A TAXONOMY OF STRATEGIES FOR SUPPORTING TIME-SHARING WITH NON-DRIVING TASKS IN AUTOMATED DRIVING

Driver distraction is one of the leading causes of vehicle crashes. The introduction of higher levels of vehicle control automation is expected to alleviate the negative effects of distraction by delegating the driving task to automation, thus enabling drivers to engage in non-driving tasks more safely. However, before fully automated vehicles are realized, drivers are still expected to play a supervisory role and intervene with the driving task if necessary while potentially having more spare capacity for engaging in non-driving tasks. Traditional distraction mitigation perspectives need to be shifted for automated vehicles from mainly preventing the occurrence of non-driving tasks to dynamically coordinating time-sharing between driving and non-driving tasks. In this paper, we provide a revised and expanded taxonomy of driver distraction mitigation strategies, discuss how the different strategies can be used in an automated driving context, and propose directions for future research in supporting time-sharing in automated vehicles.

INTRODUCTION

Autonomous vehicles are advertised as an effective way to reduce travel time costs by allowing drivers to be productive while driving (Litman, 2018). However, before fully automated vehicles are realized, drivers will continue to play a role in the driving task: for example, SAE Level 2 and Level 3 (SAE International, 2014), the state-of-the-art vehicle automation technologies in the market, still require drivers to monitor the environment (SAE Level 2) and be ready to take over when necessary (SAE Levels 2 and 3). Although it is expected that delegating some parts of the driving task to automation would spare mental and physical resources, drivers are likely to use these spare resources to engage in non-driving tasks rather than utilizing them on the driving task (de Winter, Happee, Martens, & Stanton, 2014; He & Donmez, 2019). In general, engaging in non-driving tasks can lead to drivers getting out of the loop (Merat et al., 2018), losing both physical and cognitive control of the vehicle (Cunningham & Regan, 2018), and experiencing difficulty in regaining situation awareness when they have to take-over vehicle control (Louw et al., 2017; Zeeb, Buchner, & Schrauf, 2016). Simply trying to minimize driver engagement in non-driving tasks, a view adopted by most driver distraction mitigation research for non-automated vehicles, may not help solve these automated vehicle issues as drivers of automated vehicles have been shown to experience fatigue if they do not perform non-driving tasks (de Winter et al., 2014). With increasing automation levels, it can even be argued that resuming vehicle control may be an interruption to non-driving tasks. Thus, new approaches for supporting time-sharing between driving and non-driving tasks are needed for automated vehicles.

Regan, Lee, & Young (2008, p. 34) defined driver distraction as the “diversion of attention away from activities critical for safe driving toward a competing activity”. This definition was created for non-automated vehicles but still fits well into the context of automated vehicles. However, “activities critical to safe driving” are different for automated vehicles as the role of the driver changes with the introduction of control automation. For example, while manually controlling the vehicle is less critical in automated vehicles (the automation controls the vehicle most of the time), monitoring the status of the automation would be an additional activity critical to safe driving under SAE Level 2 vehicle automation. Given that “activities critical for safe driving” are different in automated vehicles, the strategies that have been developed to mitigate distraction in non-automated vehicles, such as locking out drivers from non-driving tasks or providing feedback about driving performance and distraction levels, have to be revised for automated vehicles. These revised strategies should not only consider the demands of driving/non-driving tasks but also the state of the automation.

Designing techniques to support time-sharing and keeping the driver in the loop in automated vehicles is an emerging research area. In this paper, we propose a taxonomy to describe strategies for supporting time-sharing in automated driving in order to help guide this rapidly expanding research area. We consider the levels of automation where drivers have to take over control of the vehicle (SAE Levels 2 to 4) and present examples from recent studies where available. We also discuss the potential advantages and disadvantages of different strategies and identify directions for future research.

SUPPORTING TIME-SHARING WITH NON-DRIVING TASKS IN AUTOMATED DRIVING: A TAXONOMY

Our proposed taxonomy of strategies that support time-sharing in automated vehicles (Table 1) is based on a taxonomy of driver distraction mitigation strategies proposed by Donmez, Boyle, & Lee (2008, 2003). Donmez et al. (2003) proposed three dimensions, which we also adopted: the degree of the intervention (framed in the original taxonomy as *level of automation*), the source of the strategy’s initiation (driver or automation), and the type of task targeted by the strategy (driving or non-driving related). The strategies proposed within this original taxonomy mainly targeted pre-drive or driving periods.

Table 1: Taxonomy of strategies for supporting time-sharing in automated driving

		Driving-Related		Non-Driving-Related	
		Automation-initiated	***Driver-initiated***	***Automation-initiated***	***Driver-initiated***
Pre-Drive/ Drive	***High intervention***	Intervening	Delegating	Locking & interrupting	Controls presetting
	Moderate intervention	Warning	Warning tailoring	Prioritizing & filtering	Place keeping
	Low intervention	Informing	Perception augmenting	Advising	Demand minimizing
Post-Drive (Retrospective)		Risk evaluation		Engagement assessment	
Cumulative		Education		Informing social norms	

Donmez et al. (2008) later introduced the idea of strategy timing and its relation to strategy effectiveness; they proposed that strategies can focus on changing driver behavior through presenting feedback post-drive as well as cumulatively over time. We have also incorporated this timing view to our taxonomy. Overall, the taxonomy that we are proposing in this paper is based on the views of Donmez et al. (2008, 2003) and on a comprehensive review of research conducted to date on non-driving task engagement in and interface design for automated vehicles.

Pre-drive/Drive Strategies: Driving-Related, Automation-Initiated

Automation-initiated strategies that are driving related focus on driving safety and aim to enhance safety by informing or warning the driver, or by intervening when the driver is unable to perform the activities that they need to perform that are critical to safe driving.

Intervening may stop the vehicle or increase the level of vehicle automation when it is detected (e.g. using eye tracking systems or steering wheel sensors) that drivers are engaged in non-driving tasks at a level that degrades their monitoring or take-over ability. For example, when using the "ProPILOT Assist" feature in the 2018 Nissan Leaf, if drivers keep their hands off the steering wheel for an extended period and ignore warnings, the vehicle stops (Nissan, 2017). A simulator study by Benloucif, Sentouh, Floris, Simon, and Popieul (2017) showed that an adaptive lane keeping assist system that changes the control authority between the automation and the driver based on driver state (fatigue or distraction) resulted in better steering performance in the presence of a secondary task, compared to a non-adaptive lane-keeping assist system and to no assistance. While this study explored the benefits of adaptive automation in SAE Level 1, similar strategies can also be investigated in higher SAE Levels. However, although some form of *intervening* may be necessary to ensure safety, this strategy may also cause mode confusion (Sarter & Woods, 1995) if drivers fail to notice a change in the automation level.

Warning can alert the driver to changes in roadway demands, automation malfunctions, and when the limits of automation are exceeded. Takeover requests (TORs) are warnings that indicate an upcoming handover of vehicle control to the driver (Gold, Damböck, Lorenz, & Bengler, 2013) and are investigated widely in automated driving research. Different design parameters for TORs have been studied, such as their modality (Bazilinskyy, Petermeijer, Petrovych, Dodou, & de Winter, 2018), timing (Gold et al., 2013), and location (Politis, Brewster, & Pollick, 2017). However, TORs only provide information about the automation and road state in a discrete manner when a warning threshold is reached, and hence drivers' situational awareness may be too low to properly takeover vehicle control in the limited time available for them to do so. TORs may also lead to over-reliance on the automation if they are highly reliable, or lead to "cry-wolf effects" (Breznitz, 1984) if the rate of false alarms is high. Further research is needed to improve the design of TORs or combine TORs with other strategies (e.g. *informing*) to support time-sharing in automated vehicles.

Informing provides a continual stream of information to the driver about the state of the road and the automation (e.g. reliability, capability), which can help keep drivers in the loop so that they can react faster when a takeover is needed, and contribute to improving their mental model of the automation. Continual information about automation may also help reduce mode confusion and improve driver understanding of TORs (Naujoks, Purucker, et al., 2017). Similar to *warning* design, the modality, timing, and location of the provided information are factors that need to be investigated. Information should be presented in a manner that prevents information overload; otherwise, the information itself may become a source of distraction (Naujoks, Forster, Wiedemann, & Neukum, 2017).

Pre-drive/Drive Strategies: Driving-Related, Driver-Initiated

Driver-initiated strategies that are driving related facilitate time-sharing by having the driver activate or adjust system controls that relate to the driving task.

Delegating involves drivers delegating vehicle control to the automation by increasing the level of automation in order to engage in non-driving tasks. However, the motivation for delegating would highly depend on drivers' trust and reliance on automation, as well as their understanding of their own limits.

Warning tailoring involves drivers adjusting features of the automation to improve their ability to time-share between driving and non-driving tasks. For example, if drivers intend to perform a particularly engaging non-driving task (e.g. a conference call), they might choose to receive warnings issued by the system (e.g. TORs) further in advance or in a more salient manner (e.g. higher volume). Drivers may also choose to tailor the sensitivity of warnings, for example, by changing the time to collision threshold that would trigger a TOR. However, drivers' choices might not be optimal and previous experience with warning systems may bias their decisions.

Perception augmenting describes strategies where information about the environment and the automation is provided upon the driver's request. For example, drivers can have the option to display information about the driving task or the status of automation while they are performing a non-driving task, and not display this information when they are focusing on driving. However, the effectiveness of such strategies would depend on drivers' mental models of the automation and of relevant informational systems.

Pre-drive/Drive Strategies: Non-Driving-Related, Automation-Initiated

The strategies in this category aim to modulate drivers' non-driving task engagement automatically based on the demands of the driving task and the driver's state.

Locking and interrupting completely locks out the driver from non-driving tasks or interrupts non-driving tasks when drivers need to redirect their attention to the driving task. For example, the system can block or interrupt non-driving tasks in highly uncertain driving environments (e.g. city driving, inclement weather). Although locking and interrupting strategies can improve driving performance in non-automated vehicles (Donmez, Boyle, & Lee, 2006; Jung, Kaß, Zapf, & Hecht, 2019), they can suffer from low user acceptance. These strategies might be even less accepted in automated vehicles.

Prioritizing and filtering limits the number of non-driving related system functions that the driver can interact with. For example, if an increase in road demand is detected, the automation can allow the user to receive urgent text messages on their phone but filter out the rest. With increasing vehicle control automation, drivers' acceptance of this strategy may also be questionable.

Advising provides feedback to the drivers regarding their engagement in non-driving tasks, which can be modulated according to road demands. Such strategies have been investigated in non-automated vehicles and have been found to be effective (Donmez et al., 2006; Merrikhpour & Donmez, 2017). This type of feedback might be particularly useful for drivers to assess their own distraction levels and utilize driver-initiated strategies, such as *warning tailoring*, more effectively (e.g. drivers may choose to tailor the sensitivity of TOR warnings if they are advised that they might be experiencing high levels of non-driving task demands). This type of feedback might also lead to annoyance if drivers do not find it useful, or to information overload depending on how it is presented to the driver (Donmez et al., 2003). Further, in critical takeover situations, merely providing feedback about drivers' level of engagement with non-driving tasks would not be sufficient to help drivers return to the control loop.

Pre-drive/Drive Strategies: Non-Driving-Related, Driver-Initiated

This category includes strategies that facilitate drivers in adjusting their non-driving task engagement.

Controls presetting involves allowing the drivers to choose which non-driving related system function would be active during an entire drive or a portion of a drive. For example, a cellphone can allow users to activate a "Do Not Disturb" mode. Further, *controls presetting* may also be considered as an option that allows drivers to select what kind of non-driving tasks would trigger lockouts or warnings. However, the adoption of this category of strategies would depend on drivers' motivations and understanding of automation and their own capabilities.

Place keeping minimizes the demand of switching between non-driving and driving tasks by providing the driver the tools to place "bookmarks" or "cues for resumption" when their non-driving task is interrupted by the driving task. Extensive research available on interruption management in a variety of domains (e.g. Altmann & Trafton, 2002; Borojeni, Ali, Heuten, & Boll, 2016) can inform the design of *place keeping* strategies for automated driving.

Demand minimizing involves providing the driver with alternative methods for non-driving task engagement. Depending on the driving demands, drivers may choose to switch the method of interaction that they utilize. Engagement in an auditory-vocal non-driving task was found to improve takeover performance compared to a visual-manual one (Wandtner, Schömig, & Schmidt, 2018). Thus, drivers may choose to use voice-control over visual-manual interactions when they have to allocate more visual attention to the road and to the automation. The adoption of this strategy also depends on drivers' motivations, but also their understanding of the demands associated with the use of different interfaces.

Post-drive (Retrospective) Strategies

Post-drive or retrospective strategies provide feedback to drivers about their non-driving and driving task performance as well as how well they manage their attention allocation between the two.

Risk evaluation provides post-drive information on driving-related performance in automated vehicles, including actions in critical situations and takeover scenarios, such as takeover quality and response time, as well as monitoring performance, such as the amount of visual attention allocated to the road or automation-relevant displays. Post-drive feedback can be provided within the vehicle or through online or mobile applications that the drivers can easily access. The aim of this type of feedback is to help drivers form a better mental model of automation, and in turn calibrate their trust and reliance on automation in future drives.

Engagement assessment provides post-drive information on drivers' engagement in non-driving tasks. Post-drive feedback on distraction engagement was found to be effective in mitigating distracted driving in non-automated vehicles (Donmez, Boyle, & Lee, 2008b), and was suggested to be more accepted by drivers compared to real-time feedback (Roberts, Ghazizadeh, & Lee, 2012).

In practice, *risk evaluation* and *engagement assessment* can be integrated to help drivers learn better timesharing skills with non-driving tasks in automated driving. For example, Donmez et al. (2008b) found in a simulator study for non-automated vehicles that post-drive feedback on distraction engagement and driving performance resulted in faster responses to lead vehicle braking events and shorter glances to an in-vehicle display compared to no feedback. Given that post-drive strategies are by definition not implemented during a drive, they cannot help at the time that the driver fails to properly split his/her attention between driving and non-driving tasks. Further, their effect heavily depends on drivers' initiative to access feedback. To encourage engagement with feedback, post-drive feedback can be reinforced with other strategies, such as gamification (Xie, Chen, & Donmez, 2016) or insurance-based incentives.

Cumulative Strategies

Cumulative strategies aim to continually shape drivers' behaviours, mental models, and automation reliance, through education and social normative interventions.

Education aims to influence how drivers engage in non-driving tasks by helping them develop appropriate mental models about automation (Beggiato & Krems, 2013), through informing them of automation capabilities and limits or exposing them to automation failures in simulated settings, thus calibrating their trust in and reliance on automation. Either over-trust or under-trust may have negative effects on operators' reliance on automated systems (Lee & See, 2004): the former can result in over-reliance on automation and inappropriate non-driving task engagement, and the latter may lead to decreased use of automation when it can actually help. Thus, well-calibrated trust in vehicle automation can reduce automation-induced complacency (Parasuraman, Molloy, & Singh, 1993), and insufficient monitoring of automation. Bahner, Hüper, and Manzey (2008) found that exposing operators to automation failures during training can decrease automation complacency in process control. The benefits of training have also been observed in the automated driving domain: Payre, Cestac, Dang, Vienne, and Delhomme (2017) found that drivers who received extensive training on vehicle automation showed improved response times when automation failed, but fewer glances to the road, suggesting a more optimized trust in automation, compared to drivers who received a more restricted training. However, despite a preliminary proposal by the National Highway Traffic Safety Administration (2013), there are currently no standards for educating automated vehicle drivers.

Informing social norms refers to informing drivers of socially acceptable behaviors about non-driving task engagement in automated vehicles. Given that automated vehicles are not widely used yet, these norms have not yet been established. Through policy design, enforcement, and feedback, these norms can be shaped in a controlled and an evidence-driven manner. In general, social norms significantly affect how people behave on the road, but not all drivers are affected in the same way. Chen and Donmez (2016) have shown that younger drivers' (ages 18-30) self-reported distraction engagement behaviors are more strongly related to perceived social norms than those who are 30+. Merrikhpour and Donmez (2017) demonstrated that revealing their parents' driver distraction engagement behaviors (i.e. descriptive norms) to teenagers leads to a decrease in teenagers' distraction engagement.

DISCUSSION

The changing role of drivers in automated vehicles requires new perspectives on driver distraction and distraction mitigation. A major change lies in the attitude toward non-driving tasks: with increasing vehicle automation, it may be safer and more acceptable to engage with non-driving tasks, making strategies that aim to block non-driving activities less accepted. This change brings about a basic, but essential question: what would be considered as "safe distraction" in automated vehicles? To the best of our knowledge, so far, there are no commonly accepted standards to assess the risks associated with different driving behaviors in automated vehicles, nor metrics to define the appropriateness of non-driving task engagement under specific conditions. For example, two seconds is the threshold adopted by government agencies for risky off-road glances (National Highway Traffic Safety Administration, 2013b, 2016), but this threshold is based on research conducted in non-automated vehicles (Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006). No similar threshold has been set for automated vehicles. The lack of a threshold that identifies risky enagement in non-driving tasks in automated vehicles makes implementing the automation-initiated, post-drive, and cumulative strategies presented in this paper difficult, as many of them depend on an understanding of the relationship between driver behaviors and risk levels in automated vehicles. Future research efforts, such as naturalistic studies (e.g. Dingus et al. 2006), are needed to systematically assess the riskiness of specific behaviors that can be observed in automated vehicles.

Driver-initiated strategies in general rely on drivers' awareness of potentially risky engagements in non-driving tasks. This awareness can be generated through informing social norms and through regulation and education. But before these interventions can be put in place, the riskiness of different non-driving task engagement behaviors should be assessed. A lack of proper understanding of these risks may lead drivers to underestimate risks and overly rely on automation. This can render driver-initiated strategies less effective. Future research needs to provide guidance on liability, safety, and public acceptance of non-driving task engagement in automated vehicles.

Another challenge lies in the feasibility of driver state detection technologies in automated vehicles. As drivers no longer need to continuously control the vehicle or put their hands on the steering wheel, distraction measures that rely on driving performance would be less effective in automated vehicles. Non-invasive techniques like eye tracking may play a more important role in driver state detection in automated vehicles, but more development is needed to improve the accuracy of such techniques.

As mentioned in several places in the description of different strategies, some strategies can become more effective if combined with others. Further, strategies may need to be combined to support different phases of vehicle operation. For example, providing both TORs (*warning*) and continual information (*informing*) can help drivers better allocate their attention in both normal monitoring (via *informing*) and critical takeover (via *warning*) situations.

Lastly, although driving-related strategies for supporting time-sharing in automated driving has become an active area of research, more research is still needed. The taxonomy in general highlights areas of future research. There are no studies on how *education* and *informing social norms* can be leveraged to calibrate drivers' trust and reliance on automated vehicles and to support time-sharing between non-driving and driving tasks. Also, there is little focus on using non-driving-related strategies in automated vehicles. Future studies should explore the theoretical and practical issues for these areas.

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