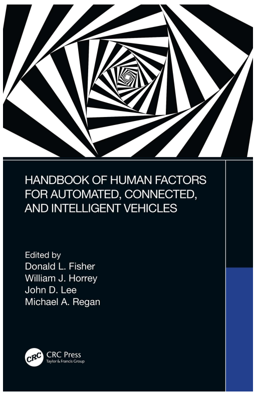

Handbook of Human Factors for Automated, Connected, and Intelligent Vehicles

Donald L. Fisher, William J. Horrey, John D. Lee, Michael A. Regan

Human–Machine Interface Design for Fitness-Impaired Populations

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John G. Gaspar

16 Human–Machine Interface Design for Fitness-Impaired Populations

John G. Gaspar
University of Iowa

CONTENTS

KEY POINTS

- The human–machine interface provides the link between driver state detection and the human operator
- Using driver state information, adaptive automated systems could be designed to adjust their demands and/or the HMI based on the capacity of the driver
- Adaptive automation requires decisions about if, how, and when the automation, including both the vehicle systems and HMI, should adapt, and whether the automation or human has authority to invoke changes in the system
- Adaptive automation applied for driver impairment needs to consider the interaction between the state of the driver and the capability of automation

16.1 INTRODUCTION

The previous chapter (Chapter 15) discussed many important design considerations for the human–machine interface (HMI) for automated and connected vehicles. One additional and significant concern is how that design might be impacted by the ability to monitor driver state. Automation may indeed increase the incidence of drivers being unprepared or incapable of safely operating the vehicle (e.g., this Handbook, Chapter 9). For instance, recent research suggests that partial automation (i.e., Level 2) increases visual disengagement from driving, even in the absence of secondary tasks (Gaspar & Carney, 2019; See also, Russell et al., 2018). Similar research demonstrates an increase in the likelihood of fatigue and drowsiness with even moderately prolonged periods of automated driving (Vogelpohl, Kühn, Hummel, & Vollrath, 2019). Recent crashes involving partially automated vehicles highlight the potential consequences of driver impairment and disengagement from the dynamic driving task (e.g., NTSB, 2017).

Driver monitoring is often presented as the remedy to driver impairment in partially and highly automated vehicles (see e.g., this Handbook, Chapter 11). Indeed, in their report following the investigation of the Williston Tesla crash, the National Transportation Safety Board recommended that driver monitoring could provide a safeguard against driver disengagement and impairment in automated vehicles (NTSB, 2017). Previous chapters (Chapters 9, 11) discussed approaches to driver monitoring and their application in automated vehicles. However, simply knowing the state of the driver is not enough to improve safety. The vehicle must adapt in some fashion to account for the reduced capacity of the driver. This could be through modifying the HMI (e.g., providing feedback), adjusting the vehicle systems (e.g., tuning lane departure warnings), or some combination of the two.

This chapter builds on discussion of driver state monitoring by discussing how driver state information can be considered in HMI design in automated vehicles. Specifically, we consider how information about the state of the driver can be used to dynamically tailor the automation to the driver's capabilities on a moment-to-moment basis. This dynamic, state-based adaptation by the HMI is referred to as adaptive automation (AA). Unlike static automation, whose functionality remains constant when engaged, AA flexibly adjusts the HMI and level of automation based on information about the state of the human operator (Rouse, 1988). AA has been applied in a variety of complex tasks involving control distribution between human operators and automated aides, from monitoring air traffic control displays (Kaber, Perry, Segall, McClernon, & Prinzel III, 2006) to controlling unmanned vehicles (de Visser & Parasuraman, 2011).

This chapter is divided into two sections. First, we provide an overview of AA and the important design decisions that should be considered in its application to driving. We then present a framework for applying AA to driving, specifically driver impairment. The framework considers both the capability of the automation and capacity of the driver, as well as interactions between the two. This framework is considered across common modes of impairment, specifically distraction, drowsiness, and drugs and alcohol (also see this Handbook, Chapter 9).

16.2 ADAPTIVE AUTOMATION

AA refers to systems that dynamically adjust the level of automation or HMI based on the state of the operator (Hancock, Chignell, & Lowenthal, 1985; Rouse, 1988). This contrasts with static automation, which maintains the same level of automation independent of operator or environmental state. The goal of an adaptive system is to tailor the level of automation to meet the needs of the operator and maintain safe operation (Parasuraman, Bahri, Deaton, Morrison, & Barnes, 1992). With impairment (e.g., distraction, drowsiness, drugs) this involves dynamically adjusting the HMI, function of the automated systems, or both, in order to mitigate the detrimental effects of disengagement from the driving task. Note that, with respect to workload, in low-workload conditions, where automation complacency is likely, more control is shifted to the human operator to increase arousal (see also, this Handbook, Chapter 6).

Adaptive systems, as depicted in Figure 16.1, consist of two components, a state monitor and task manager. The state monitor detects and classifies the state of the human operator (and perhaps also the environment; this Handbook, Chapter 11). Operator state information is then fed forward to a task manager, whose role it is to adjust the allocation of tasks between the human operator and system automation (also see this Handbook, Chapter 8). The HMI serves as the link between the operator and automated system. For instance, an HMI might provide feedback to a distracted driver to return his gaze to the forward road. The outcome of behavior (e.g., lane-keeping) and the updated state of the driver are then fed back into the system.

A considerable body of research from different domains shows benefits of AA over static (i.e., non-adaptive) automation (see Scerbo, 2008). For example, Parasuraman, Mouloua, and Hilburn (1999) compared AA that provided adaptive aiding and adaptive task allocation against static automation in a simulated flight task. Adaptive aiding consisted of the system controlling one dimension of aircraft position in high-workload situations (i.e., takeoff and landing). Task control was also temporarily shifted back to the human operator in lower-workload conditions (i.e., the middle portion of the flight). Compared with a non-adaptive control group, AA improved tracking performance and reduced subjective workload.

While AA offers advantages over static automation across a number of tasks, HMI designers face several important questions in implementing AA in vehicles.

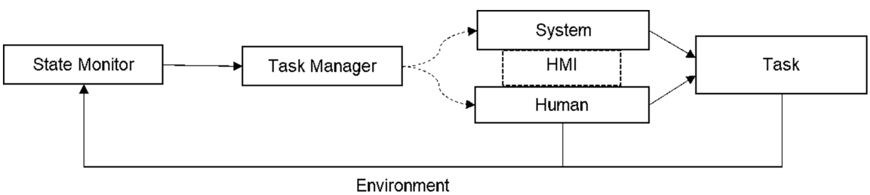

FIGURE 16.1 A framework for AA. The human–machine interface links the human operator to the automated system.

These include when the automation should adapt, what form that adaptation should take, and whether the human or automation has invocation authority. We next consider these questions in the context of vehicle automation.

16.2.1 When to Adapt?

Adaptive systems first need to identify when to adjust the HMI. This is dependent on the method used to detect driver state. Systems can be classified based on whether they monitor driver state via driver-related or driving-related measures. The driver monitoring system must then establish a threshold for impairment, beyond which the system will adjust the HMI to manage driver state or provide automated support (see also, this Handbook, Chapter 11).

State monitoring data can come from two sources, the driver and the vehicle. Driver-based measures rely on either direct assessment of operator state through physiological measures or inputs to the vehicle controls. For example, Freeman, Mikulka, Prinzel III, and Scerbo (1999) used electroencephalography (EEG) to identify changes in workload during a monitoring and tracking task. Using this index of workload, they dynamically allocated control between the human and an automated system. Previous chapters of this volume described methods for direct evaluation of driver state through camera-based and other measures (Chapter 9, 11). Eyes-off-road is a common measure of visual distraction and can be used to trigger feedback to the driver (Donmez, Boyle, & Lee, 2008). State monitoring systems might also system input (e.g., steering wheel torque) to identify changes in driver state. Vehicle-based measures use vehicle sensors to detect changes in performance related to changes in driver state. For example, increased deviations in lateral vehicle position and increased lane departure rate can be used to identify likely increases in drowsiness (Schwarz et al., 2015).

These approaches each have advantages and potential drawbacks. Measuring changes to performance is often easier and is also a more direct evaluation of changes in safety. However, because changes in performance are the eventual manifestation of particular impairment states, relying on performance metrics as a state indicator may result in late detection of impairment. For instance, using run-off-road events to identify drowsiness may let drivers become drowsy past the point where an intervention could effectively mitigate impairment. Additionally, as automation assumes a greater share of vehicle control, performance measures will no longer represent the manifestation of driver state and will therefore prove ineffective for classifying impairment.

Physiological measures, on the other hand, provide a more direct evaluation of driver state. These approaches can therefore theoretically detect impairment earlier, perhaps even before impairment reaches dangerous levels. An adaptive system could thus intervene earlier, when more options might be available to preserve safety. Such sensitivity may, however, come with costs in that drivers may not yet be aware of changes in their own state at the early stages of impairment. If systems adapt in these instances, it could be perceived as a false alarm and decrease trust in the system (Parasuraman & Riley, 1997).

16.2.2 How to Adapt?

HMI designers also need to consider what form AA should take once the task manager calls for a change in system state. Sheridan (1992) provided a useful framework for considering how automation can be applied to the human–machine relationship (see Table 16.1). The framework consists of ten levels of automation, from full manual control to fully automated. Within this range, the distribution of control (and responsibility) between the human operator and automated system varies (see also, Chapter 8). A transition point occurs between Levels 6 and 7, where the human operator either does or does not have input on an automated decision before the action is executed. Inagaki and Furukawa (2004) therefore added an additional stage 6.5, where the automation simultaneously acts and informs the operator. The goal of such a stage is to combine the benefits of automated behavior (e.g., fast responding) while preventing automation surprises, where the operator is unsure why the automation behaved in a certain way. Limiting surprises is crucial to user acceptance of automation.

Inagaki and Furukawa (2004) considered how these levels might be applied in an adaptive cruise control system. In a Level 4 system (see Table 16.1, not to be confused with SAE levels), the system might provide a forward collision warning to the driver. In a Level 6 system, the system might give a forward collision warning and if the driver does not respond, initiate emergency braking (i.e., automatic emergency braking, AEB). In a Level 6.5 system, the vehicle applies emergency braking and provides a collision warning simultaneously. This has the advantage of initiating the response faster while still making the driver aware of the system's intentions. Finally, a Level 7 system might engage emergency braking and inform the driver after the fact that emergency braking was applied due to a forward collision situation. Such information, while seemingly unnecessary in most situations, can be potentially

TABLE 16.1
Levels of Automated Control

1. Full human control
2. Automation offers a set of action alternatives, and…
3. Narrows the selection, or
4. Suggests one, and
5. Executes the suggestion if the driver approves, or
6. Allows the human a restricted time to veto before automatic execution, or
7. Simultaneously executes automatically and tells the human what it is going to do, or
8. Executes automatically, then necessarily informs humans, or
9. Informs driver after execution only if asked, or
10. Informs driver after execution if automation decides to
11. Fully automate control

Note: After Inagaki and Furukawa (2004).

useful in teaching drivers about the edge cases that define the operational design domain of a system (see this Handbook, Chapter 18).

These degrees of automated control can be dynamically applied across different components of an information processing framework consisting of four stages: information acquisition, analysis, decision-making, and action execution (see Figure 16.2; Parasuraman, Sheridan, and Wickens, 2000; see also, this Handbook, Chapter 6). A distinction can be made between lower- and higher-order processes in this framework based on the degree to which information must be cognitively manipulated. Information acquisition and action execution are considered lower-order processes and analysis and decision-making, requiring greater cognitive processing, are considered higher-order functions.

Kaber, Wright, Prinzel III, and Clamann (2005) considered the potential implications of applying AA to each stage of the information processing framework in an air traffic control monitoring task. Participants were instructed to locate and "clear" aircraft on a control display before they reached a certain location. Participants could only move a portion of the display through a viewing portal and had to shift the portal to track multiple aircrafts. Operator state was evaluated via performance on a secondary gauge monitoring task and used to trigger AA. Participants experienced four automation conditions and a manual condition. Acquisition automation controlled movement of the viewing portal. Analysis automation provided a table of all active aircrafts. Decision-making automation prioritized aircraft to clear. Action implementation automation automatically cleared aircraft the operator had selected.

Kaber et al. (2005) found that AA applied to lower-order information processing stages (acquisition and execution) improved performance relative to manual control. However, applying AA to higher-order functions actually degraded performance. Operators had greater difficulty returning to manual control in the analysis and decision AA conditions. Kaber et al. (2005) suggest this effect may be due to the transparency of automation or how easy it is for the operator to assess the reliability of the AA (i.e., how well the automation is working at any point in time). With lower-level functions, such as automatically clearing selected aircraft, it is easy for operators to determine whether the automation is active and successful. With higher-order AA, additional processing is necessary to evaluate the automation's decisions against the mental model of the operator. Furthermore, if decision-making automation repeatedly makes and executes choices in a complex environment, it may be difficult for operators to maintain a clear understanding of the situation

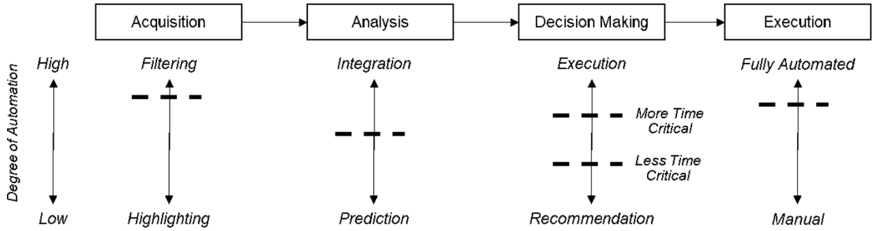

FIGURE 16.2 Automation applied to different information processing stages. Dashed lines represent the maximum degree of AA at each stage.

(Parasuraman et al., 2000). Similar costs of automation have been observed with high levels of automated information processing, such as display cueing (Yeh, Wickens, & Seagull, 1999).

The dashed lines in Figure 16.2 represent the extent to which a processing stage might be maximally automated, using the automation continuum from full manual control to full automation (see Table 16.1). Both lower-order processes can be highly automated (Levels 6.5–10), although, as noted earlier, insight into when and why automation performs a specific function might be helpful in improving driver understanding and awareness of automation functioning. Automation applied to higher-order processes, analysis and decision-making, is more likely to reduce situation awareness and take the driver out of the control loop (Scerbo, 2008). Thus high decision-making autonomy is only appropriate to the extent the driver can disengage from the driving task (see also, this Handbook, Chapters 7, 21). If drivers must remain aware of the driving situation (i.e., conditional automation), it is important that drivers at least have insight into the functions of the automation (Level 6.5 and below).

Parasuraman et al. (2000) outlined several other important considerations in how automation could be applied to the information processing framework. First, and most importantly, the resulting state of the joint driver–vehicle system should be safer with automation applied than if the driver was in full manual control. That is, the addition (or adaptation) of automation should increase safety and decrease the likelihood and severity of crashes. The goal of AA is to achieve a desired level of operator workload, not to obviate the dynamic driving task from the human operator in situations where doing so diminishes safety.

A designer must also consider the demands involved in a particular situation and the costs associated with a failure. In time-critical situations with insufficient time for the operator to respond, automated decision-making and action implementation may be ideal (Scerbo, 2008). Automatic emergency braking (AEB) is an example of such a situation, in that the vehicle can respond faster and with harder braking than a human driver possibly could. In less time-constrained high-risk situations, the extent of decision-making performed by the automation depends on the capability of the system and whether the driver is expected to intervene.

16.2.3 Invocation Authority

The third question designers need to consider is whether the system or human operator is responsible for adjusting the HMI. That is, should the system or the driver act as task manager? It is important to note the distinction between adaptive systems, where the adaptation is controlled by the system, and adaptable systems, where the human controls when and how the system adjusts (see also, this Handbook, Chapter 21). Research generally suggests that AA outperforms adaptable, human-initiated automation. Kaber and Riley (1999) compared mandated (i.e., adaptive) and elective (i.e., adaptable) automation in a radar monitoring task. Operator state was assessed via performance on a secondary task. Mandated automation adaptation resulted in significantly larger performance improvements relative to manual control compared with the elective system (see also, Bailey, Scerbo, Freeman, Mikulka, & Scott, 2006).

The major limitation of adaptable automation is that operators often lack insight into their own state. Humans are poor judges of their own mental and physical capacity and may therefore choose to invoke automation (or remain in manual control) at inappropriate times or fail to invoke automation when it is most needed, such as under high workload (Horrey, Lesch, Mitsopoulos-Rubens, & Lee, 2015; Morris & Rouse, 1986; Sarter & Woods, 1994). Indeed, Neubauer, Matthews, Langheim, and Saxby (2012) found that voluntary invocation of automation failed to reduce fatigue and stress in a sample of fatigued drivers. Humans are poor judges of the extent to which impairment states might negatively impact performance and safety. For example, Horrey, Lesch, and Garabet (2008) showed that drivers were poorly calibrated to the detrimental effects of distraction on closed-course driving. Therefore, it seems advantageous that an adaptive vehicle interface assume invocation authority in instances of driver impairment, particularly during safety-critical tasks.

Inagaki, Itoh, and Nagai (2007) proposed a situation-adaptive form of AA. The idea is that in certain situations, particularly those with high degrees of time-criticality where human operators may be incapable of responding fast enough, the automation should make decisions about when and how to respond (if it is capable of doing so). An important caveat of this idea is the importance of the automation informing the driver of its intentions, if a level of joint control is expected (see also, this Handbook, Chapter 8).

16.3 A FRAMEWORK FOR AA FOR IMPAIRED DRIVERS

The question then is how a vehicle equipped with driver monitoring technology should adapt based on different types and degrees of driver impairment. Impairment is defined by the extent to which the driver is capable of safely controlling the vehicle. As impairment increases, the capability of the human driver for safely performing aspects of the driving task decreases, shown in Figure 16.3, with shaded regions representing the transition in adaptive support provided by the impaired driver. At early stages of impairment, feedback via the HMI may be sufficient to alert the driver to a change in state and motivate corrective action. If impairment persists, the vehicle might provide adaptive support, such as tuning safety features like lane departure warning. At the highest degrees of impairment, it will be necessary for the automation to take full control of the vehicle because the operator is no longer capable of safely performing the requisite driving tasks.

Automation capability refers to the capacity of the system to assume various functions of the dynamic driving task. A key point in this discussion is that the capability of automation bounds the degree to which an adaptive system can support an impaired driver. The maximal extent to which the vehicle is capable of intervening is determined by the abilities and limitations of automation. In short, automation can only control aspects of the driving task it is capable of safely performing. Therefore, it is necessary that the driver state monitoring system intervenes before impairment exceeds the capabilities of automation.

The critical consideration in this framework thus becomes the joint human–automation capability, illustrated in Figure 16.4, where the bars represent the set of tasks that must be performed for safe driving. In certain situations, the capabilities of

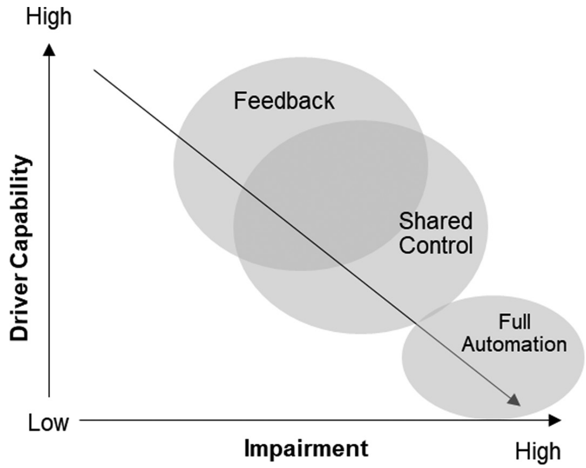

FIGURE 16.3 Relationship between capability, impairment, and vehicle adaptation, represented by the transition across shaded regions.

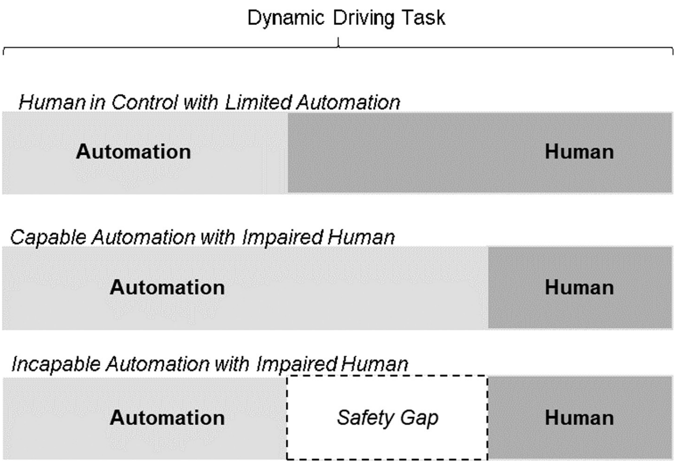

FIGURE 16.4 Relationship between human operator capacity, automation capability, and demands of the dynamic driving task.

the human operator may be limited by impairment. In such situations, the automation must intervene and control more of the driving task. If the automation fails or is incapable of intervening, this leaves a safety gap, a portion of the dynamic driving task not accounted for by either the automation or human operator. Yamani and Horrey (2018) applied this framework of shared control to the individual information processing stages (Figure 16.2). This model predicts how drivers might deploy attention across different levels of automation, considering varying levels of distributed control.

The goal of AA in automated vehicles is then to prevent the driver from reaching a level of impairment that exceeds the capability of the automated systems to control the driving task.

Consider two examples with a drowsy driver, first a vehicle with no automation and second a highly automated vehicle. In the first example, the vehicle is incapable of subsuming any portion of the driving task. The state detection system must therefore monitor the driver, and the task manager should intervene before the driver reaches a level of impairment, resulting in a safety gap between human and automated capabilities. For example, take a drowsy driver who is considering to starting a drive. A vehicle with low automation might warn the driver before the drive begins, because the automation is not capable of controlling the vehicle should the driver fall asleep. A highly automated vehicle, on the other hand, may be capable of performing the entire driving task. Such a vehicle might therefore allow the drowsy driver to disengage entirely (i.e., fall asleep), because the automation is capable of performing all tasks without leaving a gap in safety. Human input may in fact be harmful in such a situation, given how poorly drivers estimate their drowsiness levels (FHWA, 1998), and the responsibility of the AA would be to block the impaired driver from retaking control.

In specifying these impairment thresholds for adapting automation, the design must also strike a balance between safety and driver acceptance. Drivers must understand the correspondence between the impairment thresholds and changes in performance and safety. That is, they must trust the system to identify when driving is no longer safe. Changes in the HMI in situations the driver does not perceive as alarming are referred to as nuisance alerts (Kiefer et al., 1999). Nuisance warnings have a direct negative impact on trust and subsequent willingness to use a system (Bliss & Acton, 2003; Lee, Hoffman, & Hayes, 2004). Appropriate feedback about the state and function of automation is also critical to engender operator trust in both the state detection system and the automated vehicle control (Lee & See, 2004; this Handbook, Chapter 15).

In situations of joint human–automation control (i.e., partial automation), as in Figure 16.4, it is also important to consider the relationship between the expectations of the driver and the automated vehicle. For example, Inagaki et al. (2007) found that an action support system that automatically executed a response maneuver was effective at avoiding collisions. However, the system was, in general, not accepted by drivers. The authors posit that this was because the behaviors of the automation differed from the ways the driver expected the automation to behave, suggesting that the intentions of the adaptive system should match those of the driver. Similarly, in situations where the human operator is unable to detect unsafe levels of impairment or unwilling to alter unsafe behavior, automated intervention may be necessary (Saito, Itoh, & Inagaki, 2016).

16.3.1 Distraction

Distraction can be defined as the diversion of attention away from the tasks necessary for safe driving (Lee, Young, & Regan, 2008). Much research in the last 20 years has explored the effects of distraction on driver performance and safety.

Distraction can be roughly classified as visual or cognitive, based on whether a secondary task diverts a driver's visual attention from the forward roadway (see also, this Handbook, Chapters 6, 9).

Visual distraction has a clear negative impact on safety. For manual driving, research indicates an appropriate threshold may be 2 seconds of eyes-off-road time. Off-road glances longer than 2 seconds increase crash risk and lane-keeping ability, as well as slowing response times to hazard events (Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006; Russell et al., 2018; Victor et al., 2015). Visual distraction can also be measured by the total eyes-off-road time associated with a task interaction. Research suggests that 12 or more seconds of total eyes-off-road time is an appropriate threshold for manual driving (NHTSA, 2012). Cognitive distraction also has the potential to disrupt safe driving, despite a driver's gaze never leaving the forward road (Strayer, Watson, & Drews, 2011), although the impact may be a risk somewhat lower than visual distraction (Dingus et al., 2016). It is worth noting that few tasks are purely cognitive in nature, and overall interactions with non-driving activities and devices such as cell phones increase crash risk (Dingus et al., 2016). Measuring cognitive distraction is more challenging than measuring visual distraction, particularly in production vehicle environments (e.g., Baldwin et al., 2017). In such cases, driving-based methods of impairment detection may be necessary to identify degraded state.

Research mostly on manual driving and distraction suggests adaptive feedback can reduce distraction and improve performance. Donmez, Boyle, and Lee (2007) provided real-time feedback based on off-road glances (using an eye tracker). A two-tiered feedback system provided alerts to the driver through a heads-up display or via the in-vehicle task display when gaze had been off road for two and two and a half seconds, respectively. Adaptive feedback reduced the amount of time drivers spent looking at the secondary task display, which theoretically increased the amount of time drivers spent attending to the forward road. Importantly, both real-time and retrospective feedback have shown the potential to improve driving performance and to reduce visual distraction (Donmez et al., 2008) (also see this Handbook, Chapter 9).

Beyond providing feedback, more capable automated systems can offer real-time assistance to drivers in high-workload or distracted states. Dijksterhuis, Stuiver, Mulder, Brookhuis, and de Waard (2012) compared a non-adaptive and adaptive lane-keeping support system with full manual control. The lane-keeping support consisted of feedback about lateral position via a heads-up display. In the non-adaptive condition, lane position feedback was continuous, whereas in the adaptive condition, feedback was triggered when performance thresholds were exceeded (e.g., time spent near lane edge). Compared with both non-AA and no support conditions, drivers showed improved lane-keeping performance and greater acceptance with the adaptive system. Dijksterhuis et al. (2012) posit that drivers in the adaptive condition may have used the adaptation as a form of feedback to know when a performance threshold was crossed.

A key question with higher levels of automation will be where the threshold for inattention should be drawn. As automation becomes more competent, drivers will conceivably be able to look away from the driving task for longer durations. In a small naturalistic study of partially automated driving, Gaspar and Carney (2019) found a significant percentage of individual glances and off-road interactions that exceeded established thresholds for manual driving (i.e., 2 and 12 seconds, respectively). Future research must establish how long is too long to look away in with different levels of automation capability.

16.3.2 Drowsiness

Unlike distraction, which represents a relatively discrete disengagement from driving, drowsiness is a continuous and progressive state of impairment (also see this Handbook, Chapter 9). That is, over the course of a typical trip, drowsy drivers will become progressively drowsier (though see Williamson et al., 2011). Drowsiness can be simply defined as a state of reduced alertness associated with the inclination to fall asleep (Wierwille, 1995). At the early stages of drowsiness, behavioral changes such as increased reaction time manifest themselves (e.g., Kozak et al., 2005). In later stages, drivers actually begin to momentarily fall asleep, a phenomenon known as a microsleep event (Dinges, 1995). These events are marked by long (>500 ms) eyelid closures, resulting in clearly degraded driving performance, particularly the ability to maintain lateral vehicle control and heightened risk of roadway departures (Boyle, Tippin, Paul, & Rizzo, 2008).

Adaptive drowsiness countermeasures have mostly focused on providing feedback to drivers based on either physical state or driving performance (see this Handbook, Chapter 9, 11). Research suggests adaptive in-vehicle countermeasures can be effective in either mitigating or compensating for performance decrements related to drowsiness. In a simulator study, Gaspar et al. (2017) tested the effectiveness of several simple state-based drowsiness countermeasures, which were triggered based on the output of a steering-based drowsiness detection algorithm (see also, Atchley & Chan, 2011; Berka et al., 2005). The countermeasures consisted of either auditory-visual or haptic alerts and were either discrete (single stage) or staged (multiple stages of increasing urgency). These feedback warnings, and particularly warnings that escalated in severity with continued evidence of drowsiness, reduced the frequency of drowsy lane departures compared to a control group with no adaptive mitigation. The warnings in this study can be considered as a fairly straightforward type of feedback, similar to systems available in production vehicles.

Kozak and colleagues (2006) examined the effectiveness of different modalities of lane departure warnings for drowsy drivers. Warnings included steering wheel vibration, simulated rumble-strip sounds, and a heads-up display paired with steering wheel torque. Each of these warnings was effective for drowsy drivers, reducing response time to lane departures and decreasing the magnitude of lane excursions relative to baseline. May, Baldwin, and Parasuraman (2006) found that auditory forward collision warnings could reduce the chance of a head-on crash for drivers showing signs of active task-induced fatigue.

Higher levels of AA have also been employed successfully in the context of drowsy driving. Saito et al. (2016) studied the effectiveness of an adaptive lane-keeping system in a driving simulator. The adaptive system used changes in lane-keeping behavior as an index of drowsiness and implemented a staged adaptive system using corrective steering. At the first stage, which was triggered by a lane departure, automation provided corrective steering to prevent a severe lane departure (i.e., holding the vehicle in position). The driver then had time to perform a manual correction. If no manual correction was applied, the automation provided additional steering to re-center the vehicle. Saito et al. (2016) showed that this level of adaptive support was effective in preventing severe lane departures.

With drowsy driving, it is important to strike a balance between early detection of impairment and the need to avoid false alarms and nuisance alerts. As noted, the detrimental effects of drowsiness manifest early in the process of actually falling asleep. An adaptive system that can intervene at these stages may be able to keep a driver awake longer or motivate a driver to stop to rest while he is still capable of safely controlling the vehicle. However, drivers may be resistant to such systems in that they may not perceive these early signs of drowsiness as important for safety. As drowsiness detection technology becomes more sensitive to earlier symptoms of drowsiness, designers will have to consider the implications of potentially adapting automation earlier for drowsy drivers.

At the other end of the drowsiness continuum, a remaining question is what the vehicle should do in situations where a driver is too impaired to control the vehicle. In the adaptive system studied by Saito et al. (2016), if drivers repeatedly failed to provide a manual steering correction after the initial adaptive automated correction, the vehicle came to a stop in the current lane of travel. Another option would be for the automation (when capable) to pull the vehicle to the shoulder or, with more capable automation, for the vehicle to maneuver to a safe location for the driver to rest. Additional research is needed to consider the impact of such interventions and how partially and highly automated vehicles should behave when drivers are highly impaired. Another potential concern with adaptive systems is that drivers will over-rely on the automated assistance and continue driving longer than they would have without automation. For instance, Saito et al. (2016) reported instances of drowsy drivers continuing to drive with the adaptive lane-keeping system, presumably by relying on the automation to maintain safety (i.e., prevent severe lane departures) despite long eye closures. Saito et al. (2016) dealt with this situation by having the automation bring the vehicle to a stop if drivers repeatedly failed to provide a steering correction following the initial warning. Future research should focus on understanding the potential safety and long-term behavioral implications of strategies to yield appropriate reliance on AA.

Finally, nearly all the research on adaptive systems for drowsy drivers has focused on the efficacy of interventions over relatively short periods of driving (e.g., 1 hour). However, much of drowsy driving occurs during the course of long, multi-hour drives. The motivation tradeoffs in these situations become even more complicated, with drowsy drivers weighing the benefits of reaching a destination earlier against the potential safety costs of falling asleep at the wheel. Future research should address the impact of adaptive in-vehicle systems on driver behavior during longer trips.

16.3.3 Alcohol and Other Drugs

Alcohol impairment is more straightforward in that legal limits have been set defining thresholds for impairment (currently a breath alcohol concentration of 0.08 or greater). In-vehicle alcohol detection systems being developed as part of the Driver Alcohol Detection System for Safety (DADSS) program will be capable of assessing blood–alcohol content and locking the driver out when impairment above the legal limit is detected (Zaouk, Wills, Traube, & Strassburger, 2015; this Handbook, Chapter 9). As with drowsiness impairment, if alcohol thresholds exceed during the drive, the system would need to determine how best to bring the vehicle to a stop if it is incapable of fully taking control from the driver.

The situation with other drugs such as cannabis is considerably more complicated. One challenge is the lack of reliable and sensitive driver state evaluation technology (Compton, 2017). There currently exists no reliable roadside test to accurately evaluate concentrations of cannabis in the system. Instead, officers must rely on roadside impairment tests using behavior as an indicator of impairment. Furthermore, cannabis may remain in the body long after impairing effects have diminished, and chronic users may show significantly more muted impairment than novice users under similar dosages (Hall & Solowij, 1998). Similarly, prescription pain medications and other drugs have clear detrimental effects on driving performance (e.g., Brown, Milavetz, Gaffney, & Spurgin, 2018), yet measuring changes in driver state resulting from these drugs in the vehicle is a challenging task.

To this end, it may be more appropriate to use driving-based detection strategies to define driver impairment as a trigger for AA. Using performance-based vehicle adaptation has the advantage that instead of monitoring for intoxication directly, the system looks for degradation in driving performance. In most cases, there would likely be fluctuations in control of speed or lateral position (Brown et al., 2018). In such conditions, the system could provide automated support to the driver, such as the adaptive lane-keeping system employed by Saito et al. (2016) for drowsiness. Much research is needed to both identify methods for classifying and predicting impairment from drugs and to understand how an adaptive automated system might interact with a drug-impaired driver.

16.4 CONCLUSIONS

This chapter provides a framework for how adaptive automated systems can interact with impaired driving populations, using the relations among the type and degree of driver impairment, the information processing stage at which an intervention is needed, and the capability of the vehicle technology to identify the specific type of interaction that is needed. This framework considers the preceding body of research on AA in a number of tasks. In addition to the capability of the automation itself, designers of adaptive HMIs for automated vehicles need to consider how changes in automation will be invoked, when adaptation will occur, and to what degree various components of the driving task will be automated.

There are several key points that should be considered in this discussion as they relate to driver impairment. First, it is important that research helps explore how drivers will respond to these different interventions and how the joint human–vehicle system will behave under different task conditions. As Parasuraman et al. (2000) note, an automated system is only beneficial to the extent that the final human–machine relationship improves task performance and safety.

Second, it is important to consider the degree to which drivers are accepting and trusting different adaptive interfaces and behaviors. This will also require understanding the impact of factors like feedback and automation transparency in the design of adaptive interfaces. As this chapter shows, there are complex interactions between a number of factors that must be considered by HMI designers. These HMI design decisions have consequences for whether drivers will ultimately want to use particular systems.

AA has the potential to leverage exciting new developments in driver monitoring technology to make driving safer and more enjoyable for fitness-impaired populations. Yet driver state information is only useful to the extent it can be used to implement an HMI that will leverage the capability of automated vehicle systems to compliment or compensate for driver capacity.

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