Accident Analysis and Prevention 121 (2018) 28–42

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

From partial and high automation to manual driving: Relationship between non-driving related tasks, drowsiness and take-over performance

Frederik Naujoks[a], Simon Höfling[a], Christian Purucker[a,*], Kathrin Zeeb[b]

[a] Würzburg Institute for Traffic Sciences GmbH (WIVW), Robert-Bosch-Straße 4, 97209 Veitshöchheim, Germany
[b] Robert Bosch GmbH, CC-AD/EYF3, Robert-Bosch-Allee 1, 74232 Abstatt, Germany

ARTICLE INFO

Keywords:
Automated driving
Controllability
Drowsiness
Distraction

ABSTRACT

Background: Until the level of full vehicle automation is reached, users of vehicle automation systems will be required to take over manual control of the vehicle occasionally and stay fallback-ready to some extent during the drive. Both, drowsiness caused by inactivity and the engagement in distracting non-driving related tasks (NDRTs) such as entertainment or office work have been suggested to impair the driver's ability to safely handle these transitions of control. Thus, it is an open question whether engagement in NDRTs will impair or improve take-over performance.
Method: In a motion-based driving simulator, 64 participants completed an automated drive that lasted either one or two hours using either a partially or highly automated driving system. In the partially automated driving condition, a warning was issued after several seconds when drivers took both hands off the steering wheel, while the highly automated driving system allowed hands-off driving permanently. Drivers were allowed to bring along their smartphones and to use them during the drive. They engaged in a wide variety of NDRTs such as reading or using social media. At the end of the session, drivers had to react to a sudden lead vehicle braking event. In the partial automation condition, there was no take-over request (TOR) to notify the drivers of the braking vehicle, while in the highly automated condition, the situation happened right after the drivers had deactivated the automation in response to a TOR. The lead time of the TOR was set at 8 s. Driver's level of drowsiness, workload (visual, mental and motoric) from carrying out the NDRT and motivational appeal of the NDRT right before the control transition were video-coded and used to predict the outcome of the braking event (i.e., reaction and system deactivation times, minimal Time-to-collision (TTC) and self-reported criticality) with a multiple regression approach.
Results: In the partial automation condition, reaction times to the braking vehicle and situation criticality as measured by the minimum TTC could be well predicted. Main predictors for increased reaction time were drowsiness and motivational appeal of the NDRT. However, visual and mental demand associated with NDRTs did decrease reaction time, suggesting that the NDRT helped the drivers to maintain alertness during the partially automated drive. Accordingly, drowsiness and motivational appeal of the NDRT increased situation criticality, while cognitive load due to the NDRT decreased it. In the highly automated condition, however, it was not possible to predict system deactivation time (in reaction to the TOR), brake reaction time to the braking vehicle and situation criticality by observed drowsiness and NDRT engagement.
Discussion: The results suggest a relationship between the driver's drowsiness and NDRT engagement in partial automation but not in highly automated driving. Several explanations for this finding are discussed. It could be possible that the lead time of 8 s might have given the drivers enough time to complete the driver state transition process from executing NDRTs to manual driving, putting them in a position to be able to cope with the driving event, while this was not possible in the partial automation condition. Methodological issues that might have led to a non-detection of an effect of drowsiness or NDRT engagement in the highly automated driving condition, such as the sample size and sensitivity of the observer ratings, are also discussed.

* Corresponding author.
E-mail addresses: naujoks@wivw.de (F. Naujoks), hoefling@wivw.de (S. Höfling), purucker@wivw.de (C. Purucker), kathrin.zeeb@de.bosch.de (K. Zeeb).

https://doi.org/10.1016/j.aap.2018.08.018
Received 5 February 2018; Received in revised form 1 July 2018; Accepted 1 August 2018
0001-4575/

1. Introduction

Automated driving relieves the driver from having to continuously control lateral and longitudinal dynamics of the vehicle. However, depending on the level of automation (Gasser et al., 2012), the driver is still required to monitor the driving environment so that she/he can intervene in case of system limits or malfunctions (so-called “partially automated driving”), or to be available as a fallback level when the system reaches its limits (so-called “highly automated driving”). Unlike “fully automated driving”, both partially and highly automated driving still require the driver to resume manual driving at least occasionally during the drive.

Several studies have dealt with the question how drivers manage these so-called take-over situations (e.g., Gold et al., 2015, 2013; Körber et al., 2016; Naujoks et al., 2014, 2015; Naujoks et al., 2017a; Zeeb et al., 2016, 2017). Especially the time budget needed to safely deactivate the automation (so-called “take-over time”; Marberger et al., 2017) and to regain control over the vehicle (so-called “control stabilization time”; Marberger et al., 2017) have attracted considerable research interest. In a review of recent studies on take-over times during transitions from highly automated to manual driving, Eriksson and Stanton (2017) concluded that the reported times had a large variety of between 1 and 15 s.

One explanation why it takes drivers some time before they are ready to take over vehicle control may be that drivers need to switch from executing NDRTs to manual driving (Naujoks et al., 2018). Indeed, several studies (de Winter et al., 2014; Jamson et al., 2013; Large et al., 2017; Naujoks et al., 2016; Naujoks and Totzke, 2014) and surveys (König and Neumayr, 2017; Pfleging et al., 2016) have shown that drivers will likely engage in NDRTs while driving in automated mode, such as reading magazines or using smartphones. To explain the time needed to disengage from NDRTs and to re-engage in the driving task, it has been suggested that time-consuming re-configuration processes of the drivers’ *sensory* (e.g., taking one’s eyes off the NDRT and attending to relevant HMI displays), *motoric* (e.g., freeing one’s hands and taking them back on the steering wheel) and *cognitive* state (e.g., re-configuration of mental task sets or response rules) have to be performed by the driver to meet the demands of manually controlling the vehicle (Marberger et al., 2017). Indeed, research from cognitive psychology has repeatedly demonstrated that switching tasks goes along with costs in the form of increased reaction times or error rates (Altmann and Trafton, 2004; Kiesel et al., 2010; Trafton et al., 2003).

Empirical research indicates that switching costs affect taking over vehicle control after automated driving as well. Take-over performance when switching from automated driving while working on a NDRT to manual driving has been investigated in several studies, usually showing increased take-over times as compared to reference drives without NDRT (Dogan et al., 2017; Körber et al., 2016; Merat et al., 2012; Naujoks et al., 2017a). However, only very few studies have directly compared the impact of different NDRTs against each other. Zeeb et al. (2016) found that drivers who watched a video on a fixed in-vehicle display were slower to respond to take-over requests when compared to a condition without NDRT, but this was not the case when they had to write an email or read a news text. Both, watching a video and reading a news article impaired drivers’ lane keeping. In another study (Zeeb et al., 2017), the authors report that motoric task load while reading texts (i.e., taking a tablet into one’s hands vs. using a fixed in-vehicle display) increased take-over time and decreased lane keeping directly after control had been taken over. Similar results have been reported by Gold et al. (2015).

While these studies indicate that an increased workload due to the engagement in NDRTs results in increased take-over times and impairments of take-over quality, a state of cognitive underload may equally affect the driver’s take-over performance. As a result of the disengagement from driving related activities, drivers might easily get tired when their only task is to monitor the automation. In line with other researchers (e.g., Desmond et al., 1998; Schömig et al., 2015), Vogelpohl and Vollrath (2017) showed in a simulator study that due to the reduced workload drivers experienced fatigue earlier during a highly automated drive than during a manual drive. Consequently, the finding of Miller et al. (2015) that drivers who engage in NDRTs while driving in automated mode show fewer signs of fatigue is not surprising because they might counteract cognitive underload through NDRT engagement. However, in this respect the results in scientific studies are not clear. For example, Neubauer et al. (2014) could show that engagement in NDRTs reduces the perceived stress of boredom in automated driving, but reaction times to critical driving events were not improved, suggesting that engagement in NDRTs does not enhance alertness lastingly.

Taken together, the drivers’ state during the automated drive seems to have a great influence on the time needed to re-engage in the driving task. However, the “driver state transition process” (Marberger et al., 2017) is not yet completely understood to date. On the one hand, non-activity could lead to mental underload and drowsiness, resulting in prolonged reaction times and impaired manual driving performance (Jarosch et al., 2017). On the other hand, engagement in NDRTs can lead to an increase in visual, cognitive and motoric load, prolonging the time needed to re-engage in the driving task (Naujoks et al., 2018). It is also possible that a high incentive to continue the NDRT causes drivers to unnecessarily delay their reactions to potentially critical driving events or HMI messages (Ko and Ji, 2018; Wickens et al., 2015). The aim of the present study was to advance existing knowledge on the influence of NDRT engagement and drowsiness on the driver’s ability to regain manual control over a highly or partially automated vehicle. The ultimate aim of the study was to gain insights into how driver monitoring systems, such as inferring driver state information from gaze behavior, body postures and usage of smartphones (Braunagel et al., 2017a, 2017b; Louw et al., 2016; Trivedi et al., 2007) could be used to predict driver’s reactions to imminent driving situations when switching from automated to manual control.

2. Method

In this simulator study, drivers ultimately encountered an imminent lead vehicle braking scenario they had to react to when resuming control either from a partially or highly automated vehicle. During the preceding automated drive, the participants were free to use their brought-along smartphones and to engage in whatever activity they felt safe enough to do. The drives either lasted one or two hours until the target situation was reached. The aim of the study was to assess the relationship between the drivers’ reactions to the braking lead vehicle and their previous NDRT engagement and drowsiness level.

2.1. Experimental design and sample

The study was carried out in a 2 × 2 between-subjects design with $n = 16$ participants per cell ($N = 64$; independent variables: “level of automation” (partially vs. highly automated), and “duration” (1 h vs. 2 h), see Table 1). Drivers were randomly assigned to the experimental groups. The participants were recruited from the test driver panel of the Würzburg Institute for Traffic Sciences (WIVW GmbH) and had participated in an extensive simulator training program prior to the study.

Table 1
Experimental setup of the simulator study.

N = 64		Level of automation	
		Partially Automated	Highly Automated
Duration	1 h	n = 16	n = 16
	2 h	n = 16	n = 16