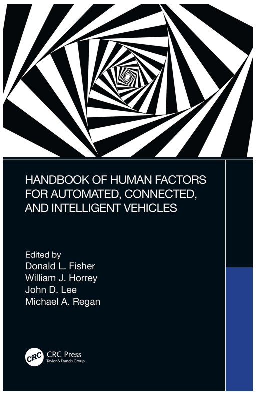

Handbook of Human Factors for Automated, Connected, and Intelligent Vehicles

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

Driver State Monitoring for Decreased Fitness to Drive

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Michael G. Lenné, Trey Roady, Jonny Kuo

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Michael G. Lenné, Trey Roady, and Jonny Kuo
Seeing Machines Ltd.

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KEY POINTS

- Governments and the automotive industry have come to recognize the need for DSM as a central safety measure in the next wave of advanced driver assistance systems (ADAS) technologies.
- There are a number of different underlying measurement approaches, such as vehicle-based measures; however, most research and industry applications now pursue camera-based approaches focusing on eye, head, and facial features.
- Driver drowsiness and distraction are two of the most studied driver states, with some algorithms now published in the research literature.
- There are a number of human factors issues to work through, including ensuring insights from the field inform development of future solutions and ensuring that vehicle technologies interface with the driver in ways that support safe performance.

11.1 INTRODUCTION–WHY DRIVER STATE MONITORING IS BEING WIDELY PROMOTED AS A VEHICLE SAFETY TECHNOLOGY

It is sobering to reflect that over 1.3 million people die annually across the world's road transport systems (World Health Organization, 2018). The leading driver behavior risk factors have held constant over several decades: drunk driving, drowsy driving, unbelted occupants, and speed. Worldwide, new road safety strategies are tackling the risks associated with distracted driving and drugged driving. Doubtlessly, directly targeting behavior and improving road infrastructure and vehicle technology have reduced road trauma, and now there are calls for novel approaches to reduce behavioral risk factors. Specifically, with respect to vehicle technologies, there is renewed focus on reducing the outcomes from a safety event causing injury (e.g., lane departure warning systems) (Cicchino, 2018) or in stopping the behavior from becoming an event (e.g., a system that alerts a distracted driver before the vehicle leaves the lane) (NTSB, 2017).

This industry shift to deliver increasing vehicle autonomy has been a key driver of change. Vehicle automation will fundamentally alter what it means to safely operate a vehicle. Future vehicles will afford the driver opportunities to decrease their active control of the vehicle through taking their hands off the wheel and taking their eyes and mind off the road. Driver State Monitoring (DSM) can be based on various methods of input, including vehicle control measures, duration of driving, and many others; however, camera-based methods are recognized to afford the greatest level of specificity in identifying risky behaviors and driver states. In an automated driving environment, a camera-based approach becomes even more critical given that other measures, including some vehicle-based measures, take on reduced significance for driver state estimation given the reduced interactions the driver has with the steering wheel and pedals. For these reasons, this approach to DSM is being actively pursued by almost all automotive original equipment manufacturers (OEMs).

In parallel, there is a huge drive by governments, regulatory bodies, academia, and the automotive industry to broadly introduce new measures to improve vehicle and road user safety. Over the past five years, the European Commission (EC) has been actively assessing a wide range of candidate technologies to reduce injury. A significant step in identifying potential new solutions was taken in 2015 when an EC commissioned report provided an overview of the feasibility of 55 candidate measures for possible inclusion in the revised General Safety and Pedestrian Safety Regulations (Hynd et al., 2015). The output of the study included indicative cost benefits to differentiate those measures that were deemed very likely, moderately likely, or very unlikely to provide a benefit consistent with the cost of implementation. Within the category of "Driver Interface, Distraction and ITS," "driver distraction and drowsiness recognition" was one of only two measures recommended for legislation, with a projected benefit cost ratio greater than one (Hynd et al., 2015).

Following much discussion over several years, the European Parliament approved measures in February 2019 to mandate the introduction of a range of new vehicle technologies. DSM, or occupant status monitoring, is one of the new safety measures that will be introduced into vehicles as a primary/active safety measure. It is a recommended approach to managing the risks associated with distracted and drowsy driving in non-automated vehicles. There is ample crash data available from organizations in the EC and from the United States (e.g., National Highway Traffic Safety Administration, Federal Highway Administration), and other regions across the world, that highlights the role of distraction and drowsiness in road crashes and the need to consider new approaches to managing these growing risks (see also, this Handbook, Chapter 9). DSM also has a key safety role in automated driving. While there is comparatively very little crash data available for automated vehicles due to their early phase of introduction to the market, emerging research papers (e.g., Favarò, Nader, Eurich, Tripp, & Varadaraju, 2017) have highlighted how driver behavior changes with these technologies and the threats to safety that need to be managed. There is considerable research, much reviewed elsewhere in this book, that points to drivers becoming "out of the loop" during automated driving (see, e.g., this Handbook, Chapters 7, 21). While the crash and incident data do not yet exist in sufficient number, it is almost certain that monitoring of the driver state is an essential crash prevention measure.

In parallel to recommendations to the European Parliament supporting the introduction of new technologies, in September 2017, the European New Car Assessment Programme (NCAP) 2025 roadmap was released that outlines targets for when these technologies will be incorporated into crash assessment protocols (Euro NCAP, 2017). Driver monitoring is introduced under Primary Safety, where it is noted that "Euro NCAP envisages an incentive for driver monitoring systems that effectively detect impaired and distracted driving and give appropriate warning and take effective action" (p.7; Euro NCAP, 2017). The roadmap also notes that "Effective driver monitoring will also be a prerequisite for automated driving, to make sure that, where needed, control can be handed back to a driver who is fit and able to drive the vehicle."

11.2 CURRENT APPROACHES TO DSM

Monitoring driver state is a primary safety measure for all forms of vehicle use. Hynd et al. (2015) review a range of methods for measuring drowsiness and distraction. It includes the following: physiological measures (e.g., ocular metrics); physical (e.g., posture); behavioral (e.g., steering inputs); and biomathematical models. In reviewing the available evidence for these different classes section F5.8 of the report concludes

> Overall, the literature indicates that eye feature detection is the most established measure for drowsiness monitoring and has the strongest evidence base for real-time detection. It is non-invasive and the latest (aftermarket) systems seem to be overcoming limitations associated with operator compatibility such as different eyewear and problems with low light. It can be combined with wider face and head detection methods using the same camera technology for improved accuracy.
>
> Of the other methods, vehicle control measures are typically most suited to highway environments as they are often based on steering inputs and lane keeping behaviour. For drowsiness monitoring they are more reactive than predictive.

> They perhaps have most relevance as part of a composite monitoring system that includes physiological measures. However, vehicle control measures are the most established method of drowsiness monitoring fitted by automotive manufacturers as original equipment. (p. 415)

While driver monitoring can potentially be done using different sensor inputs (e.g., Lenné & Jacobs, 2016), there is a consensus that camera-based driver monitoring is the best approach. This is particularly true for automated vehicles where traditional vehicle input measures are likely unavailable and vehicle metrics take on new meaning. Notwithstanding, even when vehicle-based metrics are available, there is an argument that these are more diagnostic of the driver state rather than impairment per se. For example, identifying that there is a lane departure is terrific from the safety viewpoint but provides more limited insight into the driver state that may lead to that safety event.

The following section discusses some measures and measurement approaches that are available in the literature for two of the more prominent driver states that will emerge during automated driving—distraction and drowsiness.

11.2.1 Distraction and Engagement

Driver distraction is defined as a diversion of attention away from those activities required for safe driving (Regan, Lee, & Young, 2008). In the context of automated driving this definition has evolved to acknowledge that automated vehicle technologies do allow the driver to take their focus away from the forward roadway for defined periods of time (see this Handbook, Chapter 9). Automated driving functions are likely to change the way a driver interacts with the environment, including gaze behavior, and therefore what is critical is the level of driver attentiveness or engagement for the conditions rather than only the time spent with attention directly away from the roadway.

Much of human factors research into driver state during Level 2 (L2) and Level 3 (L3) automated driving introduces the concept of the driver being "out of the loop" (Merat et al., 2018), defined as being "not in physical control of the vehicle, and not monitoring the driving situation OR in physical control of the vehicle, but not monitoring the driving situation." Recent research documents both the circumstances and the implications for performance and safety.

When assessing driver engagement there are three general distraction classes: manual, visual, and cognitive—or simply "hands on wheel, eyes on road, mind on driving" (Vegega, Jones, & Monk, 2013). Interventions to reduce manual distraction do improve response time but they do not improve visual or cognitive distraction (Victor et al., 2018). Visual attention is measured via glance behavior, with glance defined as the "maintaining of visual gaze within an area of interest, bounded by the perimeter of the area of interest" (ISO 15007-1, 2014). Visual and cognitive attention are more closely linked: improving visual attention may improve cognitive attention, and visual overfocus is an indicator of cognitive inattention.

Table 11.1 illustrates some of the distraction states and their involvement with each type of distraction. Drivers are fully attentive when they are directing

TABLE 11.1
Engagement States and Types of Distraction

State	Manually Engaged	Visually Engaged	Cognitively Engaged
Fully Attentive	Yes	Yes	Yes
“On the loop” (Merat et al., 2018)	No	Yes	Yes
Divided attention (Parasuraman, 2000)	Optional	No	Yes
“Out of the Loop” (Merat et al., 2018)	Optional	Yes	No
Completely disengaged	Optional	No	No

sufficient effort to drive effectively and are completely disengaged when they fail to direct substantive attention to the task. Divided attention is the phenomenon where attention is directed to two tasks, simultaneously, resulting in visual time sharing (VTS). “On the loop” is a state of active awareness without direct mechanical control, which may result in slightly slowed takeover due to motor skills adapting to task.

For over a decade, human factors research has measured visual distraction with eye behaviors in laboratory and field studies. Glance metrics are typically used to assess the impact of different in-vehicle display designs on driver distraction and mobile phone use. Due to this widespread acceptance, many research groups have developed statistical models or algorithms to assess or classify driver state in a more sophisticated manner. Many gaze algorithms classify disengagement and represent variations and modifications of several distinct concepts:

1. *Single Off-Road Glance Threshold*: Off-road glances should be minimal; those which exceed a threshold value (usually 2 seconds) are classified as “Distracted.”
2. *Attentive-Glance Threshold*: When drivers are considered as “Distracted,” on-road glances should be long enough for the driver to substantively improve their awareness of the road (usually 1 second) before drivers are re-classified as “Attentive” (e.g. Kircher & Ahlström, 2009).
3. *Multiple Short-Term Glances*: Assessment of gaze patterns should also account for multiple glances, as there may be no single glance that exceeds the threshold, but attention is clearly directed away from the road.
4. *Overfocusing*: Finally, it is possible to overfocus, and too much gaze fixation in one central location can be an indicator of cognitive distraction and multi-tasking. One common method is via ratios of central-vs-peripheral vision, such as implemented in “percent road center” (e.g., Victor, 2010, as cited in Lee et al., 2013).
5. *Speed-Based System Availability*: Accounting for differences based on speed helps identify differences in road types. Existing algorithms generally are designed for highway driving, and setting a cutoff for the algorithm’s operation based on speed helps exclude other driving contexts. Ideally, algorithms for multiple contexts could shift between modes.

6. *Differentiated Risk Regions*: Glances to different areas of the car carry different risks. Glances to the rear-view mirror are more relevant to driving than those to the driver's lap and should be weighted differently.
7. *Head-Tracking*: Gaze tracking requires a certain quality of video tracking the driver. When this is not available, a less-accurate approximation can be implemented from tracking the driver's head.
8. *Yaw Recalculated Road Center*: Gaze prioritizes the road center, which shifts and bends with the road's curves. Road center is shifted based on vehicle yaw.

The following are the four major algorithms that have incorporated one or more of the above concepts: AttenD (Kircher & Ahlstrom, 2009), AttenD as modified by Seppelt et al. (2017), the multi-distraction algorithm (Victor, 2010, as cited in Lee et al., 2013), and the multi-distraction algorithm as modified by Lee et al. (2013). The concepts that each of the algorithms incorporate are displayed in Table 11.2.

Instead of just classifying general "eyes off forward roadway" and "risky visual scanning patterns," the AttenD algorithm (Ahlström, Kircher, & Kircher, 2009; Kircher, Ahlström, & Kircher, 2009) compares eye movements to the world model of the vehicle, allowing for customization based on physical vehicle features. It distinguishes between three glance categories: forward roadway glances, safe driving glances (i.e., at the speedometer or mirrors), and glances not related to driving. Forward roadway glances (a visual angle of 90° side-to-side and the vehicle windows, excluding the mirrors) increment an attention buffer at 1 unit per second up

TABLE 11.2
Gaze Algorithm Feature Classification

	#1: Single Off-Road Glance	#2: Single Attentive Glance	#3: Multi-glance	#4: Overfocusing	#5: Speed Cutoffs	#6: Risk Regions	#7: Head-Tracking	#8: Yaw Center
AttenD: Kircher and Ahlström (2009)	x	x	x			x		
AttenD: Seppelt et al. (2017)	x	x	x	x				
Multi-Distraction: Victor (2010)	x		x	x	x			
Multi-Distraction: Lee et al. (2013)	x		x	x	x	x	x	x

to 2 seconds (after a 0.1 second latency), whereas glances to rearview and speedometer less than 1 second are buffer-neutral, and glances elsewhere decrement from the attention buffer at 1 unit per second.

Seppelt et al. (2017) made modifications to AttenD, and though the specifics remain proprietary, three updates are noted: changes to the increment rate of attentive glances (#2, Table 11.2), changes to latency delay effects prioritizing off-road glance region durations, and addition of an Overfocus component to detect cognitive distraction (#4, Table 11.2). Most notably, this suggests the importance of recognition of cognitive distraction, and that the time required to form a reliable model of the roadway is not 2 seconds (though it remains unclear whether it is more or less).

Victor (2010, as cited in Lee et al., 2013) developed the Multi-Distraction algorithm to identify both visual and cognitive distraction in real time through measurement of Percent Road Centre (PRC; the proportion of time focusing on a 10° radius circle, centered on the driver's most frequent point of gaze on the forward roadway). At speeds above 50 km/h, three major time windows are considered: a long single glance, a shorter PRC below 60%, and a longer PRC exceeding 92% (Figure 11.1). An additional PRC window is implemented to capture VTS, where drivers are classified distracted if PRC decreases to below 65% and subsequently increases above 75% within a 4 second window. This approach does not account for different off-road regions or differentiate between driving-related and non-driving-related glances.

Building on the original Multi-Distraction, Lee et al. (2013) made four modifications in developing their implementation: (1) if sensor quality degrades, tracking shifts from considering gaze, to head position, to posture; (2) the cognitive distraction PRC threshold is decreased to 83%; (3) speed thresholding is implemented to limit tracking to speeds over 47 km/h, with imposed hysteresis to prevent rapid switching across a single value; and (4) the center cone shifts based on vehicle yaw.

Lee et al. (2013) concluded that the modified Multi-Distraction algorithm demonstrated a comparative advantage (True Positive: 90+% vs. 70%–90%; False Positive: 40%–60% vs. 10%–30%). However, this assessment predated Seppelt et al.'s (2017) modifications. Also noteworthy are the six years of improvement in hardware and eye tracking that have occurred since publication.

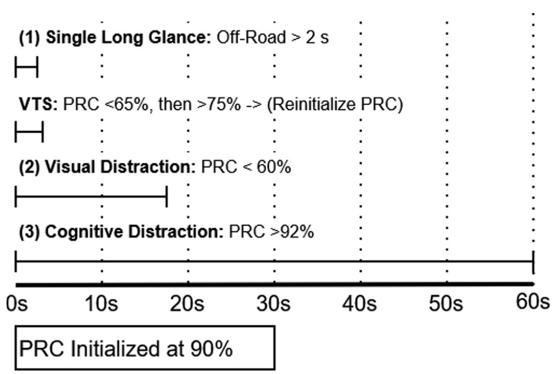

FIGURE 11.1 Representation of the multi-distraction algorithm. (Victor, 2010.)

11.2.2 Drowsiness

Alongside distraction, driver drowsiness remains a significant contributing factor to road crashes worldwide. The National Highway Traffic Safety Administration (2008) estimated that there are 56,000 crashes each year, in which drowsiness or fatigue was cited by police as a causal factor. These crashes lead to, on average, 40,000 non-fatal injuries and 1,550 fatalities per year. Driver drowsiness in the context of L2 and L3 driving remains a nascent field of research at the time of writing. However, drivers' tendency toward disengagement and "out-of-the-loop" states under automated driving, as previously discussed, would suggest the continued prevalence of and critical need to examine this form of impairment (see also, this Handbook, Chapter 9).

While electroencephalography (EEG) is often regarded as the gold standard for objectively quantifying discrete stages of sleep, existing research on its applicability to the transitional stage of drowsiness has yet to yield conclusive results. Significant variability exists in both how participants are observed as well as which candidate signals are proposed for analysis (Ahlström, Jansson, & Anund, 2017; Hung et al., 2013; Perrier et al., 2016). In contrast, greater consistency has been reported from research on ocular measures of drowsiness (e.g. Barua, Ahmed, Ahlström, & Begum, 2019). In practical terms, there is the additional advantage of using an unobtrusive, camera-based system for measuring ocular metrics (a method that, as of yet, has not been developed for measuring neural activity).

With respect to ocular measures, PERCLOS continues to be used as a drowsiness indicator (Jackson et al., 2016; McDonald, Lee, Schwarz, & Brown, 2014), though implementation and statistical approaches differ. PERCLOS is a measure of the proportion of time that the eyes are closed, or nearly closed, over a given period of time, typically between 1 and 20 minutes. The accepted use of the term PERCLOS refers to the proportion of time eyes are more than 80% closed (i.e., based on the degree of eyelid closure; Wierwille, Ellsworth, Wreggit, Fairbanks, & Kirn, 1994), although how this is determined does vary. Early studies used PERCLOS to assess drowsiness as established by performance on the Psychomotor Vigilance Task (PVT) and reported greater coherence in PERCLOS when longer time windows were used. The research by Dinges, Mallis, Maislin, and Powell (1998) found that PERCLOS was a more reliable indicator of drowsiness when considered minute-by-minute over a 20-minute window compared with shorter durations of 1 or 2 minutes, hence recommendations were made to use a 20-minute window. In these studies, PERCLOS is calculated through examination of video by manual annotators who make assessments on the degree of eye closure compared with a set of reference images. As discussed following, more recent studies have examined PERCLOS in driving studies predominantly conducted using driving simulators, for example, to use PERCLOS to either establish a level of drowsiness in a given sample or condition over a period of time.

In recent studies, there is greater interest in the use of real-time assessments of drowsiness to link with much more specific safety-related events, such as lane departure events, steering movements, and micro sleeps and other eye and facial metrics. By necessity, the 20-minute PERCLOS time window is reduced in these studies to increase the confidence that the potential drowsiness level determined through PERCLOS applies to a time at which the driving behavior of interest occurred.

When this approach is taken, the performance of PERCLOS is not as good as found with longer time windows. For example, McDonald et al. (2014) in a driving simulator used a 2-minute window and found poorer performance of PERCLOS compared with both previous research and also a novel steering-based algorithm for the detection of drowsiness associated with lane departure events. One potential explanation provided for the poor PERCLOS performance is that the 2-minute PERCLOS time window is indeed too short to accurately detect acute drowsiness associated with lane excursion events.

Related to PERCLOS, blink duration is another metric that has received considerable attention in drowsy driving research. In a study of real-world driving, Hallvig, Anund, Fors, Kecklund, and Akerstedt (2014) reported intra-individual mean blink duration to be a significant predictor of unintentional lane departures. The importance of warning latency cannot be overlooked in an operational real-world system and, in comparison to existing implementations of PERCLOS, measures of blink duration are generally able to perform closer to real time. An extension to this concept is the idea of a pre-drive assessment of fitness to drive. Using a camera-based driver monitoring system, Mulhall et al. (2018) demonstrated the significant predictive ability of mean blink duration measured before a drive on subsequent, real-world lane departure events.

As a caveat to the studies described above, it is important to note the critical distinction between DSM versus driver *eye tracking*. While the aforementioned metrics show significant promise in the real-time measurement of driver drowsiness, unidimensional ocular features form but one component of the multi-dimensional problem space that is driver state. A simple example of this can be seen in that of the drowsy driver who, with the vehicle safely stopped at a red light, voluntarily rests his/her eyes compared with the drowsy driver who suffers a microsleep event while the vehicle is in motion.

These issues are further confounded by interactions *between* driver states, where drivers have been shown to have an increased propensity toward distracting behavior following sleep deprivation (Anderson & Horne, 2013; Kuo et al., 2019). DSM systems based solely on canonical eye tracking metrics such as eyes-off-road time or eye closure are unlikely to provide the insights necessary to infer high-level driver state. This is especially pertinent in the context of autonomous driving where there is a fundamental shift in the nature of the driving task and objective risks of behaviors typically associated with safety critical events.

11.2.3 Automation-Driven Changes to Driver State

While DSM technologies are relevant for manual driving, their inclusion is driven by OEM autonomous technology development. However, increasing vehicle automation changes driver's behavior, their relationship with the vehicle, and the operating context. Drivers are accustomed to direct control and changing their role to a supervisor of automation can generate confusion and discomfort if they must drastically increase their vigilance (see also, this Handbook, Chapters 6, 7). Even in cases where individuals are skeptical of the car's ability to respond appropriately to a given event, their uncertainty slows reaction times and prevents resumption of control (Victor et al., 2018). As we require less-and-less of the driver there will be fewer indicators to determine their capability to intervene, and the indicators we do have may change. For instance, automated lane-keeping features change the requirement for drivers to visually monitor their lane position, and consequently change their scanning behavior. Shifting driving from motor-control to monitoring, driver visual behavior will change to match the task, widening the visual range that drivers scan (Louw & Merat, 2017). Further, steering is only useful as a measure of driver state when the driver is in control.

While there are vastly differing opinions on the rate at which different levels of automated driving features will be widely adopted on roads around the world, it is apparent now that the jump to mass-available autonomous vehicles is not coming all at once. Rather it is likely that waves of vehicles with Level 1 to Level 5 automation functionality will coexist on the road with widespread regional variation. It remains to be seen if dense regional centers will have rapid autonomy adoption, mirroring technologies such as cell phones and internet, as some anticipate (Litman, 2019; Corwin, Jameson, Pankratz, & Willigmann, 2016), but this will likely be determined by the degree of dependence on infrastructure improvements. For instance, GM Super Cruise automation has succeeded by implementing geofencing within regions that have been Light Detection and Ranging (LIDAR)-mapped in advance, an approach more beneficial for heavily traveled routes.

Currently, the age of the average vehicle on U.S. roads is 12 years, with 10% of vehicles being older than 20 years (Federal Highway Administration, 2017); if this pattern holds, half of the vehicles on the roads of 2030 are already here. This mixed fleet means that different levels of automation will have to interact with each other and human drivers who must anticipate behavior, changing and invalidating old patterns (see also, this Handbook, Chapter 19). New drivers will eventually lack familiarity with old modes of driving. Just as a 99.99% reliable anti-lock braking system (ABS) will result in new drivers with no concept of “pumping the brake,” some drivers may only be truly qualified to “drive” in geo-fenced areas. With increasing automation, DSM must be able to identify a wide range of driver capabilities and determine an appropriate level of engagement for the specific automation and driving context.

11.3 FUTURE DIRECTIONS AND APPLICATIONS IN DSM

Rapidly evolving trends will change what drivers need and expect to meet their goals around safety, comfort, and convenience. The automotive industry has converged toward the development, implementation, and recommendation of camera-based DSM technologies, which will be rewarded in future crash assessment programs. DSM’s early generations target both known and emerging risks to safety and will identify driver states including drowsiness, distraction, inattention, and disengagement from driving. Future applications may recognize mental workload and emotion, or other forms of impairment, such as medical conditions that result in incapacitation (see, e.g., this Handbook, Chapters 10, 17). Additionally, given the studies which show that drivers who have high levels of trust are especially likely to over-rely on their technologies, willing to let the vehicle travel outside of the operational design domain (Victor, 2010), algorithms are needed which can measure levels of driver trust using camera-based technologies. Progress has already been made in that regard (Hergeth, Lorenz, Vilimek, & Krems, 2016).

Drivers experiencing medical distress will be identifiable by their vehicles. Current detection of driver drowsiness and attention needs to expand to handle cases of unresponsive drivers, such as those experiencing cardiac arrest. Modeling advances may identify conditions such as obstructive sleep apnea, which is reportedly undiagnosed in 80% of cases, is more frequent in commercial fleets, and can cause excessive driver sleepiness (Bonsignore, 2017).

Emotionality is also of interest. While emotions do not *cause* action, they do motivate pursuit and avoidance of certain actions and increase or decrease risk aversion (Baumeister, Vohs, DeWall, & Zhang, 2007). Strong negative emotions (e.g., anger, sadness, frustration, etc.) require effort to manage and process, a form of cognitive distraction that can impact driving performance (Jeon, 2016).

Emotion recognition could also mitigate and model driver risk on an individual and aggregate level (e.g., identifying problem features within a city or vehicle fleet), help build more effective coping countermeasures, and even provide useful data fusion with existing gaze classification algorithms.

Emotional recognition has a variety of approaches: facial expression detection, voice analysis, brain scanning, physiological measures, body posture, and combinations thereof. Facial recognition is widely explored, with many applications of the Facial Action Coding System (FACS), which maps small movements in the face to Ekman et al.'s (1987) "six universal emotions" (disgust, sadness, happiness, fear, anger, and surprise). Voice is effective for interpersonal communication but is less relevant in driving. Brain scanning and physiological measures give a massive level of information on driver experience but interpreting the importance of any specific event requires a mature understanding of context as well as skillful and timely processing. Further, many powerful measures are also prohibitively invasive, making them useful only in research settings. Most of these methods are interesting, alone, but the real value lies in aggregation. For instance, body posture's strongest benefits occur when coupled with facial recognition (Aviezer, Trope, & Todorov, 2012). For a detailed methods review, we recommend Calvo & D'Mello (2010), Zeng, Pantic, Roisman, and Huang (2009), and Mauss and Robinson (2009).

Emotion tracking has its challenges. First, Ekman's six universal emotions vary in relevance to driving (Jeon & Walker, 2011) (e.g., disgust versus anger), and the claimed universality may be less reliable across cultures (Gendron, Roberson, van der Vyver, & Barrett, 2014; Russell, 1994). Further, most recognition algorithms are trained on posed emotions in ideal conditions, not the messily framed, naturally occurring emotions that are critical. Finally, to find social acceptance, emotion recognition must navigate difficult personal boundaries between observation of others' feelings and how polite it is to mention them.

11.4 HUMAN FACTORS AND SAFETY CONSIDERATIONS

Many issues must be addressed to move the industry from policy to practice, and to fully realize the benefits of driver monitoring technology. What should the minimum viable technology concepts be? For non-automated driver state measurement, the EC focuses on measuring distraction and drowsiness. These driver states can be defined and operationalized in different ways, and the implications for effectiveness are of critical concern. By necessity, there is a tension between OEMs accounting for cost and driver experience and regulators who must ensure public safety, with both priorities meriting consideration.

11.4.1 Identifying Emerging Risks

How do we ensure we learn what is happening in the real world and that these insights inform technology enhancements? Identifying the role of driver state in studies of crashes and near misses is going to be a challenge. It is likely that surrogate measures, such as takeover performance (however it may be defined) will be pivotal to assessing real-world risk until larger bodies of near-miss and incident data become available. To move forward and to continue to develop effective solutions to impairment, we must ensure we have the best understanding of the role of and types of driver states leading to crashes.

11.4.2 Interfacing with the Driver

To achieve the desired road safety improvements any driver monitoring system needs to not only effectively measure driver state but also determine the most effective time and method to communicate with the driver and/or the vehicle. According to Hynd et al. (2015), measurement thresholds and parameters are keys to DSM performance. Systems with low specificity may have high false positive rates. Further, industry stakeholders advised that warning thresholds and intrusiveness should not be irritating for drivers. An effective interface underpins the success of systems that interact with the driver and must be carefully considered (see also, this Handbook, Chapter 15).

This is particularly the case for drowsiness. Research with the Monash University Accident Research Centre has shown that multiple levels of driver feedback are required to maximally reduce the rate of drowsy driving events. Two feedback mechanisms, in-cab driver feedback and feedback to the company, were evaluated in an Australian fleet from 2011 to 2015 (Fitzharris et al., 2017). Relative to conditions where no feedback was provided, in-cab warnings to the driver resulted in a 66% reduction in drowsiness events, with a 94% reduction achieved with the provision of real-time feedback to the company in addition to in-cab warnings to the driver.

This second level of feedback has important implications for drowsiness-related human–machine interface (HMI) design in passenger and light commercial vehicles: it allows the employer to assess and manage drowsiness in real time and eliminates false positives. When an in-vehicle drowsiness alert is activated in a passenger vehicle the driver will need to make the right decision with this information available—which inevitably would involve an effective drowsiness mitigation that might include a break of some sort, ideally a power nap or longer sleep. According to research, this is unlikely to occur in a notable portion of passenger car drivers without an employer (or creative alternative) overseeing their driving. A call-back service or a smart vehicle assistant could interact with the driver after a warning, assess their drowsiness, guide them to an appropriate resting place, and ensure that an effective mitigation strategy is adopted. This function would also minimize false positives, directly improving driver acceptance—a critical issue given that even lifesaving systems, such as lane departure warnings, may be deactivated by drivers due to unacceptable annoyance levels.

Similar findings have also been reported in the context of driver distraction. Kujala, Karvonen, and Mäkelä (2016) tested the efficacy of a proactive smart phone-based distraction warning system that adjusted warning thresholds according to the expected visual demands of an upcoming driving situation, feeding information back to the driver in real time. The system detected visually high-demanding driving scenarios in which visual distraction would be particularly dangerous (based on factors such as the experience level of the driver and the proximity of intersections and pedestrian crossings ahead) and aimed to identify when the driver was looking at the phone.

The closed test track study design showed that the distraction warning system significantly increased glance time on road while multi-tasking with the mobile phone. However, no effects on individual in-car glance durations were evident, although, as noted by the authors, this may have reflected limitations associated with the gaze tracking system that was used. These results further highlight the codependency between accurate DSM and HMI in developing an effective system.

It seems inevitable that the future vehicle will modify its performance and/or take over control when it senses driver impairment. If a driver is drowsy, the vehicle could take many measures, such as alerting the driver and providing a time window to find a rest stop before disabling the engine; limiting speed; increasing the sensitivity of lane departure and other ADAS systems; communicating with nearby vehicles to coordinate passing and following distances; enabling autonomous driving; engaging the driver in conversation; guiding them to a rest stop; and so on.

11.5 CONCLUSION

Many regions in the world are striving toward the Vision Zero philosophy first implemented in Swedish Parliament in 1997. Technologies such as driver monitoring are acknowledged in EC documents to hold promise in reducing road injury. The design and implementation of these technologies will determine whether they have minimum or maximum injury reduction benefits.

There is much excitement, energy, and skepticism surrounding talk about the autonomous future and separating reality from fiction. What the introduction of autonomous vehicles has done is to get camera-based DSM into a vehicle to maintain driver safety when operating a vehicle in autonomous mode. Automation notwithstanding, this affords future benefits in non-automated driving to address longstanding risks with distraction and drowsiness. The issues noted herein must be carefully considered, however, if DSM technology is to achieve maximum benefits in reducing road injury.

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