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Assessment selection in human-automation interaction studies: The Failure-GAM^{2}E and review of assessment methods for highly automated driving

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ABSTRACT

Highly automated driving will change driver's behavioural patterns. Traditional methods used for assessing manual driving will only be applicable for the parts of human-automation interaction where the driver intervenes such as in hand-over and take-over situations. Therefore, driver behaviour assessment will need to adapt to the new driving scenarios. This paper aims at simplifying the process of selecting appropriate assessment methods. Thirty-five papers were reviewed to examine potential and relevant methods. The review showed that many studies still relies on traditional driving assessment methods. A new method, the Failure-GAM^{2}E model, with purpose to aid assessment selection when planning a study, is proposed and exemplified in the paper. Failure-GAM^{2}E includes a systematic step-by-step procedure defining the situation, failures (Failure), goals (G), actions (A), subjective methods (M), objective methods (M) and equipment (E). The use of Failure-GAM^{2}E in a study example resulted in a well-reasoned assessment plan, a new way of measuring trust through feet movements and a proposed Optimal Risk Management Model. Failure-GAM^{2}E and the Optimal Risk Management Model are believed to support the planning process for research studies in the field of human-automation interaction.

1. Introduction

Technology is constantly evolving, and there have been several occasions throughout history when advances have changed human behaviour dramatically. Over recent years we have seen the start of such a change through the development of highly automated vehicles. The role of the driver is certain to change once the task of driving can be handed over to the vehicle itself. This previously futuristic idea has become a real possibility (Akamatsu et al., 2013; Richards and Stedmon, 2016). Two motives for the development of more advanced automation in vehicles have been improving the driver's well-being and enhancing road safety (Stanton and Marsden, 1996). Automation was believed to significantly reduce human-related errors which are known to be the root cause of many accidents. Hence, one purpose of highly automated driving was, in fact, to change the role of the driver and the driver's behavioural patterns. Although automation is believed to reduce accidents, this effect needs to be verified and possible side-effects need to be identified. As Bainbridge (1983) pointed out early on, the introduction of automation might introduce additional problems that are difficult to imagine beforehand. The main question is probably not *if* there will be new types of errors but rather *what* types of errors there will be. One challenge lies in making the right error predictions. Another challenge lies in selecting relevant assessment methods that cover the predicted behavioural patterns. Technological development makes it easier and more possible to assess behaviours and reactions that previously were too complicated or too expensive to measure. However, these possibilities do not only aid the planning of studies but also makes it more complex. This paper addresses the process of selecting relevant assessment methods in general and for automated driving in particular. Much can be gained by using a well-designed study with carefully selected and well-motivated assessment methods, especially when exploring new research fields. It is believed that this paper will benefit researchers and vehicle developers exploring new research fields such as highly automated driving.

In this paper, automation at a level above driver assistance is considered. The vehicle is able to drive by itself but the driver is obliged to maintain situation awareness and should be prepared and, if necessary, be able to take over driving at all times. The automation level would be above 7 (executes automatically, then

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necessarily informs the human) according to the Level of Automation (LoA) proposed by Sheridan et al. (1978), and between 2 and 3 according to the classification proposed by the National Highway Traffic Safety Administration (NHTSA; Richards and Stedmon, 2016). According to the taxonomy proposed by Endsley (1999) the term would be Supervisory Control (SC), one step below Full Automation (FA); the difference between the two is the human's opportunity to intervene. In this paper, the term highly automated driving will be used. The term autonomous will not be used since the driver should be able to take over control (Stensson and Jansson, 2013).

The enhanced safety inherent in fully automated vehicles may, to some extent, depend on how well the driver adopts to the new driver role (Merat and Lee, 2012; Milakis et al., 2017). The introduction of driving assistance functions in vehicles, such as adaptive cruise control, changed the role of the driver slightly in the direction of a more passive and relaxed behaviour, with reduced mental workload as result (Stanton and Young, 1998). At higher levels of automation, the driver-vehicle interaction and control of the vehicle will differ dramatically from traditional driving, while the responsibility of the driver to maintain attention on the road will remain more or less the same (Richards and Stedmon, 2016). Even though automation is introduced in order to replace human manual control, planning, and problem solving, humans will still be needed for supervision and to make adjustments (Brookhuis et al., 2001). The driver will need to detect, understand and correct errors should automation fail (McBridge et al., 2014). Human error includes all planned actions, both mental and physical, that fail to achieve the intended consequences (Reason, 1990; Reason et al., 1990). The transition from manual tasks towards more automation and supervision challenge the concept of human error (Rasmussen, 1990). Rasmussen (1990) found that the chain of actions was better defined, and the cause of errors was easier to identify in manual work tasks than in more complex work tasks involving supervision of an automation process. As Banks et al. (2014) describes the situation, driving will become more of a mind-task than a manual task, and the mental workload might even increase, rather than decrease, due to a more complex monitoring responsibility. A temporarily high workload may also result as an effect of a sudden need to take over driving (de Winter et al., 2016). It is also feared drivers will have problems in maintaining their attention on the road and instead will engage in secondary tasks (Banks and Stanton, 2016). It is anticipated that lack in engagement or situation awareness will affect the ability to assume control if/when needed. Also, at lower levels of automation, when driving with adaptive cruise control, problems in resuming control of the vehicle have been found (Larsson et al., 2014; Stanton and Young, 1998). Also, as could be expected, the ability to regain control in the event of automation failure was found to decrease with increased level of automation (Strand et al., 2014). A lack of situation awareness, or out-of-the-loop performance, was described by Endsley (2015) as one of the most significant human error challenges in the automation domain. Another related issue is trust, which could match automation capabilities but which could also turn into distrust or over-trust (Lee and See, 2004).

At the time of writing this paper, a high level of automation in cars was an uncommon and fairly new concept on actual roads. The number of accidents were naturally also few. Tesla Motors was probably the first company to provide production vehicles with a self-driving mode. According to an ODI Resume (NHTSA, 2017) from the National Highway Traffic Safety Administration in U.S., the population of highly automated Tesla Model S vehicles was estimated to be 43,781. The ODI report considered the first fatal accident during fully automated driving. Automation failed and the Tesla vehicle drove into the side of a truck without braking. According to the report, the driver was obliged to maintain full attention on the road and be prepared to take over driving at any time. However, “the driver took no braking, steering or other actions to avoid the collision” and appeared to have been distracted for more than 7 s prior to the accident, according to the conclusions made in the ODI Report (NHTSA, 2017). This accident highlights the importance of designing systems with human capabilities in mind. In order to avoid similar accidents, the relationship between the human and the highly automated vehicle and human ability to cope with the new driving role needs to be even better understood and, hence, be studied.

The most common measures in traditional driving safety studies include: vehicle speed, vehicle position in relation to road markings, distance from vehicle in front, angle of the steering wheel position and amount of pressure applied to the brake pedal (Castro, 2009). Young et al. (2009) also add event detection and reaction time as common measures. These measures describe driving performance and have little merit in human-automation studies (Jamson et al., 2013), except for those parts of automated driving that actually include manual driving; as in hand-over and take-over situations. As a consequence, the assessment of driver behaviour will need to adjust to the new driving situation involving automated driving. McBridge et al. (2014) specify four categories of human-automation concerns: automation-related (such as reliability), person-related (such as complacency), task-related (such as automaton failure consequences) and so called emergent factors. The emergent factors were described as variables related to the interaction between the human and automation, as in trust, situation awareness and mental workload (McBridge et al., 2014). Other factors that should be of special concern in human-automation studies include: behavioural adaptation (as in lowered perceived risk), skill degradation, and inadequate mental model of automation functioning (Saffarian et al., 2012). All of these concerns are not inevitable; they can be mitigated by a well-designed and adapted human-automation interface (Parasuraman, 2000), with a balance between abilities, authority, control and responsibility (Flemisch et al., 2012). A better understanding is required of the driver's relationship with automation and behaviour during automated driving. An important beginning of this understanding was constructed by Heikoop et al. (2016) in their review of causalities between the most commonly studied issues in human-automation research. According to their review the most commonly studied human-automation issues were (presented from most to least frequently studied): Mental workload, Attention, Feedback, Stress, Situation awareness, Task demands, Fatigue, Trust, Mental model, Arousal, Complacency, Vigilance, Locus of control, Acceptance and Satisfaction. These issues are not fully covered by traditional driving performance measures. A similar review of issue-related assessment methods was not found. When planning a study, there is a potential value in obtaining an overview of common measures selected by other researchers in the field. Therefore, one purpose of this paper was to provide a summary of assessment methods used for behavioural studies in the field of vehicle automation.

When planning a study, an overview of possible assessment methods is not enough for the construction of a well-designed study with relevant assessment methods. With such a new field, there may be difficulty in anticipating all issues. It might be difficult to select assessment methods and construction of new assessment methods may also be needed. This challenge was encountered in a Swedish research project called Methods for Designing Future Autonomous Systems (MODAS; Krupenia et al., 2014). In the project, a new information and warning system for highly automated driving was developed, and the aim was that it should be tested in a simulated driving session with a hazardous event. If it had been a