating, stopping) and lateral (steering, lane changing, curve driving) manoeuvres (e.g., McKnight & Adams, 1970).

Although the BAST, SAE, and NHTSA definitions differ from each other, the criteria these organisations adopt to classify the levels of automation are similar (SAE, 2014). The essential criteria are how the three primary driving tasks (i.e., lateral control, longitudinal control, and monitoring) are distributed between the driver and the automation. For example, the difference between Assisted Driving (AD) and Partially Automated Driving (PAD) as defined by BASt is that in PAD the automation takes over both lateral and longitudinal control, while only one of these is automated in AD. This distinction between AD and PAD is equivalent to the distinction between Driver Assistance and Partial Automation in the SAE definition, and between 'Level 1 Function-Specific Automation' and 'Level 2 Combined Function Automation' in the NHTSA definition. Furthermore, the BASt definition says that the difference between PAD, HAD, and Fully Automated Driving (FAD) is the required monitoring frequency which decreases from 'permanently' in PAD, to 'need not permanently' in HAD, and 'need not' in FAD. This decrease of monitoring frequency with increasing level of automation is also present in the SAE and NHTSA definitions. Two other criteria that have been used to define the levels of automation are (1) system capability (i.e., the type of scenario [e.g., low speed traffic jam, merging] that the automated driving system is able to drive in) and (2) fall-back agent (i.e., whether the automation or the driver is expected to take back control of monitoring and control tasks after an automation failure), see SAE (2014). These latter two criteria are important from a legal and design perspective, but are not adopted in the present study because they mix expected behaviour (i.e., what the driver and the automation should be doing in specific environmental conditions) with actual behaviour.

When describing the distribution of the primary driving tasks between driver and automation at a given moment of time, a diagram can be drawn as shown in Figure 1. This figure illustrates the lateral/longitudinal control and monitoring of a vehicle by the automation and the driver. Here, Input is the state of the vehicle (e.g., velocity and acceleration) and environmental information (e.g., traffic signs and surrounding road users). Output is the state of the vehicle in the environment, one system step after the input. The Driver decision maker (a human agent) and the Automation decision maker (a computer agent) acquire and analyse the Input and determine the steering and acceleration target signals. Note that both the driver and automation decision makers are higher-level information processors rather than low-level trajectory-following controllers. (S_{ax}, S_{dx}) and (S_{ay}, S_{dy}) allocate control for the longitudinal and lateral directions between driver and automation, respectively, and (K_{ax}, K_{dx}) and (K_{ay}, K_{dy}) represent proportional weights of driver and automation. The target signals (e.g., steering angles and acceleration) are fed to the longitudinal and lateral driver or automation controllers, the switches, and the proportional parameters. The longitudinal and lateral controllers constitute transfer functions that generate steering and throttle/brake control signals. The vehicle actuators implement these signals to move the vehicle.

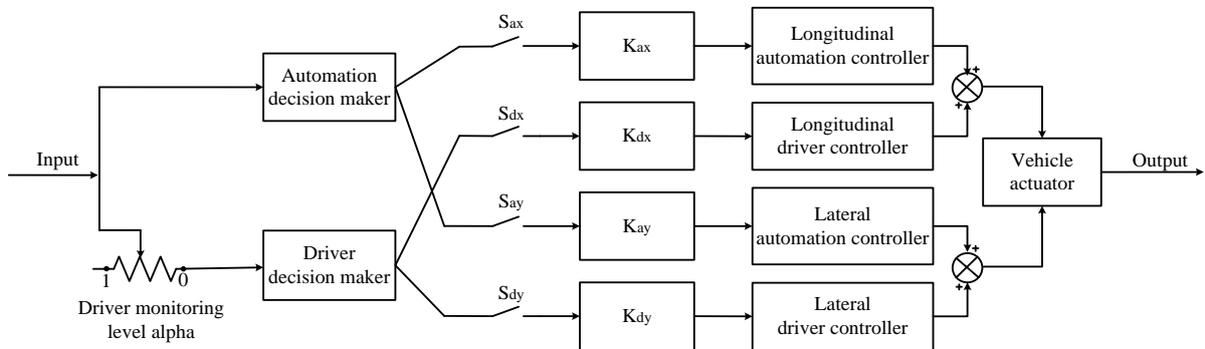*Figure 1*. Diagram describing the distribution of driving tasks (lateral control, longitudinal control, monitoring) between the driver and the automation. dx = driver longitudinal; dy = driver lateral; ax = automation longitudinal; ay = automation lateral; S = switch, K = proportional gain. In this diagram, the decision makers determine a target signal which is executed by lower-level longitudinal and lateral controllers.

Note that Figure 1 does not include a switching unit that sets the switches, and therefore does not establish *who* initiates a control transition and what the transition criteria are. Moreover, our framework is concerned with defining actual transitions (rather than attempted transitions or the consequences of transitions gone wrong), and so does not depict failure modes such as a sensor or actuator failure, exceedances of functional constraints, or mode errors (cf. Sarter & Woods, 1995). Furthermore, it is worth emphasizing that Figure 1 describes the current state of the driver-automation system; it does not describe the temporal sequence of a transition from the start of a transition (e.g., driver input or take-over request) to the end of a transition (i.e., when the agents have control of the task they were requesting or requested to have).

In Figure 1, it is assumed that the automation permanently monitors the environment because repetitive monitoring is where machines excel with respect to humans (cf. Fitts, 1951; De Winter & Hancock, 2015). The driver, on the other hand, is not a permanent monitor of the environment. The *alpha* level represents how much input information is fed to the Driver decision maker. Specifically, *alpha* at a particular moment should be regarded as a one-dimensional variable that describes the driver's monitoring activity for gaining situation awareness (cf. Endsley, 1995). *Alpha* is dependent on the driver's mental status, such as his workload and arousal level. We use *alpha* = 0 to represent a situation where the driver does not monitor the road and so receives no information and achieves no awareness of the current driving situation, such as when the driver is asleep behind the wheel. *Alpha* = 1 means that the driver actively monitors the environment so that he/she is fully aware of 'what is going on'.

The *recommended* level of *alpha* in automated driving is a function of the primary driving task allocation. In a review article, Flemisch et al. (2012) described the relationships between driver ability, responsibility, and control. Their framework shows that (1) responsibility motivates control, (2) control causes responsibility, and (3) control is enabled by ability. From their framework, we infer that if the driver is controlling, the driver has to monitor as well (i.e., *alpha* = 1) for the driving condition to be safe, or put differently, it is irresponsible to control a car without monitoring.

2.2. Definition of static driving states

Before defining transitions in automated driving, we need to define the driving states of automated driving. A driving state represents the primary driving tasks (lateral control, longitudinal control, monitoring) which the driver and automation are executing at a given moment.

We define a static driving state as a situation where control is performed either by the driver or by the automation. This means that K_{ax}, K_{dx}, K_{ay} and K_{dy} are equal to 1, and only one switch is turned on in each pair of switches (S_{ax}, S_{dx}) and (S_{ay}, S_{dy}). Six static driving states are possible according to the state of the switches and the monitoring level *alpha*:

- State 1: S_{dx} and S_{dy} are both switched on, S_{ax} and S_{ay} are both switched off, and *alpha* is 1. This state is manual driving.
- State 2.1: S_{ax} and S_{dy} are both switched on, S_{dx} and S_{ay} are both switched off, and *alpha* equals 1 (because the driver is still engaged in lateral control tasks). This state represents driving assistance with longitudinal automation such as ACC.
- State 2.2: S_{dx} and S_{ay} are both switched on, S_{ax} and S_{dy} are both switched off, and *alpha* equals 1 (for the same reason as in State 2.1). This state represents driving assistance with lateral automation only (cf. Carsten, Lai, Barnard, Jamson, & Merat, 2012; Young & Stanton, 2007).
- State 3: S_{ax} and S_{ay} are both switched on, S_{dx} and S_{dy} are both switched off, and *alpha* is still 1. This state maps to driving with lateral and longitudinal automation. The driver is monitoring permanently to be able to take over control anytime needed.
- State 4: S_{ax} and S_{ay} are both switched on, S_{dx} and S_{dy} are switched off, but unlike State 3 the driver is not monitoring permanently (i.e., *alpha* is between 0 and 1).
- State 5: The conditions of the switches are the same as in States 3 and 4, but the driver is not monitoring at all (i.e., *alpha* equals 0).

It is worth emphasizing that the above states represent what the driver and automation are actually doing, not necessarily what they should be doing or are capable of doing. For example, a driver-automation system with a driver who is monitoring permanently is classified as State 3, whereas for another driver who is using the same automation technology but does not monitor permanently, this human-automation system is classified as driving State 4.

The driving states listed above do not include 'irresponsible' driving states. Such driving states could in principle be added without altering the topology of Figure 1. An example is when S_{dx} and S_{dy} are both switched on, S_{ax} and S_{ay} are both switched off, and *alpha* is smaller than 1, which corresponds to distracted manual driving (cf. Dingus et al., 2016). Moreover, we cannot ignore the fact that situations may exist in which both the automation and the driver do not control one or both of the primary control tasks. Such a situation occurs when S_{ax} and S_{dx} are both switched off, and/or S_{ay} and S_{dy} are both switched off. We did not classify such situations as a driving state because neither agent actually performs the driving task. If such a situation is safety-critical, the automation may attempt a pre-programmed action to bring the car into minimal risk condition (see also SAE, 2014).

2.3. Dynamic driving state

It is also possible that the human and automation are jointly executing the same control task whereby the degree of control is dynamically adjusted to the momentary situation. One type of such human-machine interaction is shared control (Abbink, Mulder, & Boer, 2012; De Winter & Dodou, 2011; Johns et al., 2016; see also Sheridan, 2002; Sheridan & Verplank, 1978), a concept which has been extended towards a framework of 'cooperative control' (Flemisch, Bengler, Bubb, Winner, & Bruder, 2014). A distinction between dynamic and static driving states has also been made by Inagaki (2003) who stated: "Sharing and trading are distinguished to clarify the types of human-automation collaboration" (p. 147).

Accordingly, we define a dynamic driving state as a situation where the driver and automation are executing at least one driving control task together. This means that both switches are turned on in one or both pairs of the switches (S_{ax}, S_{dx}) or (S_{ay}, S_{dy}). The weight variables (K_{ax}, K_{dx}), (K_{ay}, K_{dy}) can be set according to the level of control of driver and automation. Note that some authors have proposed a 'coupling valve', rather than binary switches, as a conceptualization of the extent to which driver, automation, and vehicle are cooperatively in control of the driving task (Baltzer, Altendorf, Meier, & Flemisch, 2014). Also note that in Figure 1, we showed the weight variables as proportional gains for reasons of simplicity and interpretability; the actual control system design can obviously be more complex than this. As with any mathematical-psychological model (MacCallum, 2003), the model shown in Figure 1 does not fully account for all complexities of real driving, but aims to parsimoniously represent the key phenomena of interest.

In shared control, the driver always executes a control task, which may alleviate out-of-the-loop problems such as loss of situation awareness (e.g., Abbink et al., 2012). Several assistance systems currently make use of shared control, whereby an assistive force is provided on the accelerator in order to support car following or eco-friendly driving, or on the steering wheel in order to guide the driver back into its lane or to prevent colliding with a road user in the blind spot (see Petermeijer, Abbink, Mulder, & De Winter, 2015, for a review). The BASt, SAE, and NHTSA levels of automated driving do not account for the concept of shared control, because these definitions characterize the driving tasks in terms of 'trading' of control (cf. Inagaki, 2003) through terminology such as 'taking over control' and by allocating monitoring, task-execution, and fallback-performance functions to the human driver versus the automated driving system. It is currently being investigated what the role of shared control may be in future automated driving systems (Johns et al., 2016; Mok, Johns et al., 2015). The results thus far indicate that shared control may be promising as an optional driving mode to keep the driver informed and involved, especially when the automation drives imperfectly (Abbink et al., 2012; Flemisch et al., 2014; Mok et al., 2015).

2.4. Definition of transitions

Based on the above concept of driving states, a transition can be defined as a process during which the driver-automation system changes from one driving state to another driving state. For example, a transition from State 4 to 1 means that the driver resumes both longitudinal and lateral control, and that the monitoring level is set to 1.

Flemisch et al. (2008) included all possible control transitions in a spectrum of automation. We refine this spectrum by making a distinction between monitoring transitions and control transitions. Transitions among States 3, 4, and 5 concern changes in the driver's monitoring status. A transition of control refers to a transition that involves a reallocation of the longitudinal or lateral control task between the driver and the automation. For some of the control transitions, the corresponding changes of monitoring level (e.g., monitoring level increases from 0 to 1 during the transition from State 5 to State 1) are not shown, because the recommended level of monitoring is determined by the whether or not the human is in control, as explained above. Figure 2 illustrates the overall concept.
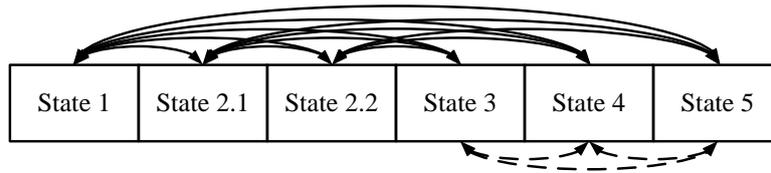
Figure 2. Monitoring transitions and control transitions between different driving states. Solid lines represent control transitions, whereas dashed lines represent monitoring transitions.

3. Classification of transitions of control

Transitions of control have a direct influence on the speed and path of the vehicle, and therefore have a direct relationship with road safety. A classification of control transitions facilitates understanding of the task demands on drivers during a transition. We classify transitions of control based on a retrospective account of a successfully completed transition, to avoid ambiguities regarding causality of attempted or unsuccessful transitions.

In a prior literature review, Martens et al. (2008) classified the possible control transitions in automated driving. In their research, three questions were used to classify control transitions between the driver and automation: (1) Who has 'it'?, (2) Who should get 'it'?, and (3) Who initiates transition?, yielding four types of transitions: (1) driver-initiated, from the driver to the automation ($D_i{\rightarrow}A$), automation-initiated, from the driver to the automation ($D{\rightarrow}A_i$), (3) driver-initiated, from the automation to the driver ($D_i{\leftarrow}A$), and (4) automation-initiated, from the automation to the driver ($D{\leftarrow}A_i$). Hoeger et al. (2011) provided an extended notation by including transitions between different levels of automation. For example, a driver-initiated transition from highly automated (HA) driving to driver-assisted driving was designated as follows: $DA_i{\leftarrow}HA$. Furthermore, Hoeger et al. introduced a notation for describing failed/refused transitions, which may occur when the activation of a particular automation mode is impossible.

We chose to deviate from the above transition classifications for several reasons. First, we argue that if a transition occurs then control will always transfer from one agent to the other (i.e., from the automation to the driver, or from the driver to the automation), and so there is no need of including both agents in the definition of a transition. Second, because we are concerned with actual transitions rather than with intended transitions, we did not consider failed transitions in our classification. Moreover, what is an intended and failed transition will be difficult to define in formal terms (for insightful reflections on the definition of 'error', see Sharit, 2006; Reason, 2013). Third, the underlying reasons for transitions are not included in the above classifications, in particular whether the transition is required or optional.

3.1 Classification tree of transitions of control

Our first dimension in the classification of control transitions is 'Who initiates the transition?', defined as who actually initiates the transition of the *control* task (i.e., not including changes in monitoring activity). Prior research indicates that *who* initiates a transition (i.e., human or automation) is an important question in the design of adaptive automation and function allocation in general. Thus, a distinction can be made between human-initiated transitions and automation-initiated transitions (Hancock, 2007; Inagaki & Sheridan, 2012; Scerbo, 1996).

The second dimension is 'Who is in control after transition?' This dimension includes two possibilities (automation and driver). It is important to define who is in control after a transition, because whoever is in control is responsible for the safe execution of the driving task.

Because the initiation of a transition is a discrete event while the control abilities of driver and automation are continuously changing, we use 'initiation of transition' and 'control after transition' as the first and second branch of our classification tree (Fig. 3). The corresponding two transition categories are 'driver-initiated transitions' and 'automation-initiated transitions'. Each of the two primary categories is divided into two subcategories: 'driver in control' and 'automation in control'. Based on these two criteria, we identify four types of transitions: 'Driver Initiates transition, and Driver in Control after (DIDC)', 'Driver Initiates transition, and Automation in Control after (DIAC)', 'Automation Initiates transition, and Driver in Control after (AIDC)', and 'Automation Initiates transition, and Automation in Control after (AIAC)'.

The third level in the classification refers to the underlying reason of the transition. At this third level, transitions are clustered into two categories: optional transitions and mandatory transitions. An optional transition occurs

when there is no requirement or decision rule that stipulates that a transition should happen (i.e., the transition is voluntary), and the driver who prefers a transition implements the transition. Conversely, a mandatory transition occurs when the agent that is in control before the transition follows a rule or is required to relinquish control (i.e., the transition has to happen). Thus, optional transitions can be described as will-based, whereas mandatory transitions can be understood as ability-based or rule-based. In our framework, optional transitions are always initiated by the driver. At the present state of technology, automation does not have the option ('free will') to choose the control tasks based on its preference, because the decision rules that are used by automation are built in its software. We recognize that developments in artificial intelligence may eventually lead to synthetic consciousness and create the possibility of optional automated-initiated transitions, but this is beyond our current scope. Thus, driver-initiated transitions can be optional or mandatory, whereas automation-initiated transitions can only be mandatory. Similarly, Varotto et al. (2015) classified transitions while driving with ACC as mandatory and discretionary transitions.

Achieving better and safer performance is one of the reasons for using automation. How and when to use automation are difficult questions that have been debated for over a century or more (e.g., Hollnagel, 2012). The answers to these questions are not only a matter of technology, but also involve social and ethical dimensions (e.g., Hancock, 2014; Hancock, 2015; Sheridan, 1970; Sheridan, 1980). Well known in science fiction are the 'three laws of robotics' by Asimov (Asimov, 1942). Some alternative principles have also been developed based on real world situations (Murphy & Woods, 2009). Within the scope of this paper, we will not discuss social or ethical aspects in much detail. Nevertheless, we propose the following practical function allocation criteria inspired by Asimov's laws: 1) in case of an imminent collision, the automation should take control in order to protect humans by avoiding collision or by reducing the severity of impact, and 2) the automated car (with or without the driver inside) should try to avoid damage to itself, but not in such a way that it harms a human or conflicts with the driver's orders. Of course, these simple rules do not solve all ethical intricacies such as trolley problems of various kinds (cf. Bonnefon, Shariff, & Rahwan, 2015; Goodall, 2014), but they may be a useful starting point for defining mandatory versus optional transitions.

3.2 Use case analysis for each category of the control transitions

Below, we adopt a use case analysis to analyse the interactions between the driver and the automated driving system for various types of transitions as defined in Figure 3.
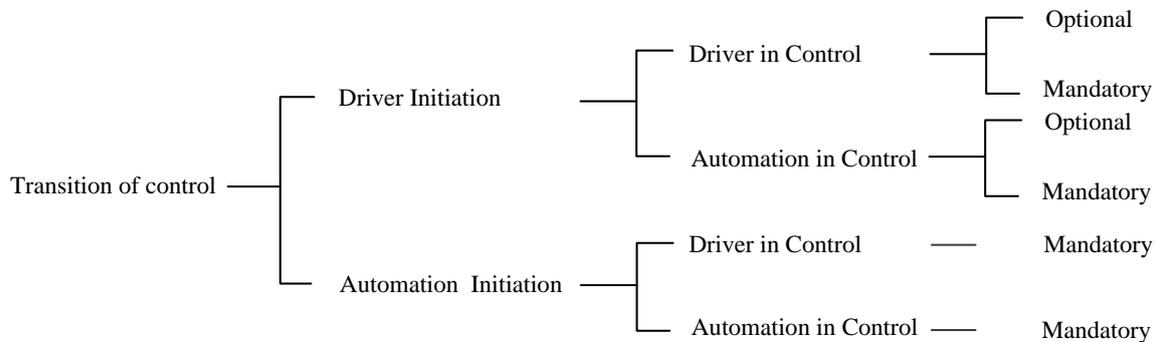

Figure 3. Classification tree of transitions of control.

3.2.1 Optional Driver-Initiated transitions

During an optional DIDC or optional DIAC transition, both the automation and the driver will usually have the ability to control the vehicle. An example is a driver who turns on (i.e., optional DIAC transition) or turns off (i.e., optional DIDC transition) the ACC on the highway in a non-critical situation. Because both agents are able to drive, this use case is less critical for safety than mandatory transitions where one of the agents is unable to control the vehicle. In this use case, the automation may suggest to the driver that it is possible to make a transition. Note that if the automation offers a suggestion about a possible transition, this does not make it an automation-initiated transition, because it is still the driver who makes the decision and initiates the transition of control. The low criticality and ordinary character of DIAC and DIDC transitions may explain why much of the research on optional driver-initiated transitions has investigated when, where, and why drivers initiate a transition of control (Klunder, Li, & Minderhoud, 2009; Pauwelussen & Feenstra, 2010; Varotto et al., 2015; Viti, Hoogendoorn, Alkim, & Bootsma, 2008). Of course, not all optional DIAC and DIDC transitions are safe;

it is possible that the driver initiates a transition at an inappropriate moment or by accident, whereby he hands over control to the automation while the automation is less able than the driver in the current environmental conditions (e.g., when driving in snow), or conversely, where the driver takes control while the automation is more capable than the driver (e.g., close car following in a high-speed platoon or when *alpha* is low).

3.2.2 Mandatory Driver-Initiated transitions

A mandatory DIDC transition can be initiated when the driver diagnoses that the automation is unable to drive, whereas a mandatory DIAC transition is initiated when the driver thinks he himself is unable or not allowed to drive. For instance, a DIDC transition can be initiated when the driver diagnoses an automation failure without warning from the automation. A DIAC transition can happen when the driver has a physical emergency, such as heart attack, or a 'cognitive emergency', such as information overload. Another example is that in future intelligent traffic consisting of platoons of automated vehicles (e.g., Hsu, Eskafi, Sachs, & Varaiya, 1993; Van Arem, Tampere, & Malone, 2003), entering a platoon may require a DIAC transition to let the host vehicle's automation cooperate with other vehicles and infrastructure automatically. Overall, driver-initiated transitions require clear information on the automation's (in)capability of driving, signalling the need for a proper human-machine interface (Inagaki, 2003).

3.2.3 Automation-Initiated transitions

An automation-initiated transition can be triggered by the automation's diagnosis regarding the driving inability of the automation itself, or regarding the inability of the driver who was controlling the vehicle before the transition. An AIDC transition may be caused by an exceedance of the automation's operational limits or by a computer failure that is detected by on-board diagnostics, a scenario also known as a 'take over' (Gold, Damböck et al., 2013). Another possibility is 'adaptive automation', whereby the automation hands over control to the human in an attempt to raise the driver's situation awareness or to reduce other out-of-the-loop problems (Gonçalves & Bengler, 2015; Hoeger et al., 2011; Merat et al., 2014; Rauch, Kaussner, Krüger, Boverie, & Flemisch, 2009; Whitmore & Reed, 2015). In modern traffic jam assistance systems, for example, the automation may disengage when the driver does not have his/her hands on the steering wheel for a period of time (e.g., between 10 and 30 s, depending on the manufacturer). For such a transition, the driving State is 3, 4, or 5 before the transition, and the driving State is 1 after the transition. This is a mandatory AIDC transition, with the hands-off interval being a predefined rule that is programmed into the automation.

An AIAC transition does not imply that the automation should overrule the human. We recommend that the automation should not make decisions and implement actions without human consent, except in the cases where, through inaction, the human will get hurt. For example, when a driver fails to drive safely during a heart attack, the automation should take over control if it can reliably determine this from a physiological monitoring system. Likewise, if a manual driver fails to react to other vehicles, the automation may temporarily take over control and initiate autonomous emergency braking (AEB) or an evasive manoeuvre. Moreover, similar to mandatory DIAC transitions, mandatory AIAC transitions occur when the driver is required to hand over control according to the rules and regulations of the automated traffic system.

3.2.4 Safety criticality of transitions

Similar to how active safety and passive safety are defined, we can classify DIDC and AIAC (which are self-activated transitions) as active transitions, and AIDC and DIAC (which are triggered interventions) as passive transitions. In active transitions (AIAC and DIDC), the agent who initiates the transition is the *same* as the agent who ends up with control. In these two transition types, whoever initiates the transition is usually prepared to take over control afterwards. On the other hand, in passive transitions DIAC and AIDC, the initiating agent and the resulting driving agent are *different* and whoever is in control after the transition may have been forced to take over control from the other agent. In DIAC and AIDC transitions, the agent who is in control before the transition needs to ascertain that the other agent has the ability to drive, and get the other agent prepared for the transition. A lack of preparation may lead to unsafe situations.

In a mandatory DIAC transition, the driver is in control before the transition, and automation control could be unstable after the automation may have been forced to take over control of the car, depending on the situation and environmental conditions. As for AIDC transitions, if drivers do not respond timely and properly, the transition could lead to an accident. The fact that AIDC transitions are essential to the safety of automated driving may explain why these transitions have been extensively studied in driving simulator experiments by human factors researchers. The most common AIDC (i.e., take-over) scenario can be summarized as follows: due to an automation limitation (e.g., the automation detects an accident in front of the host vehicle and cannot

cope with this situation), participants are warned to take over control by braking and/or steering within a time margin (e.g., Gold, Damböck et al., 2013; Lorenz, Kerschbaum, & Schumann, 2014; Radlmayr, Gold, Lorenz, Farid, & Bengler, 2014; Naujoks, Purucker, Neukum, Wolter, & Steiger, 2015; Petermeijer, De Winter, & Bengler, 2016; Telpaz, Rhindress, Zelman, & Tsimhoni, 2015; Willemsen et al., 2014; Zeeb et al., 2015). AIDC transitions have drawn attention of not only human factors scientists, but also of automotive engineers who are solving the controllability problems that AIDC transitions may cause. For example, Nilsson et al. (2015) proposed a concept whereby AIDC transitions are classified as safe or unsafe by calculating whether the current and predicted vehicle states are within the estimated driver capabilities.

Setting up experimental driving scenarios for a certain transition use case is a challenge, because everything is possible regarding future technologies. The proposed classification tree (Fig. 3) could provide guidance for designing scenarios with a theoretical basis.

4. A brief survey of human factors research on transitions of control

In this section, we review previous experimental studies using the above framework of driving states and transitions categories. The goal of this literature review is to interpret the representative empirical literature in light of our framework, and accordingly derive conclusions and recommendations for further research.

Broadly speaking, experimental human factors research on transitions can be clustered into two groups. The first group of research involves transitions between driving States 2/3 and driving State 1, or vice versa. In driving States 2 and 3, the driver constantly monitors the automation status and the outside environment, so the driver is situationally aware. Several human factors studies regarding these three driving states have focused on driver behavioural adaptation and manual driving behaviour after having used the automated driving system (Bianchi, Piccinini et al., 2013; Hoedemaeker & Brookhuis, 1998; Young & Stanton, 2007). Researchers have also examined at which moments drivers activate and deactivate their automation (ACC) system, and have modelled the impact of these transitions on traffic flow (e.g., Klunder et al., 2009; Pauwelussen & Feenstra, 2010; Varotto et al., 2015; Viti et al., 2008).

Our focus is on the second group of research: transitions where the driving state changes from State 4 or 5 to a lower state. A meta-analysis by De Winter et al. (2014) showed that drivers' overall workload while driving in SAE level 3 (driving States 3 and 4) automation is substantially lower than while driving with ACC (driving State 2.1). This low-workload situation is sometimes followed by a high-workload safety-critical AIDC transition (De Winter et al., 2014). In driving States 4 or 5, the driver is not in control and does not constantly monitor the outside environment ($alpha < 1$). If a control transition involves driving States 4 or 5, this means that the monitoring status will also change during the transition (Fig. 2). The following section discusses control transition studies that involve driving States 4 and 5, and AIDC transitions in particular.

We reviewed experimental research based on the following inclusion criteria: (1) The control transition should involve driving State 4 or 5, (2) The study should focus on driver behaviour during a transition (i.e., studies on long-term adaptation to automated systems were not included), (3) The paper should be in English. We observed that most research on driver behaviour during control transitions clustered into two periods: the late 1990s and the 2010s.

4.1. Control transition studies in the late 1990s

The first period covers the late 1990s during which several human factors experiments focused on the automated highway system (AHS). Control transitions were necessary when changing lanes from the manual driving lane to the automated driving lane, and vice versa. These studies tried to answer where and how to transition control when entering and leaving the automated lane, and measured the effects on traffic flow efficiency and the driver's preferences. For example, Levitan, Golembiewski, and Bloomfield (1998) argued that a control transition from driving State 1 to driving State 5 should happen *before* entering the automated lane. Buck and Yenamcndra (1997) found that automation-initiated transitions are more time efficient than driver-initiated transitions while entering the automated lane in terms of traffic flow. Furthermore, De Vos, Hoekstra, and Hogema (1997) found that one-step transitions from driving State 5 to driving State 1 were more subjectively preferred than gradual transitions. Note that these studies were based on the anticipation of autonomous vehicles and separated lanes in an AHS. Details regarding driver behaviour during transitions, such as eye gaze patterns, workload, and responses to transitions, were not found to be greatly covered in the 1990s. Results of these early studies generally showed that driver acceptance and driving performance were better when the automation carried on more tasks (i.e., towards the higher side of our driving state scale).

4.2. Control transitions studies from around 2010

The second period started around 2010 with an increasing number of control transition studies. These more recent studies appear to be more practically relevant than much of the research from the 1990s, because the recent studies are based on already existing driver assistance systems (cf. 1990s research focusing on envisioned but non-existing AHSs; e.g., De Waard et al., 1999). In addition, these recent experiments focused on driver's behaviour and cognitive states, including such factors as reaction times, control actions, attention allocation, and workload. As we discussed in section 3.2.4, AIDC transitions that require the driver to get back into the control loop are crucial for safety. We selected experimental studies on AIDC transitions based on the following criteria.

First, studies had to describe the type of transition and the driving states before and after the transition in sufficient detail. If the experimental protocol required the driver to engage in a non-driving task that required constant visual attention of the driver (such as the Surrogate Reference Task, SuRT), or if the scenario did not offer any visual information prior to the transition (such as simulation screen blackout), with no reported control of the vehicle and monitoring of the road prior to the transition, we defined the driving state before the transition as State 5. If the participants were requested/reported to engage in an intermittent non-driving task (i.e., a task only took part of their visual attention) or no non-driving task was offered while automation longitudinally and laterally controlled the vehicle, we defined the driving state before the transition as State 4. We noticed that the non-driving task requirements prior to the transition were often reported ambiguously. We emphasize herein that a description of the automated driving technology alone cannot represent how the driver uses the technology. Information on how drivers were tasked and how drivers actually behaved is essential in order to be able to interpret the results from the experiments. The second inclusion criterion was that a description of the transition scenario had to be reported. The reason for this inclusion criterion is that the driving behaviour is highly related to the environmental conditions (e.g., Antonson, Mårdh, Wiklund, & Blomqvist, 2009; Kaiser, Wölfing, & Fuhrer, 1999). Third, the physical design and functionalities on the human machine interface (HMI) used for transitions had to be provided or illustrated. As Norman (1990) and many others have argued, feedback about automation status is an important determinant of how humans behave when interacting with automation. An appropriate HMI enables the human to recognize the automation's intentions and to perceive the automation's limitations. HMIs have been used extensively with the aim to improve driver performance and reduce human out-of-the-loop problems in automated systems (Inagaki, 2006; Kaber, Wright, & Sheik-Nainar, 2006).

Table 1 provides an overview of the retrieved studies on AIDC transitions. In several of the experiments, the HMI was an independent variable. Toffetti et al. (2009), for example, observed that adding vocal messages to a visual-auditory warning increased the drivers' general level of awareness and yielded shorter reaction times in some of the driving scenarios. Naujoks, Mai, and Neukum (2014) found that visual-auditory warnings decreased drivers' reaction times compared to a visual-only warning. Moreover, Lorenz et al. (2014) showed that displaying a heads-up safety corridor in addition to a displayed icon for the driver to steer towards after receiving a take-over request had a positive influence on driving performance compared to driving without the heads-up display. Not only visual, auditory (vocal or acoustic) warnings have been used to bring drivers back to driving State 3 or lower; tactile feedback has been applied as well. Telpaz et al. (2015) found that tactile feedback leads to a faster response time compared to control sessions without tactile feedback, and orients the drivers' attention to the relevant stimuli in the environment.

Table 1 shows that in the AIDC transition experiments, the HMI usually offered a visual-auditory warning. Van den Beukel and Van der Voort (2013) used an auditory warning only, and Merat et al. (2014) used a visual indication only. The use of auditory warnings as take-over requests may be suboptimal when considering that a number of driving studies (Adell, Várhelyi, & Hjälmdahl, 2008; Biondi, Rossi, Gastaldi, & Mulatti, 2014) have shown that beeps can have negative effects on driver performance and satisfaction.

In addition to the display aspects of the HMI, the physical input of the HMI is a relevant design parameter as well. As shown in Table 1, almost all experiments used the steering wheel and pedals to deactivate the automation. In some cases, a button or lever could also be used to deactivate the automation. Furthermore, Kerschbaum, Lorenz, and Bengler (2014) suggested that a coupled steering wheel without visible spokes could improve driving performance during transitions, while decoupled steering wheels (i.e., remaining stationary during automated driving) might not cause negative effects on the transition processes.

A number of experiments assessed driver behaviour after making a transition from driving State 5 to State 3 or lower (Gold, Damböck et al, 2013; Radlmayr et al., 2014; Van den Beukel & Van der Voort, 2013). Generally, it has been found that: 1) The shorter the lead time, the worse the take-over quality (expressed in terms of e.g., percentage of accidents, maximum lateral and/or longitudinal acceleration), and 2) The higher the traffic density, the more time drivers need to regain situation awareness and take over manual control.

Finally, the effects of the drivers' monitoring level (cf. *alpha* in Fig. 1) on performance after the transition have been studied in experiments where the driving state was State 4 before the transition, that is, in the cases that drivers' monitoring level *alpha* was between 1 and 0 (Dogan, Deborne, Delhomme, Kemeny, & Jonville, 2014; Merat et al., 2014; Zeeb et al., 2015). Dogan et al. (2014) compared driving performance in conditions where transitions could be and could not be anticipated. Merat et al. (2014) added additional systems in the experiment to make sure that the driver was temporarily monitoring and hence did not obtain a monitoring level *alpha* of 0. Specifically, drivers were required to take control when they were looking away from the road for more than 10 s or periodically after every 6 min of automated driving with ACC and LKA. Zeeb et al. (2015) classified drivers into low, medium, and high risk types based on their gaze allocation during automated driving, and their reaction to transitions were compared. In general, these studies concluded that drivers' anticipation of transitions and higher levels of monitoring are beneficial for safety, improving driving performance after the transition. An increase of the monitoring level *alpha*, which leads to improved driver situation awareness, could change a potential AIDC transition to a DIDC transition, and increase the safety on road. Similarly, Gold, Damböck et al. (2013) proposed a concept for improving transition quality by providing drivers with a monitoring request before the critical event became manifest (i.e., transition steps: State 4 → State 3 → State 1). More generally, research has shown that the adaptive allocation of tasks from automated systems to human operators has a positive effect on the detection of automation failures (e.g., Parasuraman, Mouloua, & Molloy, 1996).

5. Discussion

In this paper we described automated driving states (static states and dynamic states) based on the allocation of three primary driving tasks: longitudinal control, lateral control, and monitoring. A transition in automated driving was defined as the process of changing from one driving state to another.

Our concept of driving states differs from the BASt, SAE, and NHTSA levels of automated driving, because these levels of automation describe how the driver and automation *should* drive, whereas our proposed driving states describe what the driver and the automation are doing at a certain moment in terms of longitudinal control, lateral control, and monitoring. By setting the switches, our framework can be used to describe automation that engages temporarily (Fig. 1). Examples are automated lane changes, automated obstacle avoidance, and AEB. The framework also allows for shared control (dynamic driving states), which according to Mok et al. (2015) "is not classified directly under National Highway Traffic Safety Administration's current Levels of Automation Model" (p. 389). Another limitation of the BASt, SAE, and NHTSA levels is that they conflate expected/required behaviour with actual behaviour. For example, BASt defines highly automated driving as follows: "The system takes over longitudinal and lateral control; the driver is no longer *required* to permanently monitor the system. In case of a take-over request, the driver *must* take-over control with a certain time buffer" (Gasser & Westhoff, 2012; emphasis added). In this definition, which describes a properly functioning system that may be deployed on the roads, it is unclear how to classify a situation where the driver monitors the system but no take-over request is provided due to a technological malfunction or limitation (e.g., a failure to detect an object, resulting in a failure to provide a take-over request), or a situation where the automation produces a take-over request but the driver fails to take over control. An accident with present-day automated driving technology would represent a discrepancy between normative and actual behaviour. According to car manufacturers, drivers should permanently monitor the system and be prepared to take over control at any time, which would classify this as partially automated driving. In reality, however, a driver may not monitor as he should, and therefore is in State 4 as defined in Section 2.2. The BASt, SAE, and NHTSA definitions cannot describe such incidents and accidents. Finally, our approach offers a more fine-grained interpretation than the levels of automation. For example, technologies that offer only lateral automation or only longitudinal automation are classified at the same level of automation in the definitions provided by BASt, SAE, and NHTSA, even though driver's workload and situation awareness are known to be different with lateral automation than with longitudinal automation (Carsten et al., 2012; De Winter et al., 2014; Stanton & Young, 1998; Young & Stanton, 2007).

Note that a temporary interruption of control without changing the actual state is not considered as a transition in our framework. For example, when a driver changes various setpoints during ACC driving without actually turning off the ACC, this would not be regarded as a transition. Furthermore, an attempted but unsuccessful or uncompleted transition does not classify as a transition. In addition, we acknowledge that factors like distraction, fatigue, and drowsiness will lower the driver monitoring level in States 1 and 2. Such unsafe driving states were not explicitly listed in our proposed driving states. However, such states could in principle be added without altering the framework of Figure 1. For example, one may define a distracted driving state as follows: S_{dx} and S_{dy} are both switched on, S_{ax} and S_{ay} are both switched off, and *alpha* is smaller than 1.

In our framework, we made a distinction between monitoring transitions and control transitions. Monitoring transitions involve changes of the monitoring level of the driver, whereas control transitions involve changes of

allocation of control tasks. Three criteria were used to classify transitions of control: 'who initiates the transition?', 'who is in control after transition?' and 'mandatory or optional?'. Our analysis showed that there are six possible categories of transitions: DIDC mandatory, DIDC optional, DIAC mandatory, DIAC optional, AIDC mandatory, and AIAC mandatory. In addition, we defined DIDC and AIAC transitions as active transitions (self-activation), and DIAC and AIDC transitions as passive transitions (triggered interventions). Lack of preparation for the agent who is in control after passive transitions may lead to unsafe situations. The duration of a transition from initiation to completion, and whether mandatory transitions are time-critical or not, are other important factors that were not explicitly included in our binary classification tree. We acknowledge that time criticality can also be used to classify transitions. However, it is problematic to formally distinguish between time-critical (emergency) and non-time-critical (non-emergency) transitions by means of a clear-cut criterion, because what is considered critical depends on numerous factors such as the specific spatiotemporal relationships of the scenario, the driver's reactions, the road characteristics, visibility, etc.

AIDC transitions have been extensively studied in driving simulator experiments. However, we recommend to not ignore other types of transitions, even if they do not have an obvious relationship with safety. If automation cannot warn the driver about its failure or if the sensors do not detect a road hazard, then a DIDC mandatory transition is the only option to avoid a dangerous situation. Moreover, results from studies on optional DIDC and DIAC transitions in ACC systems may just as well be applicable to automated systems at SAE Levels 3, 4, and 5. A few studies on DIDC transitions have shown that the higher level of automation, the slower the drivers' reaction times (Dambock, Weissgerber, Kienle, & Bengler, 2013; Strand, Nilsson, Karlsson, & Nilsson, 2014), a finding that corresponds to decades of research in psychological vigilance and human-automation interaction (see Cabrall, Happee, & De Winter, 2016; Onnasch et al., 2014, for reviews). However, questions such as 'How long does it take for drivers to detect a failure of an automated driving system?' still remain to be answered (cf. Moray & Rotenberg, 1989).

DIAC and AIAC mandatory transitions may be due to the driver's lack of ability to control the vehicle. The former implies the driver's own awareness of his/her driving inabilities, and the automation needs then to be robust enough to take control when the driver relinquishes control. The latter may involve a driver state monitoring system that diagnoses the driver's abilities. However, the association between psychophysiological measurements and the cognitive state of drivers still needs to be better understood (Whitmore & Reed, 2015). Of course, AIAC transitions can also be implemented in critical-event scenarios irrespective of assessing driver state, such as is currently done in AEB.

Automotive displays have undergone various refinements in the last decades (Akamatsu, Green, & Bengler, 2013), but their design may need to change significantly in order to inform drivers about both the transitions and automation status. As discussed in Section 4.2, the signal for getting the driver into the driving State 3 or lower is typically a visual, vocal, acoustic, or tactile warning (or combinations of these). Because of the diverse designs, research questions, and lack of detailed information, questions like 'which method is more effective?' or 'what parameter should be set for the interface?' need to be further elaborated. It has been argued that take-over requests should be multimodal rather than unimodal, because different sensory modalities can complement each other (Petermeijer et al., 2016). For example, a vibrotactile warning in the driver's seat can be a useful alerting device when a person is visually distracted or engaging on a conversation, while auditory feedback is preferred to vibrotactile feedback when the driver is driving on an uneven road, wears thick clothing, or is not in permanent contact with the seat.

Previous research has investigated whether transition quality can be improved by means of applying intermediate states. For instance, systems that encourage monitoring before a transition (e.g., State 4 → State 3 → State 1) or which deactivate the longitudinal or lateral control tasks in sequence (State 5 → State 2 → State 1) have been designed (De Vos et al., 1997; Gold, Lorenz et al., 2013; Willemsen et al., 2014), but the evaluated systems were not found to significantly improve driving performance or comfort. Dynamic driving states (shared control)—defined as a situation where human and automation are carrying out tasks simultaneously—may facilitate smooth control transitions (Inagaki, 2003; Sheridan, 2011). Control systems need to be integrated with manual/biomechanical control models describing how driver steer, brake, and accelerate during transitions, in order to understand the pros and cons of discrete versus continuous transitions. Nilsson, Strand, Falcone, and Vinter (2013) found that when drivers encounter an automation failure, they were more likely to steer than to apply the brakes. Similarly, driving simulator research by Levitan et al. (1998) found that drivers preferred to take over control from automation by first steering and then using the accelerator, instead of vice versa. Thus, the development of HMIs and control algorithms for safely transferring control between automation and drivers is a major challenge for human factors researchers in automated driving.

A final consideration, which was not explicitly included in our framework, is that of adaptive automation. Previous research has demonstrated that adaptively allocating the control task between humans and automation can be beneficial for effective human-machine interaction (Hancock et al., 2013; Kaber & Endsley, 2004; Parasuraman et al., 1996). For this purpose, one may need to create a switching agent that allocates tasks to the driver and/or the automation (Sheridan, 2011) and that can determine whether transitions should happen. Recently, Baltzer et al. (2014) built a prototype of their Mode Selection and Arbitration Unit (MSAU), which distributed responsibility and control between the automation and the driver. The ideal design of the switching agent should not only consider the conditions of the environment and automation, but should also have knowledge of the states, habits, and experience level of the driver (e.g., Beggiato, Pereira, Petzoldt, & Krems, 2015; Whitmore & Reed, 2015). For example, as Larsson, Kircher, and Hultgren (2014) showed, when drivers get accustomed to ACC, they become more aware of the system's limitations and respond quicker to emergency situations. Klein (2008) argued that humans tend to execute actions they have experienced before, instead of acting optimally in time-limited tasks. This advocates for an automatic switching agent as opposed to a human one. Furthermore, through training and experience, drivers can learn to work around automation problems.

6. Conclusion

In summary, this paper defines the different driving states from a descriptive (i.e., not a normative) function allocation perspective taken at the level of a joint team of both driver and automation. In turn, transitions in automated driving are defined based on the proposed driving states. Our spectrum also clarifies and incorporates the concept of both control transitions and monitoring transitions. Moreover, we propose a classification tree that distinguishes six possible types of transitions, and we provide use cases for these transition types. By using the elements of initiation entity and the resultant control entity of actual transitions, and by distinguishing between active and passive transitions, we assessed the safety criticality of each of the transition type. All of the above aspects taken together should support automated driving research and development as well as problem/solution design space explorations that go beyond the classic 'take-over' (AIDC) scenario.

Case in point, we applied the proposed framework to review the literature on experimental research of transitions in automated driving, and accordingly to identify convergent and divergent results and gaps in the literature. We believe that our framework can contribute to a fruitful and productive dialogue among researchers on the topic of transitions in automated driving. This paper also reminds us that human factors engineering is crucial when introducing automation to a human-machine system (and see Bainbridge, 1983; Parasuraman & Riley, 1997; Sheridan & Parasuraman, 2005). Until the driving task is wholly automated under all possible circumstances and humans are prohibited from driving manually (e.g., because the automated car does not have a steering wheel anymore), transitions between the driver and the automation will remain a key element of automated driving.

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References

Abbink, D. A., Mulder, M., & Boer, E. R. (2012). Haptic shared control: smoothly shifting control authority? *Cognition, Technology & Work*, *14*, 19–28. doi:10.1007/s10111-011-0192-5

Adell, E., Várhelyi, A., & Hjälmdahl, M. (2008). Auditory and haptic systems for in-car speed management – A comparative real life study. *Transportation Research Part F: Traffic Psychology and Behaviour, 11*, 445–458. doi:10.1016/j.trf.2008.04.003

Antonson, H., Mårdh, S., Wiklund, M., & Blomqvist, G. (2009). Effect of surrounding landscape on driving behaviour: A driving simulator study. *Journal of Environmental Psychology, 29*, 493–502. doi:10.1016/j.jenvp.2009.03.005

Akamatsu, M., Green, P., & Bengler, K. (2013). Automotive technology and human factors research: Past, present, and future. *International Journal of Vehicular Technology*, *2013*, 1–27. doi:10.1155/2013/526180

Alkim, T. P., Bootsma, G., & Hoogendoorn, S. P. (2007). Field operational test "the assisted driver." *Proceedings of the 2007 IEEE Intelligent Vehicles Symposium* (pp. 1198–1203). Istanbul, Turkey. doi:10.1109/IVS.2007.4290281

Asimov, I. (1942). Runaround. *Astounding Science Fiction, 29*, 94–103.

Bainbridge, L. (1983). Ironies of automation. *Automatica*, *19*, 775–779. doi:10.1016/0005-1098(83)90046-8

Baltzer M., Altendorf, E., Meier S., & Flemisch, F. (2014). Mediating the interaction between human and automation during the arbitration processes in cooperative guidance and control of highly automated vehicles. *Proceedings of the 5th International Conference on Applied Human Factors and Ergonomics* (pp. 2107–2118). Kraków, Poland.

Beggiato, M., Pereira, M., Petzoldt, T., & Krems, J. (2015). Learning and development of trust, acceptance and the mental model of ACC. A longitudinal on-road study. *Transportation Research Part F: Traffic Psychology and Behaviour*, *35*, 75–84. doi:10.1016/j.trf.2015.10.005

Bianchi Piccinini, G. F., Prati, G., Pietrantoni, L., Manzini, C., Rodrigues, C. M., & Leitão, M. (2013). Drivers' hand positions on the steering wheel while using Adaptive Cruise Control (ACC) and driving without the system. In D. de Waard, K. Brookhuis, R. Wiczorek, F. di Nocera, R. Brouwer, P. Barham, C. Weikert, A. Kluge, W. Gerbino, & A. Toffetti (Eds.), *Proceedings of the Human Factors and Ergonomics Society Europe Chapter 2013 Annual Conference* (pp. 207–216).

Bibby, K. S., Margulies, F., Rijnsdorp, J. E., & Withers, R. M. (1975). Man's role in control systems. *Proceedings of the 6th IFAC Congress* (pp. 24–30). Boston/Cambridge, MA.

Biondi, F., Rossi, R., Gastaldi, M., & Mulatti, C. (2014). Beeping ADAS: Reflexive effect on drivers' behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, *25*, 27–33. doi:10.1016/j.trf.2014.04.020

Bonnefon, J. F., Shariff, A., & Rahwan, I. (2015). Autonomous vehicles need experimental ethics: are we ready for utilitarian cars? *arXiv preprint arXiv:1510.03346*.

Brookhuis, K. A., De Waard, D., & Janssen, W. H. (2001). Behavioural impacts of Advanced Driver Assistance Systems – an overview. *European Journal of Transport and Infrastructure Research*, *1*, 245–253.

Buck, J. R., & Yenamcndra, A. (1997). Ergonomic issues on entering the automated highway system. In Y. I. Noy (Ed.), *Ergonomics and safety of intelligent driver interfaces* (pp. 309–328). CRC Press.

Cabrall, C. D. D., Happee, R., & De Winter, J. C. F. (2016). From Mackworth's clock to the open road: A literature review on driver vigilance task operationalization. *Transportation Research Part F: Traffic Psychology and Behaviour, 40*, 273–290. doi:10.1016/j.trf.2016.04.001

Casner, S. M., Hutchins, E. L., & Norman, D. (2016). The challenges of partially automated driving. *Communications of the ACM, 59*, 70–77. doi:10.1145/2830565

Carsten, O., Lai, F. C. H., Barnard, Y., Jamson, A. H., & Merat, N. (2012). Control task substitution in semiautomated driving: Does it matter what sspects are automated? *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *54*, 747–761. doi:10.1177/0018720812460246

Dambock, D., Weissgerber, T., Kienle, M., & Bengler, K. (2013). Requirements for cooperative vehicle guidance. *Proceeding of the 2013 16th International IEEE Conference on Intelligent Transportation Systems* (pp. 1656–1661). The Hague, the Netherlands. doi:10.1109/ITSC.2013.6728467

De Vos, A. P., Hoekstra, W., & Hogema, J. H. (1997). Acceptance of automated vehicle guidance (AVG): System Reliability and exit manoeuvers. *Proceedings of the 4th World Congress on Intelligent Transportation Systems* (paper no. 2382), Berlin, Germany.

De Waard, D., Van der Hulst, M., Hoedemaeker, M., & Brookhuis, K. A. (1999). Driver behavior in an emergency situation in the automated highway system. *Transportation Human Factors*, *1*, 67–82. doi:10.1207/sthf0101_7

De Winter, J. C. F., & Dodou, D. (2011). Preparing drivers for dangerous situations: A critical reflection on continuous shared control. *Proceedings of the 2011 IEEE International Conference on Systems, Man, and Cybernetics* (pp. 1050–1056). Anchorage, AK. doi:10.1109/ICSMC.2011.6083813

De Winter, J. C. F., Happee, R., Martens, M. H., & Stanton, N. A. (2014). Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence. *Transportation Research Part F: Traffic Psychology and Behaviour*, *27*, 196–217. doi:10.1016/j.trf.2014.06.016

De Winter, J. C. F., & Hancock, P. A. (2015). Reflections on the 1951 Fitts list: Do humans believe now that machines surpass them? *Proceedings of the 6th International Conference on Applied Human Factors and Ergonomics (AHFE), Las Vegas, NV*, 5334–5341. doi:j.promfg.2015.07.641

Dingus, T. A., Klauer, S. G., Neale, V. L., Petersen, A., Lee, S. E., Sudweeks, J. D., et al. (2006). *The 100-car naturalistic driving study, Phase II-Results of the 100-car field experiment* (Report No. HS-810 593). Washington, DC: National Highway Traffic Safety Administration.

Dingus, T. A., Guo, F., Lee, S., Antin, J. F., Perez, M., Buchanan-King, M., & Hankey, J. (2016). Driver crash risk factors and prevalence evaluation using naturalistic driving data. *Proceedings of the National Academy of Sciences, 113*, 2636–2641. doi:10.1073/pnas.1513271113

Dogan, E., Deborne, R., Delhomme, P., Kemeny, A., & Jonville, P. (2014). Evaluating the shift of control between driver and vehicle at high automation at low speed : The role of anticipation. *Proceedings of the Transport Research Arena (TRA) 5th Conference: Transport Solutions from Research to Deployment*. Paris, France.

Endsley, M. R., & Kiris, E. O. (1995). The out-of-the-loop performance problem and level of control in automation. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *37*, 381–394. doi:10.1518/001872095779064555

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors, 37*, 32–64. doi:10.1518/001872095779049543

Fitts, P. M. (ed.) (1951). *Human engineering for an effective air navigation and traffic control system*. Washington, DC: National Research Council.

Flemisch, F. O., Adams, C. A., Conway, S. R., Goodrich, K. H., Palmer, M. T., & Schutte, P. C. (2003). The H-Metaphor as a guideline for vehicle automation and interaction (Report No. NASA/ TM—2003-212672). Hampton, VA: National Aeronautics and Space Administration.

Flemisch, F., Heesen, M., Hesse, T., Kelsch, J., Schieben, A., & Beller, J. (2012). Towards a dynamic balance between humans and automation : authority , ability , responsibility and control in shared and cooperative control situations. *Cognition, Technology & Work*, *14*, 3–18. doi:10.1007/s10111-011-0191-6

Flemisch, F., Kelsch, J., Löper, C., Schieben, A., & Schindler, J. (2008). Automation spectrum , inner / outer compatibility and other potentially useful human factors concepts for assistance and automation. In D. de Waard, F. O. Flemisch, B. Lorenz, H. Oberheid, & K. A. Brookhuis (Eds.), *Human factors for assistance and automation* (pp. 1–16). Maastricht, the Netherlands: Shaker Publishing.

Flemisch, F., Altendorf, E., Baltzer, M., Lopez, D., Canpolat, Y., & Wessel, G. (2016). Cooperative guidance and control: From the transport of the past to the transport of the future. Retrieved from http://www.slideshare.net/TransportTUD/transport-thursday-2104-by-frank-flemisch-on-automated-driving

Flemisch, F., Bengler, K., Bubb, H., Winner, H., & Bruder, R. (2014). Towards cooperative guidance and control of highly automated vehicles: H-Mode and Conduct-by-Wire. *Ergonomics, 57*, 343–360. doi:10.1080/00140139.2013.869355

Gasser, T. & Westhoff, D. (2012). BASt-study: Definitions of automation and legal issues in Germany. *TRB Road Vehicle Automation Workshop*. Irvine, CA, USA. Retrieved from http://onlinepubs.trb.org/onlinepubs/conferences/2012/Automation/presentations/Gasser.pdf.

Gold, C., Lorenz, L., Damböck, D., & Bengler, K. (2013). Partially automated driving as a fallback level of high automation. 6. *Tagung Fahrerassistenzsysteme. Der Weg zum automatischen Fahren*. TÜV SÜD Akademie GmbH. Retrieved from https://mediatum.ub.tum.de/doc/1187198/1187198.pdf

Gold, C., Damböck, D., Lorenz, L., & Bengler, K. (2013). "Take over!" How long does it take to get the driver back into the loop? *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 57*, 1938–1942. doi:10.1177/1541931213571433

Gonçalves, J., & Bengler, K. (2015). Driver state monitoring systems–Transferable knowledge manual driving to HAD. *Proceedings of the 6th International Conference on Applied Human Factors and Ergonomics* (pp. 3011-3016). Las Vegas, NV. doi:10.1016/j.promfg.2015.07.845

Goodall, N. J. (2014). Vehicle automation and the duty to act. *Proceedings of the 21st World Congress on Intelligent Transport Systems*. Detroit, MI.

Hancock, P. A. (2007). On the process of automation transition in multitask human-machine systems. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *37*, 586–598. doi:10.1109/TSMCA.2007.897610

Hancock, P. A. (2014). Automation: how much is too much? *Ergonomics*, *57*, 449–454. doi:10.1080/00140139.2013.816375

Hancock, P. A. (2015). Automobility: the coming use of fully-automated on-road vehicles. *Proceedings of the 2015 IEEE International Inter-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)* (pp. 137–139). Orlando, FL.. doi:10.1109/COGSIMA.2015.7108188

Hancock, P. A., Jagacinski, R. J., Parasuraman, R., Wickens, C. D., Wilson, G. F., & Kaber, D. B. (2013). Human-automation interaction research: Past, present, and future. *Ergonomics in Design: The Quarterly of Human Factors Applications*, *21*, 9–14. doi:10.1177/1064804613477099

Hoedemaeker, M., & Brookhuis, K. A. (1998). Behavioural adaptation to driving with an adaptive cruise control (ACC). *Transportation Research Part F: Traffic Psychology and Behaviour*, *1*, 95–106. doi:10.1016/S1369-8478(98)00008-4

Hoeger, R., Zeng, H., Hoess, A., Kranz, T., Boverie, S., Strauss, M., et al. (2011). *The future of driving – HAVEit* (Final Report, Deliverable D61.1). Regensburg, Germany: Continental Automotive GmbH.

Hollnagel, E. (2012). Coping with complexity: past, present and future. *Cognition, Technology & Work*, *14*, 199–205. doi:10.1007/s10111-011-0202-7

Hsu, A., Eskafi, F., Sachs, S., & Varaiya, P. (1993). Protocol design for an automated highway system. *Discrete Event Dynamic Systems*, *2*, 183–206. doi:10.1007/BF01797158

Inagaki, T. (2003). Adaptive automation : Sharing and trading of control. In E. Hollnagel (Ed.), *Handbook of Cognitive Task Design* (pp. 147–169). Mahwah, NJ: Erlbaum.

Inagaki, T. (2006). Design of human–machine interactions in light of domain-dependence of human-centered automation. *Cognition, Technology & Work*, *8*, 161–167. doi:10.1007/s10111-006-0034-z

Inagaki, T., & Sheridan, T. B. (2012). Authority and responsibility in human–machine systems: probability theoretic validation of machine-initiated trading of authority. *Cognition, Technology & Work*, *14*, 29–37. doi:10.1007/s10111-011-0193-4

Jamson, A. H., Merat, N., Carsten, O. M. J., & Lai, F. C. H. (2013). Behavioural changes in drivers experiencing highly-automated vehicle control in varying traffic conditions. *Transportation Research Part C: Emerging Technologies*, *30*, 116–125. doi:10.1016/j.trc.2013.02.008

Johns, M., Mok, B., Sirkin, D. M., Gowda, N. M., Smith, C. A., Talamonti, W. J., Jr., & Ju, W. (2016). Exploring shared control in automated driving. *Proceedings of the 11th ACM/IEEE International Conference on Human-Robot Interaction* (pp. 91–98). New Zealand.

Kaber, D. B., & Endsley, M. R. (1997). Out-of-the-loop performance problems and the use of intermediate levels of automation for improved control system functioning and safety. *Process Safety Progress*, *16*, 126–131. doi:10.1002/prs.680160304

Kaber, D. B., & Endsley, M. R. (2004). The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task. *Theoretical Issues in Ergonomics Science*, *5*, 113–153. doi:10.1080/1463922021000054335

Kaber, D. B., Wright, M. C., & Sheik-Nainar, M. A. (2006). Investigation of multi-modal interface features for adaptive automation of a human–robot system. *International Journal of Human-Computer Studies*, *64*, 527–540. doi:10.1016/j.ijhcs.2005.11.003

Kaiser, F. G., Wölfing, S., & Fuhrer, U. (1999). Environmental attitude and ecological behaviour. *Journal of Environmental Psychology, 19*, 1–19. doi:10.1006/jevp.1998.0107

Kerschbaum, P., Lorenz, L., & Bengler, K. (2014). Highly automated driving with a decoupled steering wheel. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 58*, 1686–1690. doi:10.1177/1541931214581352

Klein, G. (2008). Naturalistic decision making. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *50*, 456–460. doi:10.1518/001872008X288385

Klunder, G., Li, M., & Minderhoud, M. (2009). Traffic flow impacts of adaptive cruise control deactivation and (re)activation with cooperative driver behavior. *Transportation Research Record: Journal of the Transportation Research Board*, *2129*, 145–151. doi:10.3141/2129-17

Kuehn, M., Hummel, T., & Bende, J. (2009). Benefit estimation of Advanced Driver Assistance Systems for cars derived from real-life accidents. *Proceedings of the 21st International Technical Conference of th Enhanced Safety of Vehicles Conference (EVS)*. Stuttgart, Germany.

Kyriakidis, M., Happee, R., & De Winter, J. C. F. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F: Traffic Psychology and Behaviour*, *32*, 127–140. doi:10.1016/j.trf.2015.04.014

Kyriakidis, M., De Winter, J. C. F., Stanton, N., Bellet, T., Van Arem, B, Brookhuis, K., Martens, M. H., Bengler, K., Andersson, J., Merat, N., Reed, N., Flament, M., Hagenzieker, M., & Happee R. (2016). *A human factors perspective on automated driving*. Manuscript submitted for publication.

Larsson, A. F. L., Kircher, K., & Hultgren, J. A. (2014). Learning from experience: Familiarity with ACC and responding to a cut-in situation in automated driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, *27*, 229–237. doi:10.1016/j.trf.2014.05.008

Levitan, L., Golembiewski, G., & Bloomfield, J. R. (1998). Human factors issues for automated highway systems. *ITS Journal - Intelligent Transportation Systems Journal*, *4*, 21–47. doi:10.1080/10248079808903735

Lorenz, L., Kerschbaum, P., & Schumann, J. (2014). Designing take over scenarios for automated driving: How does augmented reality support the driver to get back into the loop? *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *58*, 1681–1685. doi:10.1177/1541931214581351

Lu, Z., & De Winter, J. C. F. (2015). A review and framework of control authority transitions in automated driving. *Proceedings of the 6th International Conference on Applied Human Factors and Ergonomics* (pp. 2510–2517). Las Vegas, NV. doi:10.1016/j.promfg.2015.07.513

MacCallum, R. C. (2003). 2001 Presidential address: Working with imperfect models. *Multivariate Behavioral Research, 38*, 113–139. doi:10.1207/S15327906MBR3801_5

Mackworth, N. H. (1950). *Researches on the measurement of human performance. Medical Research Council Special Report Series*. Medical Research Council Special Report Series 268.

Martens, M., Pauwelussen, J., Schieben, A., Flemisch, F., Merat, N., Jamson, S., & Caci, R. (2008). *Human Factors' aspects in automated and semi- automatic transport systems: State of the art*. Retrieved from http://www.citymobil-project.eu/downloadables/Deliverables/D3.2.1-PU-Human%20Factors%20aspects-CityMobil.pdf

McKnight, A. J., & Adams, B. B. (1970). Driver education task analysis. Vol I: Task descriptions (Report

HumRRO Technical Report 70-103). Alexandria, VA: Human Resources Research Organization.

Merat, N., Jamson, A. H., Lai, F. F. C. H., Daly, M., & Carsten, O. M. J. (2014). Transition to manual: Driver behaviour when resuming control from a highly automated vehicle. *Transportation Research Part F: Traffic Psychology and Behaviour*, *26*, 1–9. doi:10.1016/j.trf.2014.05.006

Merat, N., & Lee, J. D. (2012). Preface to the special section on human factors and automation in vehicles: designing highly automated vehicles with the driver in mind. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *54*, 681–686. doi:10.1177/0018720812461374

Michon, J. A. (1985). A critical view of driver behavior models: What do we know, what should we do? In L. Evans & R. C. Schwing (Eds.), *Human behavior and traffic safety* (pp. 485–520). New York: Plenum.

Miller, D., Sun, A., & Ju, W. (2014). Situation awareness with different levels of automation. *Proceedings IEEE International Conference on Systems, Man and Cybernetics* (pp. 688–693). San Diego, CA. doi:10.1109/SMC.2014.6973989

Mok, B., Johns, M., Lee, K. J., Miller, D., Sirkin, D., Ive, P., & Ju, W. (2015). Emergency, automation off: Unstructured transition timing for distracted drivers of automated vehicles. *Proceedings of the 2015 IEEE 18th International Conference on Intelligent Transportation Systems*. doi:10.1109/ITSC.2015.396

Moray, N., & Rotenberg, I. (1989). Fault management in process control: eye movements and action. *Ergonomics, 32*, 1319–1342. doi:10.1080/00140138908966910

Murphy, R., & Woods, D. D. (2009). Beyond Asimov: The three laws of responsible robotics. *IEEE Intelligent Systems, 24*, 14–20. doi:10.1109/MIS.2009.69

Nash, C. J., Cole, D. J., & Bigler, R. S. (2016). A review of human sensory dynamics for application to models of driver steering and speed control. *Biological Cybernetics, 110*, 91–116. doi:10.1007/s00422-016-0682-x

Naujoks, F., Mai, C., & Neukum, A. (2014). The effect of urgency of take-over requests during highly automated driving under distraction conditions. *Proceedings of the 5th International Conference on Applied Human Factors and Ergonomics* (pp. 2099–2106). Kraków, Poland.

Naujoks, F., Purucker, C., Neukum, A., Wolter, S., & Steiger, R. (2015). Controllability of Partially Automated Driving functions–Does it matter whether drivers are allowed to take their hands off the steering wheel? *Transportation Research Part F: Traffic Psychology and Behaviour*, *35*, 185–198. doi:10.1016/j.trf.2015.10.022

NHTSA (2013). *Preliminary statement of policy concerning automated vehicles.* United States National Highway Traffic Safety Administration (NHTSA). Retrieved from http://www.nhtsa.gov/staticfiles/rulemaking/pdf/Automated_Vehicles_Policy.pdf

Nilsson, J., Falcone, P., & Vinter, J. (2015). Safe transitions from automated to manual driving using driver controllability estimation. *IEEE Transactions on Intelligent Transportation Systems*, *16*, 1806–1816. doi:10.1109/TITS.2014.2376877

Nilsson, J., Strand, N., Falcone, P., & Vinter, J. (2013). Driver performance in the presence of adaptive cruise control related failures: Implications for safety analysis and fault tolerance. *Proceedings of 2013 43rd Annual IEEE/IFIP Conference on the Dependable Systems and Networks Workshop* (pp. 1–10). Budapest, Hungary. doi:10.1109/DSNW.2013.6615531

Norman, D. A. (1990). The 'problem' with automation: inappropriate feedback and interaction, not 'over-automation'. *Philosophical Transactions of the Royal Society B: Biological Sciences, 327*, 585–593.

Norman, D. A. (2015). The human side of automation. In G. Meyer & S. Beiker (Eds.), *Road vehicle automation 2* (pp. 73–79). Switzerland: Springer International Publishing. doi:10.1007/978-3-319-19078-5_7

Onnasch, L., Wickens, C. D., Li, H., & Manzey, D. (2014). Human performance consequences of stages and levels of automation: An integrated meta-analysis. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *56*, 476–488. doi:10.1177/0018720813501549

Parasuraman, R., Mouloua, M., & Molloy, R. (1996). Effects of adaptive task allocation on monitoring of automated systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *38*, 665–679. doi:10.1518/001872096778827279

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *39*, 230–253. doi:10.1518/001872097778543886

Pauwelussen, J., & Feenstra, P. J. (2010). Driver behavior analysis during ACC activation and deactivation in a real traffic environment. *IEEE Transactions on Intelligent Transportation Systems, 11*, 329–338. doi:10.1109/TITS.2010.2043099

Petermeijer, S. M., Abbink, D. A., Mulder, M., & De Winter, J. C. F. (2015). The effect of haptic support systems on driver performance: A literature survey. *IEEE Transactions on Haptics, 8*, 467–479. doi:10.1109/TOH.2015.2437871

Petermeijer, S., De Winter, J. C. F., & Bengler, K. (2016). Vibrotactile displays: A survey with a view on highly automated driving, 17, 897–907. *Transactions on Intelligent Transportation Systems*. doi:10.1109/TITS.2015.2494873

Radlmayr, J., Gold, C., Lorenz, L., Farid, M., & Bengler, K. (2014). How traffic situations and non-driving

related tasks affect the take-over quality in highly automated driving. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 58*, 2063–2067. doi:10.1177/1541931214581434

Rajamani, R., Tan, H. S., Law, B. K., & Zhang, W. B. (2000). Demonstration of integrated longitudinal and lateral control for the operation of automated vehicles in platoons. *IEEE Transactions on Control Systems Technology, 8*, 695–708. doi:10.1109/87.852914

Rauch, N., Kaussner, A., Krüger, H. P., Boverie, S., & Flemisch, F. (2009). The importance of driver state assessment within highly automated vehicles. *Proceedings of the 16th World Congress on ITS.* Stockholm, Sweden. Retrieved from http://haveit-eu.org/LH2Uploads/ItemsContent/25/3117-FULL-PAPER-THE-IMPORTANCE.pdf

Reason, J. (2013). *A life in error: from little slips to big disasters*. Surrey: Ashgate Publishing.

SAE (2014). Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems (Standard No. J3016). SAE International. Retrieved from: http://standards.sae.org/j3016_201401/

Sarter, N. B., & Woods, D. D. (1995). How in the world did we ever get into that mode? Mode error and awareness in supervisory control. *Human Factors, 37*, 5–19. doi:10.1518/001872095779049516

Scerbo, M. W. (1996). Theoretical perspectives on adaptive automation. In R. Parasuraman & M. Mouloua (Eds.), *Automation and human performance: Theory and applications. Human factors in transportation.* (pp. 37–63). Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Schermers, G., Malone, K. M., & Van Arem, B. (2004). Dutch Evaluation of Chauffeur Assistant (DECA): Traffic flow effects of implementation in the heavy goods vehicles sector. *Proceedings of the ITS World Congress.* Nagoya, Aichi.

Seppelt, B. D., & Victor, T. W. (2016). Potential solutions to human factors challenges in road vehicle automation. In G. Meyer & S. Beiker (Eds.), *Road vehicle automation 3* (pp. 131–148). Switzerland: Springer International Publishing. doi:10.1007/978-3-319-40503-2_11

Sharit, J. (2006). Human error. In G. Salvendy (Ed.), *Handbook of human factors and ergonomics*, 3rd Ed. (pp. 708–764). New York, NY: John Wiley & Sons.

Sheridan, T. B. (1970). Big brother as driver: New demands and problems for the man at the wheel. *Human Factors*, *12*, 95–101. doi:10.1177/001872087001200114

Sheridan, T. B. (1980). Computer control and human alienation. *Technology Review, 83*, 61–73.

Sheridan, T. B. (2002). *Humans and automation: System design and research issues*. New York, NY: John Wiley & Sons, Inc.

Sheridan, T. B. (2011). Adaptive automation, level of automation, allocation authority, supervisory control, and adaptive control: distinctions and modes of adaptation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *41*, 662–667. doi:10.1109/TSMCA.2010.2093888

Sheridan, T. B., & Parasuraman, R. (2005). Human-automation interaction. *Reviews of Human Factors and Ergonomics*, *1*, 89–129. doi:10.1518/155723405783703082

Sheridan, T. B., & Verplank, W. L. (1978). *Human and computer control of undersea teleoperators*. Man-Machine Systems Lab Department of Mechanical Engineering MIT. Retrieved from http://www.dtic.mil/dtic/tr/fulltext/u2/a057655.pdf

Stanton, N. A., & Young, M. S. (1998). Vehicle automation and driving performance. *Ergonomics*, *41*, 1014–1028. doi:10.1080/001401398186568

Storie, V. J. (1977). *Male and female car drivers: differences observed in accidents* (TRRL Research Report No. 761). Crowthome: Transport Research Laboratory.

Strand, N., Nilsson, J., Karlsson, I. C. M., & Nilsson, L. (2014). Semi-automated versus highly automated driving in critical situations caused by automation failures. *Transportation Research Part F: Traffic Psychology and Behaviour*, *27*, 218–228. doi:10.1016/j.trf.2014.04.005

Telpaz, A., Rhindress, B., Zelman, I., & Tsimhoni, O. (2015). Haptic seat for automated driving: preparing the driver to take control effectively. *Proceedings of the 7th International Conference on Automotive User Interfaces and Interactive Vehicular Applications - AutomotiveUI '15* (pp. 23–30). Nottingham, UK. doi:10.1145/2799250.2799267

Toffetti, A., Wilschut, E., Martens, M., Schieben, A., Rambaldini, A., Merat, N., & Flemisch, F. (2009). CityMobil: Human Factor Issues Regarding Highly-automated Vehicles on an eLane. *Transportation Research Record: Journal of the Transportation Research Board*, *2110*. doi:10.3141/2110-01

Treat, J. R., Tumbas, N. S., McDonald, S. T., Shinar, D., Hume, R. D., Mayer, R. E., et al. (1979). *Tri-level study of the causes of traffic accidents: Executive summary* (Report No. DOTHS034353579TAC(5)). Washington, DC: National Highway Traffic Safety Administration.

Van Arem, B., Tampere, C. M. J., & Malone, K. M. (2003). Modelling traffic flows with intelligent cars and intelligent roads. *Proceedings of the IEEE Intelligent Vehicles Symposium* (pp. 456–461). Columbus, OH. doi:10.1109/IVS.2003.1212954

Van den Beukel, A. P., & Van der Voort, M. C. (2013). The influence of time-criticality on situation awareness when retrieving human control after automated driving. *Proceedings of the 16th International IEEE*

Conference on Intelligent Transportation Systems (pp. 2000–2005). The Hague, the Netherlands. doi:10.1109/ITSC.2013.6728523

Varotto, S. F., Hoogendoorn, R. G., Van Arem, B, & Hoogendoorn, S. P. (2015). Empirical longitudinal driving behaviour in case of authority transitions between adaptive cruise control and manual driving. *Transportation Research Record: Journal of the Transportation Research Board*, *2489*, 105–114.

Vlakveld, W. (2015). *Transition of control in highly automated vehicles. A literature review* (Report No. R-2015-22). SWOV Institute for Road Safety Research.

Viti, F., Hoogendoorn, S. P., Alkim, T. P., & Bootsma, G. (2008). Driving behavior interaction with ACC: results from a Field Operational Test in the Netherlands. *Proceedings of the 2008 IEEE Intelligent Vehicles* (pp. 745–750). Eindhoven, the Netherlands. doi:10.1109/IVS.2008.4621199

Willemsen, D., Stuiver, A., Hogema, J., Kroon, L., & Sukumar, P. (2014). Towards guidelines for transition of control. *FISITA World Automotive Congress 2014* (F2014-ACD-009). Maastricht, the Netherlands.

Whitmore, A., & Reed, N. (2015). The role of physiological monitoring in the implementation of vehicle automation. *Engineering & Technology Reference*, 1–9. doi:10.1049/etr.2014.0057

Young, M. S., & Stanton, N. A. (2007). What's skill got to do with it? Vehicle automation and driver mental workload. *Ergonomics*, *50*, 1324–1339. doi:10.1080/00140130701318855

Young, M. S., & Stanton, N. A. (2002). Malleable attentional resources theory: a new explanation for the effects of mental underload on performance. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *44*, 365–375. doi:10.1518/0018720024497709

Zeeb, K., Buchner, A., & Schrauf, M. (2015). What determines the take-over time? An integrated model approach of driver take-over after automated driving. *Accident Analysis & Prevention*, *78*, 212–221. doi:10.1016/j.aap.2015.02.023

Table 1

Retrieved experimental studies on AIDC transitions.

Paper	Traffic scenario	Driving state		HMI						
		Before transition	After transition	Informing interface				Deactivation interface		
				Visual	Vocal	Acoustic	Tactile	Button/ Lever	Steering wheel	Pedals
Toffetti et al., 2009	The drivers needed to take control from automation (automated driving was realized using the Wizard of Oz technique) when the car exited the automated driving lane, automation failed, or infrastructure was out of order.	State 4	State 1	*	*	*		*	*	*
				*		*				
Gold, Damböck, Lorenz, & Bengler, 2013	The drivers needed to take control to avoid a car accident in two time-to-collision conditions (5 s, 7 s).	State 5	State 1	*		*		*	*	*
Van den Beukel & Van der Voort, 2013	The drivers needed to take control due to an emergency brake of the leading car in three time-to-collision conditions (1.5 s, 2.2 s, 2.8 s).	State 5	State 1			*			*	*
Dogan et al., 2014	The drivers needed to take control from a Traffic Jam Assist system under two conditions: when traffic jam resolved and the speed exceeded 50km/h (anticipated situation) and when drivers were still in a dense traffic jam (unanticipated situation).	State 4	State 1	*		*		*	*	*
Kerschbaum et al., 2014	Drivers were requested to take over approximately 150 m before the construction site, and followed the yellowed guide lines by using a decoupled steering wheel or a coupled steering wheel with hidden spokes.	State 5	State 1	*		*		*	Decoupled	*
									Spoke hidden	
Lorenz et al., 2014	The drivers needed to take control to avoid the sudden car accident in 7 s time-to-collision conditions with heads-up information of safe corridor or accident area in addition to a display icon.	State 5	State 1	Safe corridor		*			*	*
				Accident area		*				
Merat et al., 2014	The automation was disengaged based on time or drivers' gaze allocation to keep drivers visual attention on the road. Near the end of the drive, drivers were required to resume control due to a three lane highway reducing to one lane situation.	State 4	State 1	*					*	*,
Naujoks et al., 2014	The drivers needed to take control under three traffic conditions: missing lane markings (easy), temporary lane changing (moderate), and high curvature lane (difficult), which automation could not control.	State 4	State 1	*				*	*	
				*		*				
Radlmayr et al., 2014	The drivers needed to take control under four different traffic conditions in terms of density and driving lane that automation could not control with two different non-driving tasks.	State 5	State 1	*		*			*	*

Telpaz et al., 2015	Five scenarios with different road types (5 or 2 lane freeway), driving lane, and transition events (static object or slow moving cars) were designed where drivers needed to take back control, to test spatial vibration strategy from haptic seat.	State 5	State 1	*		*	*		*	*
				*		*				
Zeeb et al., 2015	The drivers needed to take control due to a broken car in front in three time-to-collision conditions (4.9 s, 5.7 s, 6.6 s) with automated deceleration.	State 4	State 1	*		*		*	*	*

Note:1) "*" means this kind of interface was used during the experiment. 2) Control conditions are not included.