Trucking Fleet Concept of Operations for Automated Driving System-equipped Commercial Motor Vehicles

Chapter 5.4 Test Driver State Monitoring

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Abstract

Automated Driving Systems (ADS) are set to revolutionize the transportation system. In this project, the research team led by the Virginia Tech Transportation Institute developed and documented a concept of operations (CONOPS) that informs the trucking industry, government agencies, and non-government associations on the benefits of ADS and the best practices for implementing this technology into fleet operations.

The sections of Chapter 5 provide guidance on a range of topics for fleets to consider and apply when preparing to deploy ADS-equipped CMVs in their fleet. The topics cover fleet-derived specifications, ADS installation and maintenance, ADS inspection procedures, driver-monitor alertness management, insuring ADS-equipped trucks, identification of ADS safety metrics/variables, ADS road assessment, and data security/transfer protocol and cybersecurity best practices.

This section explores the integration of Driver State Monitoring (DSM) technologies with Automated Driving Systems (ADSs) in commercial motor vehicles (CMVs). The research identifies key challenges and opportunities in leveraging DSM to enhance safety operator vigilance and readiness during ADS operation. Through a three-phase approach, including a literature review, industry interviews, a technology scan, and on-road testing, the study highlights the complexities associated with DSM-ADS integration. Findings underscore the need to improve the accuracy and reliability of DSM systems to mitigate false alarms and inaccuracies that may compromise ADS decision-making. Furthermore, the study emphasizes the importance of designing DSM technologies as supportive tools for safety operators rather than strict supervisors. Future research directions include enhancing DSM system performance across varied driving conditions, exploring their impact on safety operator behavior, and investigating their role in informing ADS decision-making processes. By addressing these challenges and pursuing outlined research avenues, stakeholders can advance the understanding and implementation of DSM technology in the context of automated driving, fostering safer transportation systems.

This report may be useful to fleets, ADS developers, monitoring technology developers, policy- and decision-makers, and safety operators in recognizing the need for implementation and the current capabilities of DSM technologies.

The following chapter has been extracted from the final report. For access to the full report, see this link: https://www.vtti.vt.edu/PDFs/conops/VTTI_ADS-Trucking_CONOPS_Final-Report.pdf

5. GUIDELINES

5.4 TEST DRIVER STATE MONITORING

On April 6, 2022, a CMV operating with automation active while being monitored by a test driver or safety operator veered left into a median.(1) The safety operator was able to regain control of the vehicle, and the CMV suffered only minor scrapes. However, the integrity of testing prototypical ADS on public roadways was again brought into question.

The Automated Vehicle Safety Consortium (AVSC) is considered the guiding body for developing principles to lead industry-wide standards for ADSs. The AVSC(2) published a "best practices" report for in-vehicle fallback test drivers, or safety operators. These terms are considered synonymous, but this section will refer to these drivers as safety operators. The role of a safety operator is to "supervise the performance of prototype Level 4 (L4) ADS-operated vehicles in on-road traffic for testing purposes."(3) The safety operator is responsible for responding to unexpected scenarios where the ADS acts incorrectly or even hazardously; however, these failure events are not frequent. Therefore, these drivers are highly trained in vigilance maintenance and uphold strict selection criteria. In addition to taking frequent breaks to maintain vigilance, drivers are prohibited from tasks that may impede their ability to drive a vehicle. These tasks include using personal electronic device use, eating, smoking, vaping, and alcohol or drug use. Unique to safety operators, an attentive driver is discouraged from engaging in conversation irrelevant to the driving task and is encouraged to always maintain hand position on or near the steering wheel.

The necessity for these operators is evidenced by the April 6 incident in which an ADS-equipped CMV executed a dangerous maneuver on a public roadway. The attentive safety operator reacted swiftly and correctly to prevent a potentially more serious crash. A similar incident detailed in a 2019 National Transportation Safety Board Accident Report(4) involved a light-vehicle safety operator driving an Uber equipped with Uber's ATG Developmental ADS. Unlike the attentive safety operator who had both hands on the wheel and was constantly monitoring the roadway to anticipate a takeover, this operator was interacting with a personal device when the system transferred emergency control due to a foreign object detected in the roadway. Due to several factors, including the driver's inattention, the safety operator did not assume control of the vehicle and it fatally collided with a pedestrian.

These cases exemplify the need for an actively engaged and attentive safety operator when operating L4 ADS-equipped vehicles. The AVSC report(5) defines criteria for safety operator selection, training, and expectations and recommends equipping ADS test vehicles with a driver state monitoring (DSM) system to ensure the driver is fit to assume control during an emergency takeover request. DSM systems are designed to track metrics (i.e., physical, physiological, psychological, and/or behavioral variables) that may be indicative of driver inattention or inability to react appropriately. There are many applications of DSM, including those for ADS-equipped vehicles. Although there are many recommendations from the AVSC, there are no standardized requirements for individual fleets. This means each ADS developer is responsible for assigning specific tasks to the safety operators. Therefore, it is unknown exactly what a safety operator's responsibility is to ensure the vehicle is operating appropriately.

The purpose of this investigation of DSM technology and practices was to compile available information through a detailed literature review and outreach about DSM and compare commercially available systems on the market through a technology scan and exploratory evaluation. The following sections outline the findings from each of these collection techniques.

5.4.1 Information Collection

The literature review sought to establish information about specific driver state metrics and thresholds for takeover ability relevant to a CMV safety operator. For example, it was unclear which physiological or behavioral metrics (e.g., heart rate [HR], eye-glance behavior, posture, hand position) translate to specific driver capacity. Specifically, this literature review determined specific driver characteristics that may impact readiness to take control of an ADS vehicle and the metrics or thresholds indicative of a driver's state. Additionally, the review considered the differences in thresholds of driver states necessary for a safety operator who is highly trained as an ADS-equipped CMV safety operator versus a typical CDL holder operating an ADS-equipped CMV. For example, a safety operator may be held to a higher attentional standard due to the unpredictability of an ADS malfunction. For the benefit of future research, the results from this literature review provided insight into the types of DSM technologies (i.e., sensors) that warrant specific testing in an ADS-equipped CMV to monitor the safety operator appropriately.

5.4.1.1 Literature Review Methodology

The initial literature search involved reviewing databases in the transportation industry such as the Transportation Research Information Services & Documentation Database (TRID), the Repository & Open Science Access Portal (ROSAP), and the Virginia Transportation Research Council (VTRC) database. The search was expanded to target publications from the Institute of Electrical and Electronics Engineers (IEEE), ResearchGate, ScienceDirect, and PubMed to consider physiological measures of human state not yet introduced to the transportation industry. The query terms used for each database included *driver monitoring* and *state detection*, and more specific searches for each individual driver state included *distraction detection*, *drowsiness detection*, etc. The resulting literature consisted of 91 papers detailing DSM research and criteria for defining various human states. Several papers were excluded from the final review due to (1) irrelevance to the driving context such as blood work or other invasive medical devices, (2) a lack of converging evidence, and (3) investigating irrelevant features of DSM relative to the scope of this literature review such as light-vehicle applications or vehicle-based metrics. Eighty-one papers remained for inclusion in the final literature scan. These papers were selected based on their relevance to DSM in the context of ADS-equipped CMVs or their contribution to understanding how to define and monitor a driver's state while in a vehicle. The following sections detail the results of the literature review and provide an understanding of how to effectively monitor a safety operator using DSM technology.

5.4.1.2 Driver Sate Monitoring

Halin et al.[(6)] conducted the most comprehensive review to date of DSM literature and relevant concepts. This review builds on Halin et al. by considering the unique perspective of the safety operator and adding updated technology, but the current review is narrower in scope due to solely addressing DSM in the context of safety operators of prototype ADS-equipped CMVs. The five important driver states discussed in this paper are drowsiness, mental workload, distraction, emotions, and driving under the influence. The following sections outline (1) how the literature defines these respective states, (2) the behavioral and physiological metrics used to indicate the respective states, (3) sensors that can be used to assess the metrics in a driving context, and (4) considerations for safety operators.

The most common and accurate identifiers of a degraded driver state are driver performance variables determined by vehicle-based metrics.[7,8] Vehicle-based metrics include following distance, lane deviation, and speed variability that can indicate diminished driving ability. However, Leicht et al.[9] pointed out that vehicle-based metrics only change once a driver's state begins to impact performance of the vehicle. Thus, a more proactive detection method is needed to effectively prevent performance degradation. Additionally, ADS-equipped CMVs are designed to maintain control of the vehicle, so vehicle-based metrics are irrelevant measures for safety operators who are monitoring the ADS for malfunctions. For the successful integration of DSM systems into ADS-equipped CMVs, the determination of driver state should be done proactively and through measures that do not require a driver's influence on the vehicle. For these reasons, all indicators discussed in this paper are driver-based. Driver-based metrics include behavioral indicators (i.e., yawning, holding a phone, eye position) and physiological indicators (i.e., HR, pupil dilation) that monitor a human's level of awareness regardless of the ADS operating performance.

5.4.1.3 Driver State: Distraction

Driver distraction is defined as a mismatch between a driver's attention and the attention needed to safely perform the tasks required to operate the vehicle.[10] These "activities" fall into four main categories based on the source of distraction: visual, manual, auditory, and cognitive. Visual resources are needed for most driving tasks, while the remaining tasks are allocated to auditory, tactile, and haptic resources.[11] Therefore, visual distraction is one of the most frequently studied forms of distraction and is caused by activities such as reading a text message or any activity that causes the eyes to look away from driving-relevant information. Safety operators are prohibited from using cell phones, but cell phones are only one cause of visual distraction. Manual distraction occurs when the hands, body, or feet required for the driving task are performing irrelevant activities such as reaching for a purse or adjusting the air conditioning. Cognitive distraction, such as being lost in thought or problem solving, is one of the most elusive forms of distraction because it is difficult to observe. The final category is auditory distraction, which can occur when a driving-irrelevant sound (e.g., radio, music) masks a driving-critical sound (car horn, emergency vehicle) or when an auditory input such as speech uses cognitive resources that diminish performance on a driving task.[12] A task may result in one or some combination of all these forms of distraction. For example, texting while driving is considered a visual-manual distraction due to the use of both the hands and eyes to complete the task, but it also requires cognitive resources. Although many researchers have defined distracted driving, few have defined the parameters of an attentive driver. Kircher and Ahlstrom[13] defined an attentive driver as one who sufficiently samples enough information to meet the demands of the driving task. Therefore, an effective DSM system should be able to accurately identify each form of distraction to alert the ADS of possible inattention.

Gaze patterns are one of the best behavioral indicators for determining manual and visual distractions. There are different ways to characterize gaze behavior. One method is Percent Road Centre (PRC), or the percentage of gaze points that fall within the road center. If a driver is not looking at the road center for the majority of the time interval collected, they are considered distracted. The average PRC of a baseline driver is 70% to 80%. PRC above 92% is considered cognitive distraction and below 58% is considered visual distraction.[14] This method fails to consider other areas of the vehicle where a driver may look to assess safety-relevant information such as mirrors or cross traffic. Therefore, a more popular method used to determine gaze behavior is gaze duration, which assesses whether a driver is actively looking in a direction relevant to the driving task. Two methods are commonly used to identify gaze behavior: eye/facial landmark detection or head position. The driver's head position and eye pose are determined by using computer vision detection of major facial landmarks and pupil detection. An algorithm then classifies the positions of these features using decision pruning. Fridman et al.[15] considered six major "driving-relevant" regions: road, center stack, instrument cluster, rear-view mirror, and left and right mirrors. One issue with this method is that it fails to account for driving-relevant tasks outside these specific gaze zones, such as cross traffic when entering an intersection. A proposed method to account for this issue is the attentional buffer technique. Ahlstrom et al.[16] used an attentional buffer of 2 seconds in any gaze direction to define "situational awareness" as opposed to attention. These authors asserted that if the driver looks too long in any one direction, they are not gathering and searching for more information relevant to the driving task. Several studies support the attentional buffer due to findings indicating that longer fixations denote cognitive distraction and shorter fixations denote visual distraction, regardless of direction.[17,18,19]

Another method used to detect driver distraction is monitoring the driver's positions and interactions with other objects in the vehicle. Yan et al.[20] used hand monitoring and driver position algorithms to assess six categories of behavior: talking on the cell phone, eating while driving, shifting gears, hands on wheel, phone use, and smoking. Due to the lack of standardization of safety operator tasks, it is unclear what secondary tasks a safety operator may be able to perform when monitoring the ADS-equipped CMV. Zhao et al.[21] and C. Yang et al.[22] outlined the benefit of monitoring posture and foot position as a way of determining whether a driver is ready to take over a vehicle. If a driver's feet are not near the pedals, nor their hands near the steering wheel, they cannot be expected to react to an emergency takeover request in a timely manner. Safety operators are encouraged to keep their hands near the wheel at all times, yet each fleet can individually decide the extent to which they do so. Therefore, a DSM system specific to safety operators should assess whether a driver is abiding by this practice.

Researchers have mostly used camera-based systems to monitor observable behaviors because computer vision and AI can be used to extract information from the driving scene. Several studies used infrared light (IR) cameras to record video from participants due to their ability to capture changes in facial landmarks in complete darkness. The cameras were all mounted on the dashboard pointed at the driver's face.[23,24,25] Other researchers used an eye tracking software that combined information about head movement, eye opening, pupil activity, and blink behavior to understand distraction in two different camera-based studies.[26,27] All aforementioned studies commented on the difficulty of using camera-based detection due to the interference of the driving environment. For example, varying levels of illumination, vibration, and items that can block the sensors are typical challenges in determining the type of sensors to use. IR lights or cameras with IR technology help with nighttime driving because they illuminate the human's face even in complete darkness, but they are sometimes impeded by drastic variations in lighting such as broad daylight.[28]

One unique exception to the benefit of observational measures of distraction is cognitive distraction. It is difficult to outwardly observe cognitive distraction, so a few researchers have investigated the value of physiological measures such as brain activity and attempted to assess this type of distraction.[29,30] These studies suggest that arithmetic and conversational loads cause the focal points of the eyes to narrow and overall gaze direction to become concentrated to a particular range. Therefore, by combining pupil diameter, gaze direction, and HR, these studies were able to improve the detection rate over simply using gaze behavior. McDonald et al.[31] concluded that perinasal perspiration, palm electrodermal activity (EDA), HR, and breathing rate were effective in distinguishing an attentive driver from a cognitively distracted one. Although it may be difficult to assess the masking qualities of sounds in the vehicle to safety critical sounds in the environment, auditory distraction that induces cognitive distraction elicits similar behavior in drivers.[32] However, these metrics were combined as one illustration of driver state, so it is difficult to say if one of these measures alone was the contributing factor or if using all metrics combined produced the most accurate results. Similarly, although these metrics were seen as valuable contributors to the picture of driver state, it is questionable how feasible it is to put these sensors in a driving environment or implement them in an ADS-equipped CMV. Safety operators are banned or strongly discouraged from most visual-manual distraction activities (cell phone use, eating, smoking, etc.), so they are most susceptible to cognitive distraction. Therefore, extra care should be taken to find effective methods for detecting cognitive distraction.

5.4.1.4 Driver State: Drowsiness

Drowsiness is the physiological desire to fall asleep.[33] This is not to be confused with fatigue, however, which is the feeling of exhaustion or tiredness that occurs after mental and physical over- or under-exertion.[34] Although the motivations and variables that influence each of these states should be differentiated, their effect on driver safety is similar. Both states are characterized by mood alteration, impairments of psychomotor performance, poor decision-making, reduced reaction time, and other attentional issues that all increase performance errors and crash risk.[35,36] Drowsiness and fatigue are major concerns for CMV drivers, as the demands of a professional driving career often involve irregular sleep hours, long periods of hypovigilance, and highly demanding tasks.[37,38] In this report, drowsiness monitoring will be covered in this section, while fatigue, which is typically indicated by mental workload, will be discussed in the following section.

Because drowsiness is a physiological impulse similar to hunger or thirst, it is most accurately measured through physiological indicators. The most researched physiological indicators for drowsiness are heart rate variability (HRV), skin conductance, breathing rate, pupil response, and brain waves.[39] Sahayadhas et al.[40] illustrated that HRV can be a valid physiological measure of drowsiness. An electrocardiogram (ECG) is a common method used to measure HRV. However, direct contact with skin is necessary, which causes issues for use while driving or discourages people from using it consistently. There are some watch models, finger rings, and patches available on the market,[41] but these devices require the user to put them on, keep them charged, or keep them clean; therefore, the feasibility of implementing these devices into ADS-equipped CMVs is questionable. Similarly, CMV drivers frequently enter and exit the vehicle to unload cargo and interact with customers, so any device that requires constant removal or adjustment would be especially bothersome. Another valid measurement of drowsiness, often used in the medical field, is monitoring electrical brain activity.[42] Using an electroencephalogram (EEG), the activity of theta band (4–8 Hz), which is associated with drowsiness, can be compared to the beta band (13–25 Hz), which is associated with alertness, to measure drowsiness. Awais et al.[43] combined an EEG sensor that measured brain activity and an ECG sensor that measured HRV and achieved a 90% accuracy rate for detecting drowsiness, which illustrates a common understanding that combining methods is more effective than using a single indicator. However, EEG and ECG devices are highly invasive when considering the driving environment. Some research has investigated the effectiveness of wearable technology or sensors that are integrated into steering wheels, seat belts, or seats, but the motion artifacts from wearable technology testing can decrease the clarity of the signals.[44, 45, 46, 47] Jeanne et al.[48] investigated the use of a camera-based HR monitoring system in the variable lighting conditions that characterize the driving environment. An IR-based remote photoplethysmography (PPG) camera system was used to detect micro-blushes in the skin of a driver to measure the HR and HRV. The authors achieved a 99% accuracy rate when comparing this with ground truth metrics. Another study achieved similar results by using PPG imaging.[49] Although HR has shown less correlation with drowsiness than HRV, there are studies that have shown correlation between decreased HR and self-rated sleepiness.[50] Considering the improvements from combining multiple metrics, a case can be made for improving the validity of HR as a measure of drowsiness by combining it with other camera-based indicators.

Behavioral indicators of drowsiness are more easily identified using camera-based methods. Wierwille and Ellsworth[51] developed a continuum of rating drowsy behaviors called the Observer Rating of Drowsiness (ORD). This continuum defines the stages of drowsiness by observable mannerisms such as rubbing the face or eyes, scratching, glassy-appearance, fixed gazes, and eventually prolonged eye closures, lack of activity, and microsleeps. These observations were made by human raters, and the study concluded that rater assessment is a viable method of drowsiness assessment using video images of the vehicle operator. In an experiment reviewing naturalistic driving data, drowsy drivers were classified based on similar observable behaviors such as blink rate, yawning, stretching, and heaviness of the eyelids.[52] Barr et al.[53] used a computer vision algorithm that tracks facial features and body movements to identify instances of drowsiness. Considering the results from Wierwille and Ellsworth, future machine learning algorithms may act as "raters" to provide drowsiness measures in real time. Several eye-based metrics have shown potential in drowsiness monitoring due to the relationship between eye movements and sleep stages.[54] Hanowski et al.[55] referred to the percent of eye closure (PERCLOS) as the "gold standard" of drowsiness detection and argued that it is the most valid driver-based drowsiness measure. PERCLOS is the percentage of eye closures over the pupil over time where drowsiness is defined as the amount of time in 1 minute that the eyes are at least 80% closed. This measure describes eye behavior as "droops," as opposed to blinks, to characterize the slower movement of the eyes as a human becomes drowsy.[56] Dinges et al.[57] found that PERCLOS was the only drowsiness metric evaluated that consistently covaried with the validation criterion for drowsiness. Hanowski et al. mentioned that although PERCLOS is a highly valid measure for drowsiness, the limiting factor is the quality of the sensor used to measure PERCLOS due to the highly dynamic driving environment (e.g., lighting variation) and driver variability (glasses, hats, etc.). Therefore, the DSM effectiveness can only be as strong as the technology being used, and the strongest technologies are those that account for this dynamic driving environment.

Meyer and Llaneras[58] recognized that using more "gross level" behavior such as head position, mirror checks, yawning, or stretching may be supplementary information that can corroborate the decision to classify a driver as drowsy. Several studies have used drivers' facial expressions (e.g., brow raising, yawning, jaw drop) gathered from IR-camera video recordings to classify a driver as drowsy.[59,60,61] Lew et al.[62] found that drivers actually yawned less in the moments leading to critical drowsiness, not more; therefore, yawning may only be indicative of the earlier stages of drowsiness and not a reliable indicator of late-stage drowsiness. This study also supported the conclusion that blink rates such as PERCLOS and slow blinking were the most accurate determinants of drowsiness across all participants.

Overall, it seems the least invasive method for determining drowsiness is using an IR camera to capture PERCLOS, HRV, or facial movements. However, further innovation in less intrusive technology such as wearables or integration into steering wheels, seats, or seat belts may put EEG, ECG, and other physiological measures at the forefront of drowsiness detection in DSM systems.

5.4.1.5 Driver State Mental Workload and Fatigue

As mentioned previously, drowsiness and fatigue are not synonymous in this paper. Much of the literature on fatigue is really referencing drowsiness, or the physiological urge to fall asleep. This section defines fatigue as it is related to cognitive load, or mental workload. Williamson et al.[63] defined fatigue as the state of reduced mental alertness that impairs performance of cognitive and psychomotor tasks, including driving. According to the Yerkes–Dodson law (Figure 45), the optimal state of an operator is enough stimulation to stay engaged in the driving task without being bored or over-stressed.[64]

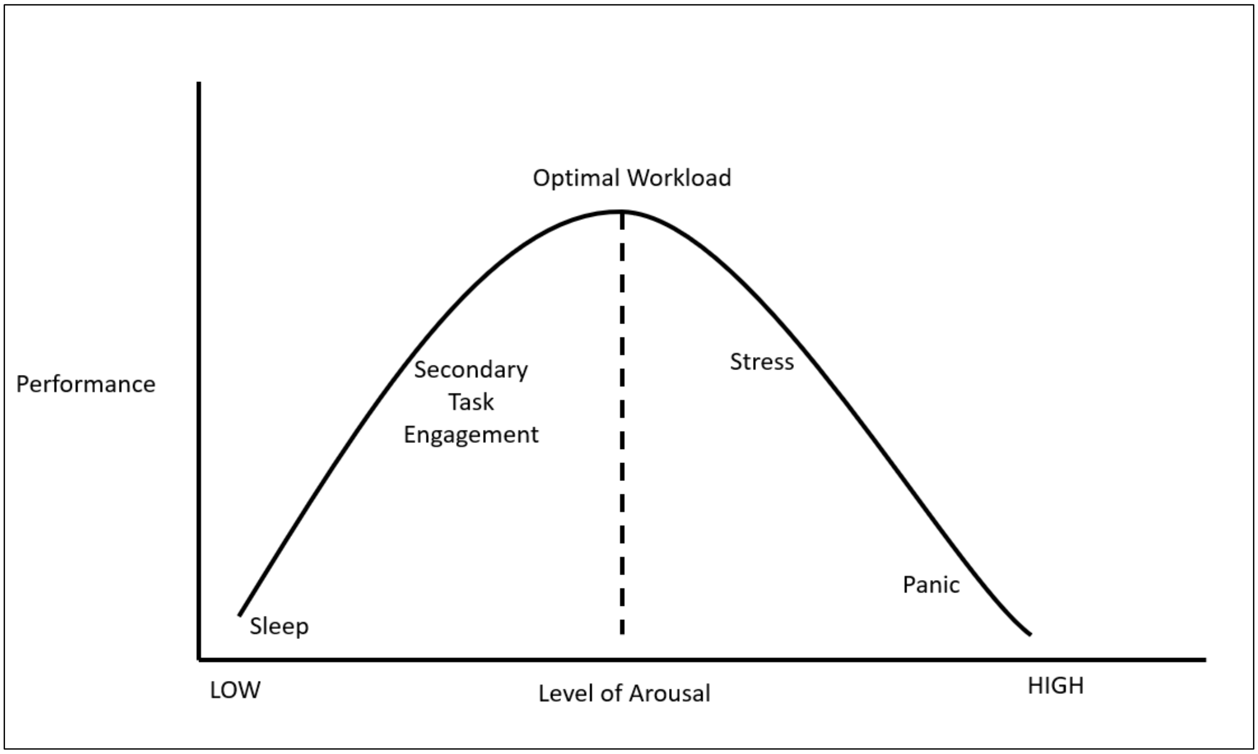

Figure 1. Diagram. Illustration of the Yerkes-Dodson Law of Arousal. As arousal level increases from sleep, the performance level increases until it reaches an optimal state. As arousal increases past this optimal state, performance decreases due to overloading of limited resources.

Therefore, with high-level automation, one of the main concerns for safety operators is the monotony of monitoring an ADS-equipped CMV without really "driving." Low vigilance can impact a driver's reaction time, efficiency, decision-making capabilities, situational awareness, and, therefore, safety.(65,66) Additionally, to mitigate fatigue and drowsiness, drivers naturally tend to engage in secondary tasks to generate stimulation, potentially leading to distraction-related inattention errors that further decrease safety.(67) However, protective effects of hands-free phone use and CB radio use have been reported with CMV drivers.(68) These tasks may stimulate the driver enough to mitigate the effects of fatigue without adding to visual-manual distraction. It is important to note that safety operators are prohibited from common in-vehicle distractors such as cell phones and are even prohibited from non-task-related conversation with other passengers. Therefore, the current regulations on safety operators may be so stringent that they add to the performance decrement experienced by prolonged periods of vigilance. Statistics show that between 10% and 20% of all traffic crashes are due to drivers with a diminished vigilance level.(69) Protective effects of secondary task engagement specific to safety operators should be investigated, which may lead to alternative standards for safety operator behaviors.

The status of a human's cognitive workload is best assessed using physiological techniques. EEG results show that changes in alpha and theta waves indicate high cognitive load.(70) Yamamoto and Matsuoka(71) showed decreases in performance occur when long-lasting theta waves are present in EEG results. HR and HRV are also shown to increase with higher driver workload, and decreased HR and HRV are correlated with low driver workload.(72,73,74) Although physiological indicators are highly indicative of fatigue, there is still an issue with the intrusiveness of the technology that make it unrealistic in real-world driving environments. Wierwille[75] suggested that computer vision is the most promising noninvasive driver monitoring technology for monitoring driver alertness. Rahman[76] used a video-based computer vision system and IR cameras to achieve a correlation of 0.96 between HR, saturation of peripheral oxygen (SpO2) monitoring, and fatigue measures. Eye-based metrics are also highly correlated with fatigue and mental workload. Barr et al.[77] used computer vision to assess PERCLOS with an IR camera. Wang et al.[78] used an IR-illuminated space with a high-definition camera to track eye blinking and closures, the 3D gaze of the eyes, and head/facial feature positions even under highly variable lighting conditions characteristic of a driving environment. Nakano et al.[79] illustrated that eye blink frequency increases as cognitive load increases. The study found that the average person spontaneously blinks at a rate of 15 to 20 times per minute, so an increase in this rate is usually an indicator of increased cognitive load. Another important consideration of fatigue is that the likelihood of experiencing fatigue increases with task time.[80] Therefore, the machine learning algorithms assessing the state of the driver should consider the length of time the driver has been on the road.

5.4.1.6 Driver State: Emotions

There is not a common definition of emotion in the literature. Many authors have recognized the difficulty in producing a consistent definition of emotion due to the subjective and multifaceted nature of human beings.[81] Young[82] argued that the reasons for this difficulty are the variations in perspectives and the idea that emotions are individually experienced. For the purposes of this paper, emotion is defined as the "mood" of a driver, or the arousal of a driver based on external or internal circumstances. The four most commonly researched driving-related emotions are happy, sad, angry, and neutral.[83,84] Zimasa[85] emphasized the relationship between mood and attention. The author argued that as mood changes, the attention placed on the driving task is diminished as the person diverts attention to the cause of the mood-altering event. The impacts of aggressive driving and road rage are well-established effects of negative moods.[86] Knapton[87] stated that the risk of a crash is increased by 14% when a driver is experiencing emotions such as sadness or anger, which is correlated with effects such as aggressive driving and road rage. Dingus et al.[88] analyzed naturalistic driving data and found that drivers exhibiting clearly negative emotions such as anger, sadness, crying, or emotional agitation increased crash risk by 9.8 times. Techer et al.[89] showed that drivers of higher levels of ADS-equipped vehicles tended to grow frustrated with the "cautious" driving style of the vehicle and lack of control. Van Huysduynen et al.[90] supported this idea by adding that drivers of lower-level ADS-equipped vehicles take control when they feel the driving style of the vehicle is disrupting the flow of driving. This is of particular interest to safety operators due to the novelty of the vehicles being tested. These drivers may grow frustrated with the behaviors of drivers around the vehicle and the subject vehicle's ADS.

Anger and stress cause a high arousal state for the body and are well monitored through physiological metrics.[91] HR and electrodermal activity are the indicators with the highest correlations to high-arousal emotions.[92,93] As mentioned previously, the limiting factor in using devices measuring HR and electrodermal activity is the sensor, as it must (1) accommodate the variability in the driving environment, (2) not impede the movement or visibility of the driver, and (3) be comfortable to wear in real-world working conditions. For these reasons, emotion detection currently relies on the idea that facial expressions are an outward display of a driver's emotions.[94] Gao et al.[95] proposed a real-time driver emotion monitoring system using a camera-based method and a highly trained convolutional neural network to analyze facial expressions. Kowalczuk et al.[96] used a similar method by exploiting the facial emotion recognition (FER) algorithm that assesses a person's emotional state by collecting facial landmark information. This study pointed out that the detection accuracy and classification of emotional state based on facial features is only as capable as the machine learning algorithm being used to assess it. Similarly, the driver's head position can decrease the accuracy of the computer vision information acquisition. Therefore, when considering which method to use in a DSM application, technology is the limiting factor. Tavakoli et al.[97] noted an interesting caveat in the capability of emotion detection using facial features. The authors emphasized the individual nature of human expression and illustrated that natural face states may mimic expressions of anger when the person is actually experiencing a neutral state. Similarly, some authors argued that there are cultural variations in the appearance of basic facial expressions of emotion between Western and Eastern cultures.[98,99,100] These findings support the need for combined data sources such as physiological measures with diversely trained facial detection algorithms to classify a driver's emotional state more accurately across all driver types.

5.4.1.7 Driver State: Under the Influence

Halin et al.[101] defined driving under the influence (DUI) or driving while intoxicated (DWI) as the operation of a vehicle by a driver who has consumed alcohol or drugs to the point where their performance is significantly impaired compared to someone who had not consumed alcohol or drugs. In 2018, 25% of fatal motorcycle crashes and 21% of fatal light-vehicle crashes involved a blood alcohol concentration (BAC) of 0.08.[102] The prevalence of DUI among CMV drivers is lower, as 3% of CMV drivers involved in fatal crashes had a BAC of 0.08 or higher.[103] This may be because CMV drivers are considered to be professional drivers and their legal BAC limit is 0.04. However, in a study conducted by Crouch et al.,[104] fatal CMV driver crashes were analyzed in eight states over a 1-year period. One or more drugs were detected in 67% of the drivers, and 33% had detectable blood concentrations of psychoactive drugs/alcohol. The most commonly found drugs were alcohol followed by cannabinoids. If the delta-9 concentration of 1.0 ng/mL and/or a BAC of 0.04 or higher were present, the impairment of the driver was found to be the cause of the crash.

The majority of drug- and alcohol-related traffic incidents are found after the fact. A proactive, real-time approach to monitoring the drug and alcohol use of a driver should be considered. The current standard for preventing drunk driving is using an alcohol interlock device (AID) on a vehicle. The driver is expected to provide a deep-lung breath sample by blowing into a plastic tube before starting the vehicle. Ferguson and Draisin[105] pointed out that this process, although highly effective and accurate, takes time and is difficult for some drivers due to the volume, flow, and exhalation time. Similarly, they commented that these systems need frequent calibration and constant maintenance due to the condensation of breath. Fournier et al.[106] proposed a driver alcohol detection system for safety (DADSS) that measures a driver's BAC non-invasively through either tissue spectrometry or distant spectrometry. This solution does not, however, allow for the real-time monitoring of the state of the driver and does not prevent the driver from drinking alcohol after starting the engine. Celaya-Padilla et al.[107] created a continuous monitoring device by using a metal oxide semiconductor that detects the presence of alcohol vapor in a driver's breath. This method achieved an accuracy of 0.989, but the authors mentioned that improvements could be made by moving the sensors closer to the driver. Several studies have investigated camera-based methods that identify saccadic eye movements and gaze position of the driver.(108,109) Sussman(110) found success using eye unsteadiness as a method for alcohol detection. Identifying an intoxicated driver can also be achieved by using an IR camera that capitalizes on the expansion of blood vessels in the forehead when a person is under the influence of alcohol, the pupil dilation of the driver, and differences in body temperature.(111,112,113) Most research has been conducted in the context of alcohol impairment; monitoring the impacts of over-the-counter drugs and drugs in general is not well understood in the driving context.

5.4.1.8 Summary of Literature

Table 29 summarizes the indicators and sensors used in DSM literature to define each of the five driver states. The indicators are characteristics of humans (behavioral or physiological) that can be used to signify a driver's state. The metrics are the specific trends or methods used to determine whether the indicator is signifying a negative or neutral state. Sensors are the technology used to capture or assess the information.

Table 1. Summary of findings.

Driver State	Indicators	Metrics	Sensors
Distraction	Head Position	Looking at driving-relevant information	IR Camera + Computer Vision
Distraction	Gaze Behavior	PRC	IR Camera + Computer Vision
Distraction	Gaze Behavior	PRC	Eye Tracking
Distraction	Gaze Behavior	Gaze Duration	IR Camera + Computer Vision
Distraction	Gaze Behavior	Gaze Duration	Eye Tracking
Distraction	Gaze Behavior	Attentional Buffer	IR Camera + Computer Vision
Distraction	Gaze Behavior	Attentional Buffer	Eye Tracking
Distraction	Posture	Hand & Feet Position	IR Camera + Computer Vision
Distraction	Posture	Hand & Feet Position	IR Camera + Computer Vision
Distraction	Posture	Hand & Feet Position	Seat Monitor
Distraction	Object Detection	Cell Phone, Food/Drink, Cigarette, Purse, etc.	IR Camera + Computer Vision
Distraction	Pupil Diameter	Increase/Decreased Size	IR Camera + Computer Vision
Distraction	Pupil Diameter	Increase/Decreased Size	Eye Tracking
Distraction	HRV	Increase/Decrease	IR Camera + RGB Camera + Computer Vision
Distraction	HRV	Increase/Decrease	Wearable Monitor (Watch, Ring, etc.)
Distraction	HRV	Increase/Decrease	ECG Electrodes on Body
Distraction	HRV	Increase/Decrease	Integrated Sensor (Steering Wheel, Seat Belt, Seat)
Drowsiness	Posture	Slouching, Stretching, Touching Face, Slapping Face	IR Camera + Computer Vision
Drowsiness	Facial Features	Droopy Eyes, Mouth Open, Brow Angle, Eyes Open/Closed	IR Camera + Computer Vision

Driver State	Indicators	Metrics	Sensors
Drowsiness	PERCLOS	Slow Eye Closure Rate	Eye Tracking
Drowsiness	PERCLOS	Slow Eye Closure Rate	IR Camera + Computer Vision
Drowsiness	HR	Decrease	IR Camera + RGB Camera + Computer Vision
Drowsiness	HR	Decrease	Wearable Monitor (Watch, Ring, etc.)
Drowsiness	HR	Decrease	ECG Electrodes on Body
Drowsiness	HR	Decrease	Integrated Sensor (Steering Wheel, Seat Belt, Seat)
Drowsiness	HRV	Decrease/Increase	IR Camera + RGB Camera + Computer Vision
Drowsiness	HRV	Decrease/Increase	Wearable Monitor (Watch, Ring, etc.)
Drowsiness	HRV	Decrease/Increase	ECG Electrodes on Body
Drowsiness	HRV	Decrease/Increase	Integrated Sensor (Steering Wheel, Seat Belt, Seat)
Drowsiness	Brain Activity	Theta & Beta Wave Activity	EEG Electrodes on Body
Drowsiness	Brain Activity	Theta & Beta Wave Activity	EEG Headband/Hat
Drowsiness	SpO2 level	Decreases	IR Camera + RGB Camera + Computer Vision
Mental Workload	PERCLOS	Slow Eye Closure Rate	Eye Tracking
Mental Workload	PERCLOS	Slow Eye Closure Rate	IR Camera + Computer Vision
Mental Workload	HR	Increase	IR Camera + RGB Camera + Computer Vision
Mental Workload	HR	Increase	Wearable Monitor (Watch, Ring, etc.)
Mental Workload	HR	Increase	ECG Electrodes on Body
Mental Workload	HR	Increase	Integrated Sensor (Steering Wheel, Seat Belt, Seat)
Mental Workload	HRV	Increase/Decrease	IR Camera + RGB Camera + Computer Vision
Mental Workload	HRV	Increase/Decrease	Wearable Monitor (Watch, Ring, etc.)
Mental Workload	HRV	Increase/Decrease	ECG Electrodes on Body
Mental Workload	HRV	Increase/Decrease	Integrated Sensor (Steering Wheel, Seat Belt, Seat)
Emotions	Facial Expressions	Happiness, Neutral, Anger, Sadness	FER Algorithm & IR Camera + Computer Vision
Emotions	HR	Increase/Decrease	IR Camera + RGB Camera + Computer Vision
Emotions	HR	Increase/Decrease	Wearable Monitor (Watch, Ring, etc.)
Emotions	HR	Increase/Decrease	ECG Electrodes on Body
Emotions	Electrodermal Activity	Increase for Negative Emotions	Electrodermal Electrodes on Body
Emotions	Electrodermal Activity	Increase for Negative Emotions	Integrated Steering Wheel
Under the Influence	Gaze Behavior	Erratic Eye Movements, Unsteadiness of Eyes	Eye Tracking

Driver State	Indicators	Metrics	Sensors
Under the Influence	Gaze Behavior	Erratic Eye Movements, Unsteadiness of Eyes	IR Camera + RGB Camera + Computer Vision
Under the Influence	Pupil Dilation	Pupil Size Increases w/ Drugs & Alcohol	IR Camera + Computer Vision
Under the Influence	Pupil Dilation	Pupil Size Increases w/ Drugs & Alcohol	Eye Tracking
Under the Influence	Tissue Spectrometry	Imaging of Micro-blushes	High-resolution Imaging + Computer Vision
Under the Influence	Air Vapor Analysis	Alcohol Vapors Present in Air	Semiconductor Vapor Sensors
Under the Influence	Blood Vessel Dilation	Blood Vessels Increase in Size	IR Camera + RGB Camera + Computer Vision
Under the Influence	Blood Vessel Dilation	Blood Vessels Increase in Size	IR Camera + Computer Vision
Under the Influence	Blood Temperature	Blood Temperature Increases w/Alcohol	Temperature Camera + High-resolution Imaging + Computer Vision

5.4.1.9 Evaluating the Driver Monitoring System

Halin et al.(114) divided driver monitoring into two components: (1) characterizing the state of the driver and (2) deciding what action to take based on this assessment. The focus of this paper was only on the first piece. The second component delves into the study of providing feedback to the driver. Boyle et al.(115) asserted that the main goal of the DSM is to improve driver performance and safety on roadways. This sentiment falls under the second piece of driver monitoring, for performance and safety cannot be impacted unless the driver is aware of his or her degraded performance. Therefore, when considering the evaluation of DSM systems, this paper looked exclusively at metrics involving the assessment of technology, not the behavior of the driver after receiving feedback. Although the reaction of the ADS is important, it is considered out of scope as the purpose of this report guideline is to understand DSM technologies.

Bowman et al.(116) compiled a list of several specifications a DSM system must meet to be assessed appropriately. First, the DSM system must be robust or adaptable to the various environmental conditions in a vehicle such as illumination levels, different operators, driver characteristics (e.g., skin color, glasses), driver behaviors, vehicle vibrations, and temperatures. Second, the technology must hold high construct validity and accuracy of the real-time driving environment. The device should accurately, continuously, and in real-time measure the intended state(s) by minimizing the disparities between the estimated state and the true state of the operator while simultaneously minimizing the prevalence of false alarms and misses. Third, the technology must meet a human's interface needs. For example, the device should not distract from the driving task or impede the driver's vision of the roadway or mobility and must also be easy for an operator to interact. Fourth, the device should not be cumbersome to calibrate or maintain, nor should it require high costs to maintain. Barr et al.(117) added to this list by including three more valuable design requirements. The monitoring system should consider the security of the driver in terms of protecting sensitive information that may be captured by the system. The device itself should preferably be automatically activated and deactivated when the vehicle is powered on and off. However, if manual activation and deactivation are necessary, it should not be cumbersome for the driver. Similarly, it should not allow intentional or unintentional misuse of the system. Finally, the authors stressed the importance of driver acceptance and stakeholder buy-in. They asserted that regardless of the safety benefits of the system, successful deployment is unlikely if the users do not deem the device acceptable.

Combining works from Dinges and Mallis,[(118)] Whitlock,[(119)] Bekiaris et al.[(120)], and Barr et al.[(121)] conceptualized a methodology using five criteria to assess user acceptance of new and emerging technologies. The two most relevant to DSM are perceived value and advocacy. Perceived value is the extent to which drivers view the benefit of the technology as outweighing possible costs. It is important for drivers to understand the safety benefits of monitoring and the data confidentiality of the information being collected about their driving behavior. Advocacy is the desire to endorse their fleet's purchase of the new technology. Advocacy is important because although perceived value may be high, the willingness of drivers to support the process of obtaining it is just as important. Peng et al.[(122)] investigated the perception and attitudes of 37 CMV drivers towards DSM systems. Over half of the participants viewed the DSM as improving safety and regarded the system in a mostly positive light. Six of the participants were classified as overly trusting of the DSM system and were strong proponents of its implementation. Eight of the participants viewed the system negatively and were concerned with the privacy issue of being continuously monitored. Ghazizadeh et al.[(123)], Greenfield et al.[(124)], and Camden et al.[(125)] found similar results with issues of privacy. Therefore, it is recommended that fleets educate their drivers on privacy protection, their role in safety, and the functions of the system in detail before implementing this new technology.

5.4.1.10 Literature Review Conclusions

The purpose of this literature review was to determine thresholds of driver characteristics such as fatigue, drowsiness, distraction, negative emotions, or impairment that may impact a safety operator's readiness to take over an ADS-equipped CMV. Additionally, the review considered the differences in thresholds of driver states necessary for a safety operator who is presumed to be a highly trained individual versus a typical CDL holder supporting operations onboard an ADS-equipped CMV.

Considering the complexity of the driving environment, many technologies measuring physiological indicators are currently too invasive to monitor driver state in real-world, everyday driving environments. For example, some of the most accurate indicators of driver state such as EEG or ECG require skin contact or other invasive eyewear/headwear. The least invasive indicator is a wearable watch or ring to monitor HRV, yet the compliance rate of these devices has not been investigated with safety operators. Safety operators have been distinguished from the general CMV professional driving population due to their rigorous training on vigilance and ADS technology, so it is unclear whether wearable technology would have higher compliance rates with this population. Despite the difficulties with physiological measures, IR camera-based systems show great potential for their ability to monitor a wide range of driver states, including some physiological measures, in a robust and adaptive manner. These camera-based sensors rely on computer vision to classify objects, facial features, or body posture, and a machine learning algorithm determines whether the characteristics of the driver represent an impaired state. Therefore, the DSM systems with the most potential use deep learning algorithms to classify data captured by advanced external sensors in real time and in highly variable conditions.

Overall, there are gaps in the literature for understanding DSM as it applies to safety operators; however, DSM systems show promise for integration with ADS-equipped CMVs. As developers of ADS-equipped CMVs continue to seek safety assurance for their vehicles with new features and operational design domains, the role and standards for safety operators will continue to evolve through iterative testing and deployment. Similarly, different ADS fleets have individual standards for their safety operators, which may not be reflected in the AVSC standards. For example, the AVSC[(126)] recommends certain driver behaviors such as keeping hands on the wheel or taking frequent breaks, yet individual fleets choose the exact rules for their drivers. Moving forward, investigating currently available DSM systems for their applicability to safety operators is necessary to understand how these defining metrics of driver state support the safe driving of safety operators in the future. Additionally, gaining an understanding of the exact responsibilities of a safety operator across various fleets through a task analysis or function allocation should be done to correctly design a DSM system for this population.

5.4.2 Technology Scan

The purpose of this technology scan was to identify commercially available DSM technologies that can be applied to and inform the safe operation of ADS-equipped CMVs. The scope of the scan is limited to technologies that monitor driver characteristics identified by the literature review (i.e., distraction, impairment, drowsiness, mental workload, and emotions) and technologies that could be used to assess the ability of a safety operator to take over control of an ADS-equipped CMV during a planned or unplanned ADS disengagement. For example, monitoring HR alone may not provide a full understanding of driver state; however, combining video monitoring, HR, and manual control checks may accurately illustrate the condition of the driver and their ability to take over driving tasks. This technology scan established what DSM technologies and systems are available and their functions, capabilities, limitations, and use cases when integrated and applied with ADS operations.

5.4.2.1 Technology Scan Results

An initial internet search was conducted using various publicly available search engines. The following keywords were used to find company websites mentioning DSM systems: *driver monitoring system*, *driver monitoring*, *video-based monitoring*, *commercial vehicle driver monitoring*, *driver impairment monitoring*, *fleet camera systems*, *driver alcohol sensors*, *in-vehicle alcohol sensor*, and *in-vehicle drug sensor*. Each website that mentioned DSM systems or some form of monitoring system was included in a document along with a link to the site. The results from this initial scan are shown in Table 30.

Table 2. Full list of providers and technologies from the initial results of the technology scan.

Vendor	DSM Technology
Aptiv	Driver Monitoring System
AT&T	FleetComplete Vision
Azuga	SafetyCam
BlackVue	BlackVue AI-powered Driver Monitoring System
BlueArrow Telematics	SurfSight
Brickhouse Security	Driver-facing Camera

Vendor	DSM Technology
CalAMP	Vision AI-driven dash video and analytics
Cambridge Mobile Telematics	Driver Monitoring System
Clearpath GPS	Driver Facing Camera
Coretex	Driver Facing Camera
Denso	Driver Monitoring System
E-Drive Technology	E-Driver Facing Camera
Faurecia	Active Wellness
FieldLogix	Wireless Dash Cam
Fleet Complete	Driver Facing Camera
FleetCam	FleetCam
FleetHoster	FleetFlix AI + Pro Dash Cam
FleetOptix	Driver Facing Camera
Forward Thinking	Fleetcam 3.0
Garmin	Garmin Instinct Watch
Geotab	Third-party Dash Cams
GPS Insight	Driveri
GPSTrackit	VidFleet
GreenRoads	VideoSense
Harman	Ready Care
HD Fleet	GOS Tracking Cam (Same as FleetOptix)
Insight Mobile Data	Driver Facing Camera
ISR Tech	Driver Facing Camera
JJKeller	Driver Facing Camera
Linxup	Dashcam
Lytx	DriveCam
Lytx	SurfSight
MixTelematics	Mix Vision
Motive	AI Dash Cam
Nauto	AI Cam
Netradyne	Driveri
NexTraQ	Driver Facing Camera
Orbcomm	Driver Facing Camera
Orion Fleet Intelligence	Orion Vision: AI Dashcam
Pedigree Technologies	Driver Facing Camera

Vendor	DSM Technology
Rand McNally	Driver Facing Camera
RoadHawk	Driver Facing Camera
Rosco Vision Systems	DV6 “Dual Vision”
Samsara	AI Dash Cam
Seeing Machines	Guardian
SkEYEwatch	SkEYEvue AI-powered smart dash cam
SmartCap	LifeBand
SmartEye	SmartEye Driver Monitoring
SmartWitness	KP2: Modular Dual Camera Solution
Solera	SmartDrive
Spireon FleetLocate	FL360 Camera
SureCam	SureCam
Teletrac Navman	Driver Facing Camera
TitanGPS	AI Fleet Smart Camera System or In-CAB
Trac Star International	SmartWitness
TrackNet	Truck Dash Cam (Same as FleetOptix)
Trimble	Cabin Intelligence Monitor (CIM)
Verizon Connect	Intelligent AI Dashcam
Vision Track	VT3000-AI
Zenduit	Zenducam AD Plus
Zen-tinel	Surveillance Cam
Zonar System	Zonar Coach
Zonepro	Zonepro ADAS And Driver’s Camera

Ineligible technologies were those that could not be integrated or applied to a SAE L4 ADS. For example, technologies were removed from the list if they used only vehicle-based metrics (e.g., lane departures, speed) to determine driver state. In an SAE L4 AV, the vehicle is assumed to have control over longitudinal and lateral functions; therefore, these functions would not be influenced by driver state. Additionally, technology was removed if it did not assess the state of a driver continuously and in real time. Some technologies merely record events for later review, which would not proactively determine a driver’s state before an incident. Lastly, technologies were removed if they used invasive sensors to measure driver state. Excessively invasive designs included headbands/caps with electrodes, sensors that covered the fingers, wires that extended from the hand, wrist, or body, and glasses or headwear. These technologies were excluded because they rely on the drivers to properly calibrate and adjust the devices, which may negatively impact the compliance rate. Furthermore, these technologies may cause discomfort for the driver or fail to address the individual differences in drivers’ characteristics. The remaining companies were categorized based on the items in Table 31.

Table 3. Description of each of the metrics collected from the DSM technologies.

Characteristic	Definition	Examples
1. Driver State Metrics	The data collected about the physical condition of the driver that can be used to determine state	HR, head position, eye glances, etc.
2. Driver State Evaluation	The states of the driver that can be classified by the system	Visual distraction, manual distraction, drowsiness, intoxication, etc.
3. Sensors	The method for collecting driver state metrics data	Cameras, IR lights, HR monitor, etc.
4. Driver Involvement	Yes/No – Does the technology require driver involvement?	Frequent calibration, turning the system on/off each drive, wearing a device, etc.
5. Stand-alone or Combined	The capability of the identified technology to assess DSM independently and effectively or the need to be used in conjunction with another technology	HR monitor – must be combined Video-based monitoring – stand-alone

Each remaining technology was assessed based on these characteristics. Table 32 shows the results from the final technology scan. Each column in Table 32 represents a different metric collected from each of the DSM technologies identified in each row. The results from this table were identified using public websites belonging to each of the technology developers listed in the rows of the table. The wording used in each category is standardized due to the variability in terminology from each of the DSM companies. For example, some DSM companies used the term "fatigued" to describe the stages leading to falling asleep; however, the term "drowsy" is used to describe that state here. In the Driver Involvement column, the term "unknown" is used when a company's website failed to mention the maintenance or driver action required. The term "unknown – assumed minimal requirements" is used when the company's website mentioned "easy maintenance" or otherwise indirectly mentioned simple driver involvement but did not detail the exact requirements. Otherwise, the driver involvement is described. Overall, the term "unknown" is used when a company's website did not provide enough information to make a conclusion about the capability of the DSM technology in the respective category.

Table 4. Final technology scan results.

Technology	Driver State Metrics	Driver State Evaluation	Sensors	Driver Involvement	Stand-Alone/Combined
BlackVue AI-powered Driver Monitoring System	Head Position	Visual Distraction Hand-Held Cell Phone Distraction Drowsy	Camera AI Infrared LEDs	Unknown – Assumed Minimal Requirements	Combined
DriveCam	Head Position	Visual Distraction Manual Distraction	Camera AI Infrared	No	Combined
Driveri	Facial Recognition	Distraction Drowsy	Camera AI	Unknown – Assumed Minimal Requirements	Combined
Field Logix Wireless Driver Cam	Unknown	Visual Distraction Manual Distraction	Camera AI Infrared	No	Combined
FleetCam	Eye Movement Head Position	Visual Distraction Manual Distraction Drowsy	Camera AI	Unknown – Assumed Minimal Requirements	Combined
FleetCam 3.0	Eye Movement Head Position	Visual Distraction Manual Distraction Drowsy	Camera AI Infrared	Unknown – Assumed Minimal Requirements	Combined
FleetComplete Vision	Head Position	Visual Distraction	Camera AI	Unknown	Combined
FleetFlix AI + Pro Dash Cam	Unknown	Visual Distraction Hand-Held Cell Phone Distraction Drowsy Cell Phone Use	Camera AI Infrared	Unknown – Assumed Minimal Requirements	Combined

Technology	Driver State Metrics	Driver State Evaluation	Sensors	Driver Involvement	Stand-Alone/Combined
FleetOptix Driver Facing Camera	Head Position Facial Landmarks Eye Movement	Visual Distraction Manual Distraction Drowsy	Camera AI Infrared	Unknown – Assumed Minimal Requirements	Combined
Garmin Instinct Trucker Watch	HR Respiration Rate Pulse Oxygen Energy Monitor Stress Monitor Sleep Monitor	Stress	Wearable Watch	Yes	Combined
JJ Keller Dash Cam PRO advanced	Unknown	Visual Distraction Drowsy	Camera AI	No	Combined
Motive AI Dual-Facing Dash Cam	Head Position	Visual Distraction	Camera AI Infrared	No	Combined
Orion Vision AI Dashcam	Eye Movement Head Position Facial Recognition	Visual Distraction Hand-Held Cell Phone Distraction	Camera AI Infrared	Unknown – Assumed Minimal Requirements	Combined
Rosco DV6	Eye Movement Head Position Facial Landmarks	Visual Distraction Drowsy Hand-Held Cell Phone Distraction	Camera AI Infrared	No Manual Updates	Combined
Samsara AI Dashcam	Head Position	Visual Distraction	Camera AI Infrared	No	Combined
Guardian	Eye Movement Head Position	Visual Distraction Drowsy	Camera AI	No	Combined

Technology	Driver State Metrics	Driver State Evaluation	Sensors	Driver Involvement	Stand-Alone/Combined
SkEYEvue AI Powered Smart Dash Cam	Unknown	Visual Distraction Drowsy Manual Distraction	Camera AI Infrared	Unknown	Combined
Smart Drive	Eye Movement Head Position	Visual Distraction Drowsy	Camera AI Infrared	Unknown	Combined
Smart Witness KP2: Modular Dual Camera Solution	Head Position	Visual Distraction Drowsy	Camera AI Infrared	Unknown	Combined
SmartEye Driver Monitoring	Eye Movement Head Position Body Posture	Visual Distraction Manual Distraction Drowsiness	Camera AI Infrared	Yes	Combined
SurfSight	Head Position Facial Landmarks	Visual Distraction Drowsy	Camera AI Infrared	No	Combined
Trimble Cabin Intelligence Monitor (CIM)	Unknown	Visual Distraction Drowsy	Camera AI Infrared	Unknown	Combined
Verizon Intelligent AI Dashcam	Unknown	Visual Distraction	Camera AI Infrared	Unknown	Combined
VideoSense	Unknown	Visual Distraction Manual Distraction Drowsy	Camera AI	No	Combined
VidFleet	Eye Movement Head Position	Visual Distraction Manual Distraction	Camera AI Infrared	Unknown	Combined

Technology	Driver State Metrics	Driver State Evaluation	Sensors	Driver Involvement	Stand-Alone/Combined
Vision Track VT3000-AI	Unknown	Visual Distraction Manual Distraction Drowsy	Camera AI Infrared	Unknown	Combined
Zenduit Zenducam AD Plus	Head Position Facial Landmarks	Visual Distraction Manual Distraction Drowsy	Camera AI Infrared	Unknown	Combined

5.4.2.2 Selection Criteria

To determine the most appropriate DSM for safety operators, the various technologies were assessed based on their ability to meet the criteria defining an ideal DSM system. These criteria were adapted from the evaluation standards for DSM systems defined by Bowman et al.[(127)] and the AVSC's[(128)] description of safety operators. The DSM technology should:

1. Assess a safety operator's level of drowsiness, level of distraction (cognitive, visual, manual, and auditory), emotional state, level of intoxication, and mental workload.
2. Be robust to the dynamic driving environment consisting of temperature changes, vibration, illumination changes, and varying safety operator characteristics (e.g., skin color, glasses, eye shape).
3. Assess the state of the safety operator continuously, in real time, and with high accuracy.
4. Not be cumbersome to calibrate or maintain, nor should it require high costs to maintain.

5.4.2.3 Technology Scan Conclusions

Currently, no commercially available DSM system meets all criteria for an ideal DSM system for a safety operator. First, none of the technologies capture all driver states. Most systems assess whether a driver is distracted visually or manually but fail to consider cognitive and auditory distraction. Most systems assess driver drowsiness using eye behavior or head position but do not attempt to measure physiological signs of drowsiness. No DSM systems currently offer alcohol/drug detection or mental workload assessments. HRV monitors and alcohol/drug monitors are available separately, but few companies consider their products in the driving context; therefore, many of the devices are cumbersome or require the user to engage with the device, which they could not do while driving.

To measure all driver states with the available DSM systems, a combination of technologies is needed. For example, a DSM system measuring distraction, drowsiness, and emotions can be combined with an external alcohol monitor and wearable watch that measures workload to capture all aspects of the driver's state. Second, most companies offering DSM systems mention robustness to temperature variation and vibration and include an infrared light for night driving, yet they fail to discuss variability in operator characteristics. Third, all the DSM systems in this review monitor the safety operator continuously and in real time; however, it is difficult to understand the accuracy of each of the technologies without a standardized comparison criterion. This aspect of the technologies would need to be tested further in an experimental design or more detailed analysis. Lastly, it is assumed that most camera-based DSM systems activate when the vehicle starts and deactivate when the vehicle is off, which would require no involvement from the driver. However, the websites rarely mention maintenance requirements or frequency of updating the AI algorithms.

Based on the evaluation criteria defined above, the Smart Eye Driver Monitoring System was used for testing in the next phase of research[(129)] in parallel with the Empatica smart watch.[(130)] This DSM system currently captures the states of drowsiness and both visual and manual distraction. Additionally, Smart Eye claims their DSM system stands up to vibration and difficult lighting conditions found in heavy vehicles. The Smart Eye system also uses gaze position, eye movement, and pupil size to determine a driver's state, which is a more robust measure of distraction and drowsiness than head position alone, which several companies use. Lastly, the Smart Eye website mentions easy installation, allowing drivers to install and interact with the system using a tablet.

The Empatica watch was selected to fit the needs of the study as well. When considering physiological measures, the selected device needed to be a non-intrusive item, such as a wearable smart watch device. Additionally, most smart watches currently available are designed for messaging and internet access; however, for data security during research, the watch selected needed to have a dedicated platform for data analytics and ensured security. Lastly, the Empatica watch has great battery life, measures several crucial data points such as HRV and EDA, and it is FDA approved. Although the Smart Eye and Empatica devices were used in testing, this selection does not imply endorsement of any Smart Eye or Empatica products mentioned in this report. Other systems may be desired for reasons not prioritized in this study.

The Smart Eye DSM system and Empatica device meet several criteria relevant to human drivers; however, it is unclear whether the exact needs of safety operator monitoring are being met. This is due to a lack of information on the tasks a safety operator performs during their ADS duties. This gap in knowledge illustrates the need for a task analysis of safety operator responsibilities across various ADS fleets. This task analysis would establish the exact states and activities a DSM system would need to monitor relevant to a safety operator.

5.4.3 Driver State Monitoring Industry Interviews

Currently, the AVSC recommends including a DSM system in ADS-equipped test vehicles to ensure a safety operator is fit to assume control during an emergency takeover request.[(131)] This requires DSM technology to accurately identify inappropriate driving behaviors and correct them in real time. As stated earlier, a literature review and technology scan were conducted to compile available information about state-of-the-art DSM systems. From these results, it is evident that the technology required to integrate DSM systems and ADS-equipped vehicles and to accurately monitor a safety operator is still developing. Additionally, it is unclear exactly what responsibilities a safety operator has at the wheel given the additional monitoring requirements of ADS technology with the rarity of failure events. In other words, it is unclear if the features of current DSM technologies are sufficient to monitor a safety operator given that DSM systems are designed for regular CMV drivers.

During this effort the research team sought to understand the role of safety operators and the present gaps in the technology used to monitor them. The objective of this phase was to connect research with industry practices by interviewing representatives from two critical sectors: ADS developers and DSM technology providers. The interviews gathered information about the integration of DSM into ADS-equipped CMVs through questions about barriers to integration, roles of a safety operator, and current use of DSM technology. The following section presents the processes and results of the interviews with DSM technology providers and ADS developers about DSM systems being integrated in ADS-equipped CMVs.

5.4.3.1 Interview Methodology

The team planned to interview up to nine representatives from each group using existing relationships with industry contacts. Many companies chose not to participate due to proprietary concerns. A total of seven representatives from DSM providers and three representatives from ADS developers agreed to participate in the interview process. All interviews lasted 30 minutes and were conducted via an online video platform.

The DSM providers were asked seven questions about their efforts to improve and integrate DSM technology. The ADS developers were asked 13 questions about safety operators and the possibility of DSM integration with their systems. The results from those questions are grouped by theme and presented below.

5.4.3.2 DSM Technology Providers

Terminology: To understand terminology used by individual companies, participants were asked if their company referred to their system as "DSM," and if they did not, they were asked what they called the video technology used to assess driver state while driving. Only one of the seven participants said that their company specifically called their system DSM (14%). Two of the participants said that they called it a driver monitoring system, and another two said that they had different names for the system but would agree the capabilities were similar. All companies agreed that calling the technology a DSM system was appropriate. The exact names of the alternative technologies have been left out to protect the anonymity of the companies, but they all referenced specific features of the technology as opposed to the general term DSM.

Integrating DSM with ADS-equipped CMVs: Regarding DSM, the participants were asked whether their companies were exploring ways to integrate their systems with ADS-equipped vehicles. The responses to this question are shown in Figure 46. As shown in Figure 46, the majority (57%) of the participants indicated that their companies are not exploring ways to integrate with ADS-equipped vehicles. The main reason that these participants said they were not interested in integrating their systems with ADS-equipped vehicles was that it was not their business focus. They were primarily focused on providing aftermarket solutions for vehicles that are currently on the road.

As a follow-up question, the participants were then asked why they have or have not considered ways to integrate their systems into AVs. Many participants again cited the need to cater their systems to their current customers who drive non ADS-equipped CMVs and did not find it advantageous to explore AVs. Another participant claimed they were not exploring integration because their company focuses heavily on driver behavior coaching, which may become obsolete in the field of ADS-equipped CMVs, as the industry is moving towards driverless trucks. Other participants cited the desire to improve the depth of the current technology as opposed to the breadth of their operations.

For participants who indicated their companies were considering integration, the reasons for doing so varied. One reason was the upcoming European requirement of DSM in all new vehicles.[132] The other two reasons were more focused on the goal of DSM technology to improve safety: DSM systems could optimize the relationship between human drivers and ADSs by predicting when the human may need a break from the driving task to help prevent collisions, and DSM systems could help prevent human drivers from becoming complacent with ADS technology in their vehicles.

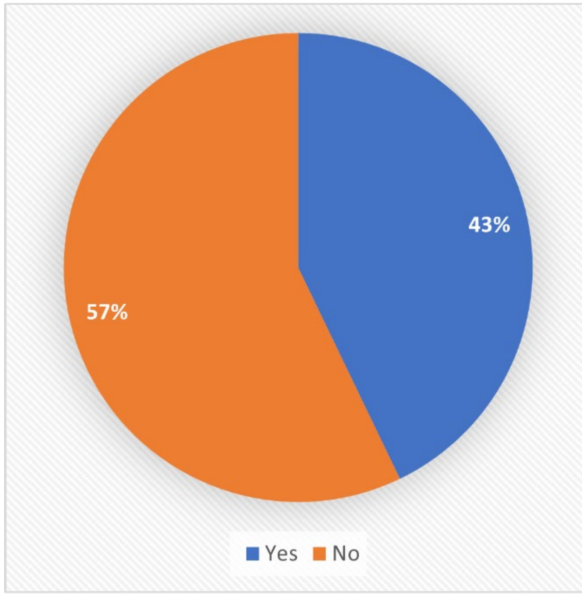

Figure 2. Chart. Percentage of responses to the question, "Is your company currently exploring ways to integrate driver state monitoring with autonomous vehicles?"

Barriers to Integration: Next, participants were asked about current barriers their company is facing in the efforts to improve DSM technology. There were two major trends in the answers to this question. The largest barrier that the participants mentioned was access to the right data to make improvements, which was indicated as a barrier by four of the participants. One participant mentioned the major trade-offs of making an aftermarket solution that is affordable while being small enough to fit on a windshield and processing enough data to make it accurate. Billions of data points are needed to understand the edge cases in human behavior that the providers need to detect, so large processors are needed to run through this data. Additionally, one provider mentioned there are issues with sensors on the vehicles being insufficient for collecting data and that some of the available data is proprietary. The participant emphasized that not only are the sensors insufficient, but many do not communicate properly with each other, especially with an aftermarket solution. These factors make using vehicle data for improvement difficult. Another barrier that participants noted was privacy laws, which were brought up by three of the participants. There is an issue with drivers not wanting the technology in their vehicles, so the providers need to try to gather data while protecting driver privacy.

Methods of Improvement: Participants were also asked what methods their company uses to improve DSM technology. The most common response to this question (57%) was using customer feedback to make improvements to their technology. The providers want to use information from customers to make sure they are targeting the most relevant improvements. Several companies utilize human review to check the decisions made by the software. The reviewers use customer feedback to flag the most relevant issues from reviews. Along with this, another method of improvement mentioned by one of the participants included scanning data for near misses and using this to look for early warning indications and patterns of behavior to improve precision for detecting certain behaviors. For example, if many drivers nod their head before falling asleep, instead of triggering an alert when the driver is fully asleep, alerts can begin when the driver first shows signs of drowsiness. A final method of improvement identified by one of the participants was using data from other DSM system providers, released research, and white papers to validate their findings and make sure they are moving in the right direction.

Methods for Testing Effectiveness: In addition to methods of improvement, the participants were asked what methods their companies are using to test DSM technology effectiveness. Most of the participants (86%) said that customer feedback was a method their company was using to test effectiveness. For example, if they notice a high level of negative feedback from their customers, this may indicate a need to adjust the algorithm or to do further testing. The second most common method among the participants (57%) was using large datasets to test their system's effectiveness. The new datasets help train their algorithms on edge cases, which helps improve effectiveness and accuracy. Then, along with these methods, participants also mentioned using live testing with drivers and simulations such as installing the systems in employee's vehicles.

Other Monitoring Factors: The last question participants were asked was whether their company had considered monitoring for other factors like emotions, alcohol use, or drug use. For alcohol and drug monitoring, 57% of the participants said that their companies are considering this type of monitoring. However, the other participants said that their companies are more focused on monitoring behaviors instead. Across the board, emotion monitoring was not an interesting factor to the companies. There was concern among the participants that it would be difficult to detect emotions, and that there would not be much that the system could do to try to change an operator's emotions. Additionally, emotional aspects could likely be identified through driving behavior, so there would not be much need for the DSM to look for emotional factors.

5.4.3.3 ADS Developers

Terminology: To ensure they understood the terminology being used in the interview, the first question ADS developers were asked was whether their company agreed with the name "safety operator" as someone who monitors an AV for possible failure. All three of the developers that were interviewed agreed with that naming convention.

Once the terminology was established, the developers were asked if they used safety operators in their fleets, and if so, they were asked how many safety operators were employed at their fleet. All three developers said they did use safety operators. All the companies shared the number of safety operators in their fleet; however, they did not feel comfortable with us publishing the number of safety operators, as this may reduce their anonymity. All companies had over five safety operators.

Team Driving: Next, the participants were asked if their safety operators operate in teams. Two of the three developers responded that their safety operators do not drive in teams, but they have a remote operator or dispatcher to interact with the safety operator. The last developer stated that their safety operators operate alone most of the time, but occasionally have a co-pilot or ride-along depending on the task.

Safety operator Training: The following question pertained to the type of training the safety operators received. Developers were asked where their safety operators were trained and whether they refer to the AVSC guidelines in training. All three of the developers indicated that they do their safety operator training in-house. One participant specifically noted that they do both an in-classroom training and road testing, where safety operators demonstrate their ability to do maneuvers. Only two of the developers said that they refer to the AVSC guidelines specifically. These two companies stated that they use these guidelines to see where the safety emphasis is identified.

Safety Operator Responsibilities: The next four questions that the developers were asked all related to the specific responsibilities of the safety operators and what actions they are prohibited from doing. The responses to these questions for all three developers are displayed in Table 33.

Table 5. Responses for all ADS developers about safety operator responsibilities and prohibited actions.

Responsibility or Prohibited Action	Yes (All Companies)	No (All Companies)
Monitor roadway and vehicle behavior	✓	
Disengage if necessary	✓	
Keep hands on wheel (or hover)	✓	
Screen/Phone use prohibited	✓	
Drinking prohibited		✓
Eating prohibited	✓	
Talking prohibited		✓

In general, safety operators are expected to always remain alert to the roadway and vehicle behavior with their hands on or near the wheel so they would be capable of taking control of the vehicle in a failure case. One company required that the safety operator always keep their hands on the wheel, while the other two companies required their safety operators to hover their hands over the wheel and feet over the pedals. Respondents emphasized that safety operators are expected to perform all the roles of an ordinary driver while behind the wheel.

Many of the checks the safety operators perform on the vehicle are communicated via laptop to the passenger or via in-cab alerts to the safety operator. For example, one company stated they use a combination of simple visual, verbal, and auditory alerts to communicate the state of the vehicle to reduce distraction for the safety operator.

As the table above shows, the main actions that are prohibited for safety operators are eating and using a phone or some other screen. If an operator must drink water, they are expected to disengage from ADS mode. Secondary tasks performed by the safety operator should be kept to a minimum. One company stated that they have zero tolerance for electronics and if a safety operator uses an electronic device while driving, they are immediately terminated. The AVSC guidelines discourage conversation between safety operator and co-pilot unless it is about work-related matters; however, none of the companies claimed to adhere strictly to this suggestion, as they feel light conversation helps reduce the safety operator's cognitive load. Two companies mentioned that their safety operators often communicate with dispatchers via verbal interaction as well.

DSM Use and Integration: The last three questions that developers were asked involved whether DSM technologies are currently in use in test vehicles and what the possibilities of DSM integration would be in the future. All three of the developers said that they do use some type of third-party DSM in their test vehicles. Two companies discussed using multiple different DSM systems and testing multiple types of DSM technology. However, they all noted that there are significant issues with false positives for the behaviors they claim to assess. One company provided further insight by stating they do not think DSM technology is feature deficient, as it does monitor for the correct behaviors, but that it is rather capability deficient, as it does not accurately detect behaviors. As a result of these issues with available DSM technologies, only one ADS developer said that their company is interested in integrating a DSM system with ADS-equipped vehicles. In addition to the efficacy issues of DSM technologies, some of the other barriers to integration that developers identified included the following: apprehension of safety operators to have inward-facing cameras, limits to installation locations given other cameras in the vehicle, and lack of DSM system predictive capabilities. Two of the companies claimed they are looking into developing their own DSM system, as the technology between ADSs and DSMs are similar.

5.4.3.4 Industry Interview Conclusions

These conversations provided valuable insights into DSM and ADS technologies. ADS developers recognize the utility of DSM systems for monitoring their safety operators, acknowledging their importance in ensuring safe operation. However, the path to seamless operation will require further refinement of DSM technologies before ADS developers can confidently integrate these systems into their vehicles. False positives and efficacy concerns are among the challenges that need to be addressed. DSM providers must continue to enhance the technology's accuracy and reliability. Other barriers to integration include data access limitations and driver apprehension about inward-facing cameras. Without further technological innovation, DSM developers may struggle to find the tedious balance between affordability, size of the device, and computing power sufficient to improve accuracy. The barriers to DSM use are not insurmountable but require concentrated efforts to overcome.

The evolving landscape of ADS-equipped CMVs requires ongoing dedication to ensure the safe and effective deployment of ADS technology on U.S. roadways. As ADS-equipped CMVs become an integral part of the transportation environment and demands on drivers become more complicated, addressing the challenges associated with DSM integration becomes critical. These interviews highlight areas for future research in enhancing the accuracy of DSM technologies, exploring innovative approaches to reducing false positives for safety operators, and devising methods to gain driver buy-in for the use of driver-facing cameras while considering privacy law concerns. Overall, there is a clear need for collaboration between stakeholders in this field to improve DSM technology so that it can be integrated into ADS-equipped CMVs.

5.4.4 Exploratory Technology Evaluation

As made evident from the previous two sections of this report, ADS developers desire to have DSM systems in their vehicles to monitor their safety operators for inattention, fatigue, and other safety measures like seat belt use. However, each of the developers commented on the inaccuracies and false alarms present in the aftermarket technologies currently available for purchase. When considering integration, the ideal DSM technology would communicate with the ADS and remote assistants about driver state and take corrective action based on the operator’s degraded takeover ability. Developers that are interested in future integration of DSM systems with their ADS-equipped CMVs must consider the efficacy of these systems. Successful integration of DSM technologies in an ADS-equipped CMV is only possible if those technologies overcome the barriers of inaccuracy. Other barriers to integration include establishing valuable training datasets, sensor limitations, and affordability of aftermarket solutions. The purpose of this data collection was to explore the capabilities of two DSM systems by documenting possible shortcomings and by exploring how effectively a state-of-the-art DSM system meets the needs of safety operator monitoring. Additionally, this report serves to recommend future research opportunities that can build upon these findings.

This evaluation used two testing environments. The first part of testing occurred on a controlled test-track where the DSM system was installed in a CMV and the driver performed various behaviors relevant to a safety operator. Recent developments in DSM systems point towards a research need in testing DSM systems in naturalistic driving settings without manipulating operator state triggering.[133] Therefore, the second part involved collecting naturalistic data from a DSM system installed in an ADS-equipped CMV with a safety operator.

5.4.4.1 Methods

This testing included two monitoring technologies. The first technology was the Smart Eye Aftermarket Installation System (AIS) (Figure 47).

Figure 3. Photo. Smart Eye AIS hardware.

This technology was selected based on the criteria listed earlier. This technology represents a video-based monitoring system that tracks the driver’s eye and head positions to determine driver states such as drowsiness and distraction. Material in the literature review noted that future research with DSM systems should consider integrating different state indicators such as video-based and physiological indicators.[134] Two separate DSM systems were used in parallel during testing to begin addressing this research need. In addition to the video-based system, a smart wearable device called Empatica (Figure 48) was included in the data collection. This technology represents a wearable physiological data sensor.

Figure 4. Photo. Empatica smart wearable device.

The two DSM systems were evaluated using two driving contexts: (1) a naturalistic automated driving in a port and (2) a controlled test track experiment using emulated driver states. In the first evaluation, the systems were installed in a CMV owned by a participating fleet with the ADS provided by Pronto integrated into the CMV. The driver of the truck was a safety operator. The ODD for the Pronto truck was a breadcrumb trail around a shipyard in Alaska. The truck was practicing moving freight across the yard to prepare for active barge operations. The safety operator was tasked with monitoring the system during this 2-hour practice in the ODD, which is part of their regular job duties. The system was installed in the fleet's ADS-equipped CMV according to the Smart Eye AIS installation procedures documented both on their website and in the mobile app by a VTTI installer. The Smart Eye system was set to default system settings for all behaviors and the speed limit was set to "simulated" so that driving tasks could be performed at any speed. Images of the Smart Eye system installed in the Pronto truck and the driver are not included for privacy reasons. Video recording of the vehicle operation was collected, but no footage of the driver was taken during the practice due to privacy concerns. The driver was interviewed after the drive to inquire about tasks completed during monitoring and general fatigue level. The driver wore the Empatica watch on the left wrist (non-dominant). Both systems were checked to ensure they were collecting data properly before testing was initiated.

In the second evaluation, the systems were installed in a conventional semi-truck provided by VTTI. The driver of the truck was a Class A CDL holder employed by VTTI. Testing took place on the Virginia Smart Roads for 2 hours during daylight. The same Smart Eye system used in Alaska was installed in the VTTI truck by the same VTTI installer. The installation position is included in Figure 49.

Figure 5. Photo. Installation position for Smart Eye.

The driver also wore the Empatica watch on the left wrist (non-dominant), as shown in Figure 50.

Figure 6. Photo. Empatica watch on driver.

Both systems were checked to ensure they were collecting data properly before the driver started piloting the CMV. The two systems were evaluated by having the driver emulate three common driver states: drowsiness, distraction, and high mental workload. Additionally, since ADS developers often mentioned false alarms for their DSM systems during the interviews, quasi-distraction behaviors were also included to test the system's discernment of distraction. For example, testing included whether or not looking in the side mirrors was categorized as distraction. Each task was standardized to ensure the driver performed similarly across each trial. Additionally, timers and audio cues were used to ensure the timing of each task matched the protocol. The protocol for each task is listed below.

To emulate a state of distraction, the driver texted multiple messages on a smartphone and held a phone to their ear as if taking a phone call. For the phone call task, the following protocol was used to test the device's ability to identify the behavior:

1. The driver looked down at the cup holder, where the phone was sitting, once.
1. The driver reached for the smartphone in the cup holder with their right hand.
2. The driver looked at the phone as if to unlock it.
3. The driver held the phone to their ear for 30 seconds while looking at the road.

Figure 51 illustrates how the driver held the phone during testing.

Figure 7. Photo. Phone call.

For the texting task, the following protocol was used to test the device's ability to identify the behavior:

1. The driver looked down at the cup holder, where the phone was sitting, once.
2. The driver reached for the smartphone in the cup holder with their right hand.
3. The driver held the phone in their right hand at an elbow bend of 45 degrees within view of the camera.
4. The driver looked up and down at the phone for 2 seconds with eyes off road and 1 second with eyes on road twice, for a total of 6 seconds, based on Olson et al., which found that drivers dialing their phone tended to look down for an average of 3.8 seconds over a 6-second period.[135]

Figure 52 illustrates the driver following the procedure for sending an outgoing text message.

Figure 8. Photo. Texting behavior

To emulate a state of drowsiness, the driver performed several behaviors that characterize symptoms of a sleepy driver, as well as pretending to fall asleep. The driver blinked slowly, drooped his head, closed his eyes, and yawned. For the yawning task, the driver simply yawned three times per trial by opening his mouth wide. The driver attempted to stifle any yawns that occurred outside of the trial. Figure 53 illustrates how the driver followed the yawning procedure.

Figure 9. Photo. Yawning

For the slow blinking task, the following procedure was used to test the device's ability to identify the behavior:

5. The driver slowly closed his eyes over the course of 3 seconds until they were shut.
6. The driver held his eyes shut for 1 second, then opened them.
7. The driver held his eyes open for 3 seconds.
8. The driver blinked slowly five times.

Figure 54 illustrates the driver following the procedure for the slow blinking.

Figure 10. Photo. Blinking slowly.

For the closing eyes task, the driver emulated a microsleep with eyes closed and head up. In terms of procedure, the driver simply closed his eyes for 5 seconds per trial. Figure 55 illustrates the driver following the procedure for closing eyes.

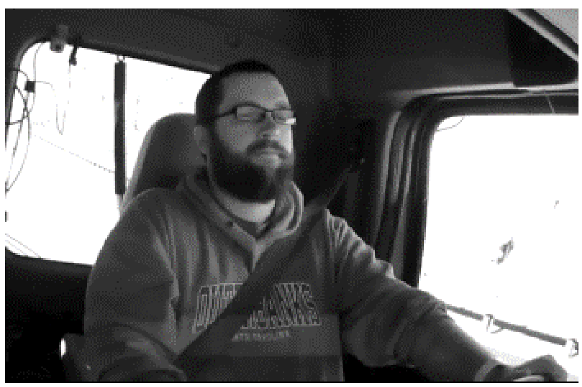

Figure 11. Photo. Closing eyes.

For the drooping head task, the driver emulated a microsleep with eyes closed and head down. The following procedure was used to test the device's ability to identify the behavior:

1. The driver slowly drooped his head down towards his chest over the course of 5 seconds.
2. The driver lifted his head quickly and opened his eyes.
3. The driver repeated this three times per trial.

Figure 56 illustrates the driver following the procedure for drooping head.

Figure 12. Photo. Drooping head

To induce a state of mental workload, the driver was asked to count backwards from 1,000 by 3, 7, and 13, once per trial. The driver maintained his gaze on the road during this task.

To understand how normal driving behaviors could be confused for improper driver state, the driver was instructed to check his mirrors, look at the dashboard, and focus on pedestrians outside of the vehicle. For the mirrors and dashboard tasks, the driver looked at the object for a total of 3 seconds. For the pedestrian task, the driver was asked to follow the pedestrians with his gaze until they were out of comfortable view. The setups for the pedestrians are included in Figure 57 and Figure 58.

Figure 13. Photo. Motorcycle and bicyclist road users positioned at intersection.

Figure 14. Photo. Adult, male pedestrian positioned at intersection.

The analysis of the results differed for each testing environment. For the observational data collected in the shipyard, the frequency of alerts was taken for each of the collected behaviors to understand how often the driver was notified of improper behavior. Each count corresponds to an in-cab alert delivered to the driver over the course of the 90-minute drive. The number of false alarms was not collected during this drive, as in-cab video was not recorded due to privacy concerns. Summary statistics received from the Empatica watch, such as HR, HRV, and EDA, were gathered for each of the metrics collected.

For the Smart Roads testing, the number of successful alerts was determined for each category (i.e., texting, phone call, etc.). In the event there were multiple successful alerts for the same behavior, only the first behavior was included in the count. Although the number of false alarms could be totaled, this metric is considered outside the scope of this exploratory effort. Instead, it was noted whether there was at least one false alarm in each category and whether the system incorrectly identified at least one behavior. This decision was made because this project is not a benchmarking effort to understand the exact capabilities of two particular driver monitoring systems, but rather an attempt to understand possible shortcomings of all DSM systems when integrated with an ADS-equipped CMV.

5.4.4.2 Results

The following section presents the results obtained from the exploratory data collected in this study, which aimed to investigate the general success of a DSM system to monitor a safety operator during both naturalistic driving and closed test track driving.

Smart Roads Testing

For Smart Roads testing, the driver was instructed to emulate 11 driving behaviors, or tasks. The number of alerts during each trial was documented for each of the 11 tasks. The results are included in Table 34.

Table 6. Emulated driving behaviors and tasks.

State	Task	Number of alerts	Number of Trials
Distraction	Phone Call	3	3
	Texting	3	3
Drowsiness	Yawning	1	3
	Blinking Slowly	3	3
	Drooping Head	3	3
	Close Eyes	3	3
Mental Workload	Counting Backwards	0	3
Other	Looking at Instrument Panel	3	3
	Looking at Pedestrian Crossing	2	9
	Looking at Left Mirror	3	3
	Looking at Right Mirror	3	3

It is important to note that the number of trials for all tasks is three, except for the pedestrian tasks, which had nine trials. The pedestrian task had nine trials because three configurations of pedestrians were used with three trials in each configuration (Motorcycle & Bicycle, Adult Male Pedestrian, and Child Male Pedestrian). The number of alerts represents the number of alerts that went off during testing for that task. This did not capture whether the alert was incorrectly assigned to the task, nor if there were multiple alerts for the same behavior, as only the first alert was counted. During testing, at least one false alarm was produced, and at least one false categorization occurred.

From the Empatica watch, beats per minute (BPM) over the trip time was graphed to understand how the driver's HR changed during the trip (Figure 59).

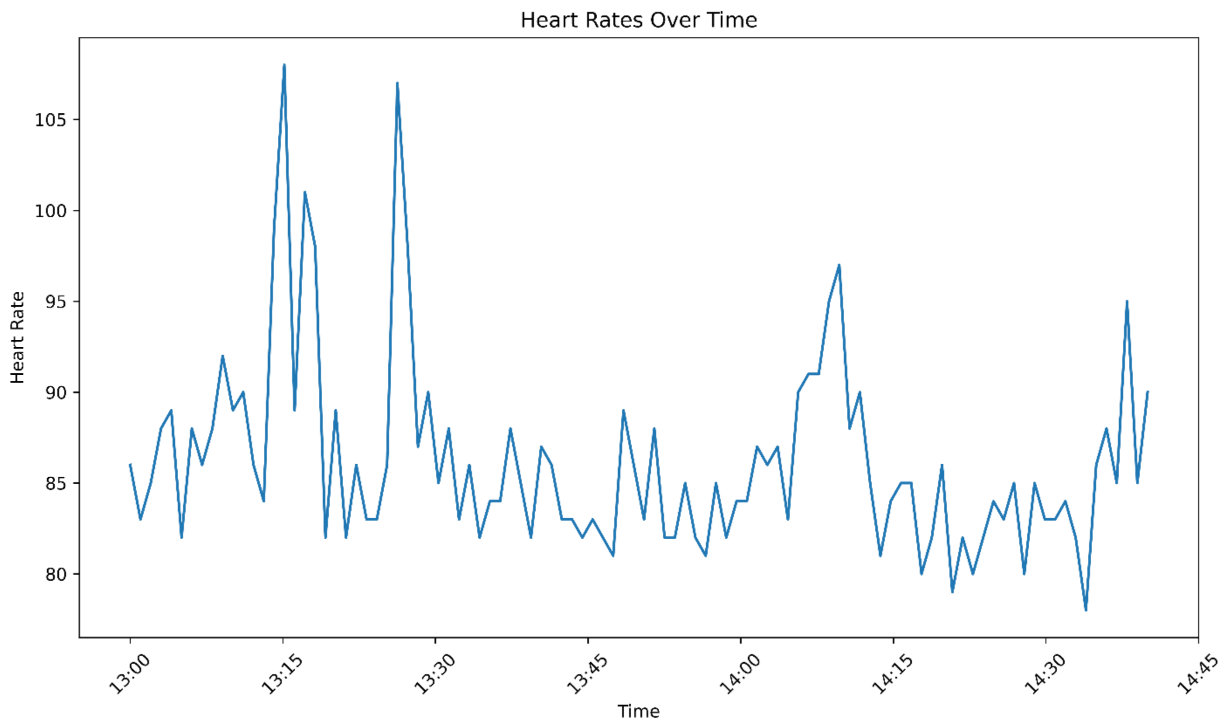

Figure 15. Changes in HR (in BPM) over time for the Smart Roads driver.

The points of interest in the HR graph are the four peaks. The times of these peaks were compared to footage of the driver to understand possible causes. From 13:14 to 13:17, the driver was outside the vehicle helping with the setup for the pedestrian models. The driver was standing, moving, and lifting heavy mannequins during this period, which was likely responsible for the first peak. During the second peak around 13:30, the driver was again outside the vehicle aiding with breakdown for the pedestrian setup. From 14:06 to 14:10, the driver and researcher took a stretch break outside of the vehicle. The mental math trials occurred from 14:20 to 14:29. There were no obvious spikes in the HR during this time that would indicate the driver was experiencing heightened mental workload. The final, fourth, peak is interesting, although it is outside of the testing window. From 14:35 to 14:40, the driver was moving the truck from the closed test track to a facility further down the road. He encountered live traffic during this time, which seems to account for the spike in HR. Although this is outside the scope of this project, it is an interesting data point.

The EDA amplitude collected from the Empatica watch over the trip time was graphed to understand how the driver's EDA changed during the trip (Figure 60).

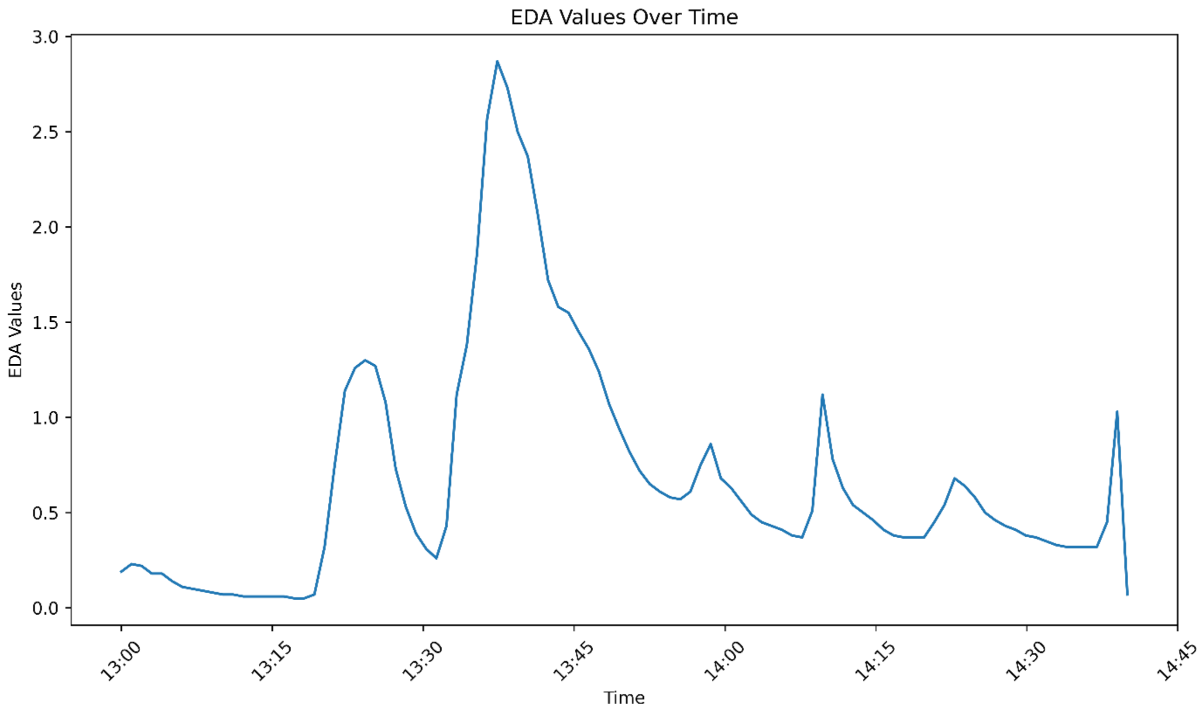

Figure 16. Photo. Changes in EDA over time for the Smart Roads driver.

The points of interest in the EDA graph are the six peaks in phasic skin conductance response, or the faster varying process that fluctuates within seconds and minutes and the general shift of the tonic skin conductance level, or the slower varying process that fluctuates more slowly across time. The first three peaks and the general increase in EDA amplitude line up with the times where the driver was outside of the vehicle helping with the pedestrian setup (13:14 to 13:17; 13:30 to 13:40; 13:50 to 14:00). The fourth peak around 14:10 corresponds with the stretch break the driver took outside of the vehicle, which may be responsible for the peak in EDA amplitude. Interestingly, the mental math trials occurred from 14:20–14:29, which corresponds with the fifth peak. Although there was no indication of increased mental workload on the HR graph, there is an indicator on the EDA graph of increased arousal. The final, sixth, peak lines up with the time where the driver left the closed test track and encountered live traffic while dropping the truck off at another location.

Port Testing: During shipyard testing, the driver was not instructed to complete specific behaviors. Instead, the driver was monitored while working as a safety operator. The behaviors listed in Table 35 are self-reported behaviors the driver completed during the drive. These were reported in an interview after the drive.

Table 7. Driver self-reported behaviors during drive.

Behaviors reported by driver during drive	Collective time spent on task
Talking on a walkie-talkie	10 minutes
Looking at forward roadway	30 minutes
Drinking water	3 minutes
Looking at cellular device	10 minutes
Checking mirrors	30 minutes

The context of the drive is important for interpreting these results. The vehicle had a top speed of 12 mph around the yard. Additionally, the vehicle alternated between stop and movement during the loading and unloading procedures. The driver would often be sitting in the truck waiting to be loaded or unloaded, where they would look for nearby vehicles, which did not involve looking at the forward roadway. The driver also used a walkie-talkie instead of a handheld cell phone device for communications with other yard operators such as forklift drivers. The operator explained that the cellular device use was because the truck was controlled partially by an app on the mobile device.

The number of alerts is documented for each of the 11 tasks listed in Table 34. The results are included in Table 36.

Table 8. Number of alerts for each of the 11 tasks.

Smoking Detected	Distraction Detected	Microsleep
1	89	39

The device alerted once to smoking; however, the driver did not smoke during the drive. There were 89 instances of distraction detected during the drive and 39 instances of microsleep detected. The driver reported a high level of distraction during the drive but did not report feeling tired.

From the Empatica watch, the BPM over the trip time was graphed to understand how the driver's heart rate changed during the trip (Figure 61).

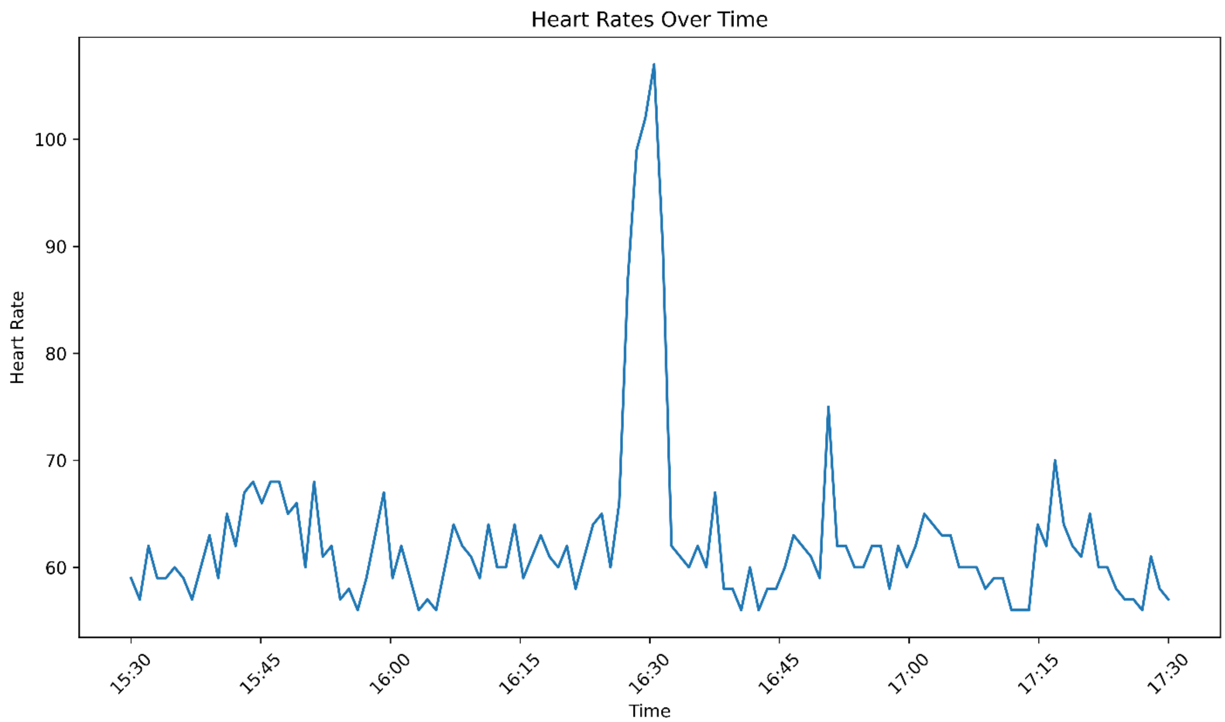

Figure 17. Graph. HR in BPM for during the shipyard trip.

The points of interest on the BPM graph are the two spikes in HR. Unfortunately, due to privacy concerns, the driver was not recorded during the drive, so it is unclear exactly what caused the two spikes. However, the research team was present in the yard in a separate vehicle during the drive and was able to listen to the walkie-talkie communication between the yard operators. During the drive, there were several times where the truck got stuck on the ice and needed to be put in manual mode to be driven. Speculatively, the spikes in HR could be caused by the shift from monitoring to manual driving.

The EDA amplitude from the Empatica watch over the trip time was graphed to understand how the driver's EDA changed during the trip (Figure 62).

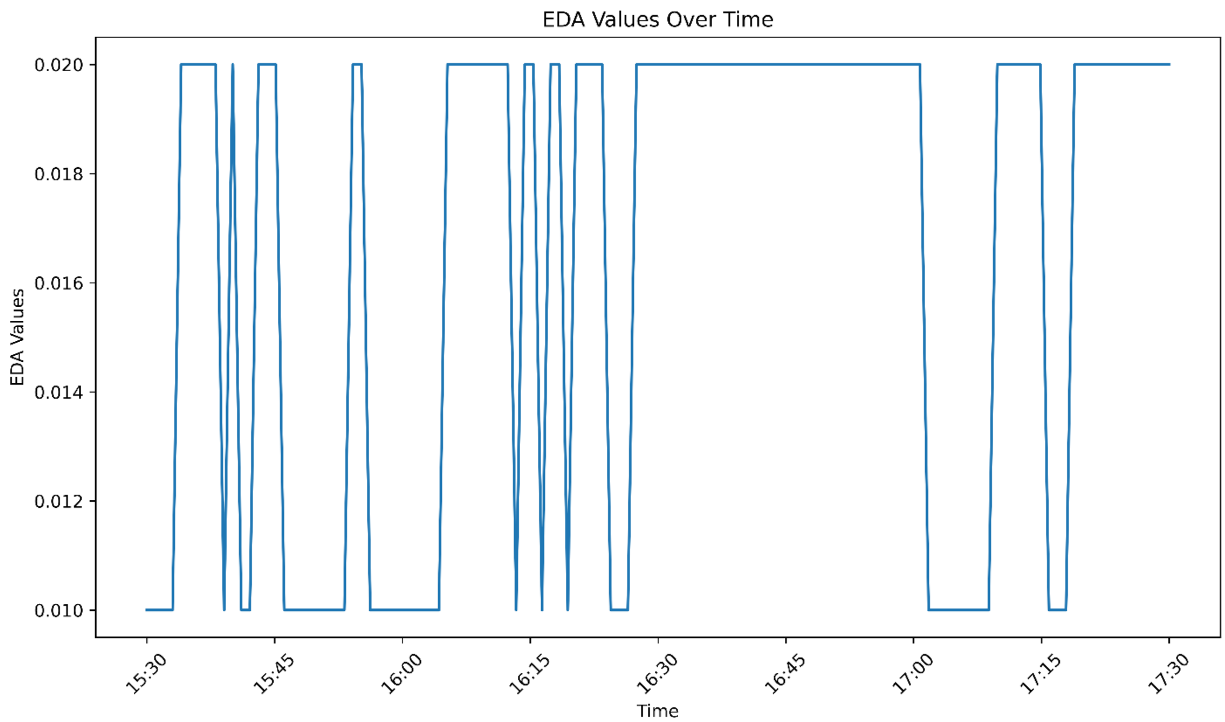

Figure 18. Graph. Empatica EDA amplitudes over trip duration.

Compared to Figure 60, the Figure 62 graph has a much smaller vertical range. External factors such as temperature and humidity can make EDA results inconsistent. In Alaska, the temperature was very cold, and the humidity level was very dry, which may have impacted the driver's EDA amplitude. Based on the lack of baseline and no video, it is difficult to produce meaningful results from this graph.

5.4.4.3 Exploratory Conclusions

Overall, this exploratory research aimed to investigate the capabilities and shortcomings of DSM systems and understand how effectively a state-of-the-art DSM system meets the needs of safety operator monitoring. Interviews with ADS developers indicated that DSM systems are feature sufficient but accuracy deficient, meaning they can detect the desired behaviors, such as distraction, but the accuracy of this detection is questionable.

The results from testing support these anecdotal reports. The device was able to detect distraction, drowsiness, and policy violations such as smoking, but these specific testing environments produced at least one false alarm and at least one false categorization, which threatens accuracy. If these systems are to be integrated into ADS-equipped CMVs, then accuracy is paramount to correctly inform the system and protect drivers. For example, in one interview with an ADS developer, the representative stated the company has a zero-tolerance policy for cell phone use. With this DSM system, there was no way to verify the validity of alerts with recorded footage. If a driver was falsely reported to be distracted, this could have negative implications for their career. This points towards the necessity for footage review of DSM systems or, at a minimum, image captures of instances where the driver is categorized as distracted. Another important aspect of inaccurate alerts is false categorization. When a DSM system is integrated into a vehicle, if the system inaccurately labels drowsiness as distraction, the decision-making vehicle needs to be able to accurately respond to the driver's state. If the driver is categorized as distracted, the system may only provide an alert, whereas if the driver is identified as being drowsy, it may trigger the vehicle to pull over. This indicates the need for highly accurate monitoring prior to integration.

The results also underscore the criticality of maintaining context of the DSM systems for interpreting results. When comparing testing at the port and on the test track, the vehicle environments were completely different. In Alaska, the ADS-equipped CMV drove at a top speed of 12 mph with icy road conditions. One of the driver's duties was to monitor the environment for other yard operators getting near the truck. The driver needed to look in many directions, which may have increased the number of distraction alerts even though the driver was successfully completing his job. On the test track, the driver maintained a speed of 25 mph to 45 mph on a relatively straight road with clear conditions. When turning the vehicle around, the driver looked in the direction of the turn, which was the forward roadway, but the systems often alerted to this as being distraction. Meaning, even though the driver was looking where the vehicle was going, the device categorized these instances as distraction because the driver was not looking "straight." These types of false alerts may discourage drivers from accepting DSM systems because they may feel they are doing their job correctly, while the alerts indicate otherwise. Adjusting the alert sensitivity may help alleviate the onslaught of alerts. If the device were integrated into the vehicle and received information about the external context of the vehicle, then the DSM system could adjust categorization more effectively.

The collected physiological data was best interpreted with video context. Without knowledge of driver's activities and timing, there was no real way to decipher the EDA and HR data. In the future, if DSM systems intend to integrate physiological data, a way to contextualize the information with video is worthwhile. Another consideration of physiological data is the cost. Several DSM system manufacturers commented that one major barrier to integration is cost, as they are trying to keep aftermarket products scalable to large fleets. When considering the added cost of current wearable technologies, this may be economically out of reach for large fleets. This points to the differences in OEM versus aftermarket technologies. Although there are benefits to including DSM systems as aftermarket products in terms of cost, effectiveness may be severely limited without full integration with the vehicle.

5.4.4.4 Limitations and Future Needs

As this was an exploratory study, there are several limitations to consider. First, the decision to assess a single video-based DSM system, while based on pre-established criteria, does not consider the diverse landscape of available DSM technologies. Many DSM technologies available require a minimum number of devices to be purchased, which was not cost-effective for the project. Additionally, many platforms have a subscription-based service that must be purchased to access the dashboard data. By excluding consideration for system carriers that mandated minimum purchases or subscription services, the study's outcomes may not holistically reflect the efficacy and applicability of DSM systems across different market offerings. Consequently, the findings derived from this study may not be generalizable to other DSM systems, potentially limiting their broader relevance and applicability within the field.

However, the results emphasize the importance of continued research in this field before DSM systems can be fully integrated into and trusted to manage ADS-equipped CMV testing operations. Additionally, given the rapid evolution of technology, the information collected in the technology scan and literature review in October 2022 may not accurately reflect the current state-of-the-art in DSM technology.

The study's sample size, comprising only two drivers who underwent approximately 2-hour trials each, imposes constraints on the depth and breadth of insights gained. While the exploratory nature of the study necessitated a focused approach, the limited duration of trials and the small number of participants may not adequately capture the nuances of driver behavior and fatigue detection. Longer trial durations, coupled with deliberate induction of fatigue, could offer a more nuanced understanding of the DSM system's performance in real-world driving scenarios. However, ethical considerations and practical constraints may hinder the feasibility of such approaches, highlighting the delicate balance between research objectives and participant well-being.

The study's data collection process was inherently context-specific, conducted within a specific time of day, location, and with a single safety operator. While this controlled approach may enhance internal validity, it simultaneously compromises the external validity and generalizability of the study's findings. Future research endeavors should strive to broaden the scope of data collection across diverse driving scenarios, environmental conditions, and more participants to better understand the robustness and adaptability of DSM systems in real-world contexts.

This study had a limited exploration of false alarms, a common issue with DSM systems. While acknowledging the varying sensitivity levels of DSM systems in detecting specific driver behaviors, the study's scope did not include a detailed examination of false alarm rates and their implications for driver safety and system usability. Future studies might prioritize comprehensive evaluations of false alarms to elucidate their prevalence, underlying causes, and potential mitigation strategies.

The lack of integration between the DSM technology and the vehicle's ADS presents another significant limitation. Integration of DSM systems with ADS holds promise for enhancing driver safety and overall system effectiveness. However, fully integrating the two DSM systems with one another and the vehicle was outside of the scope of the project. The absence of such integration limits the understanding of the synergistic effects between DSM alerts and existing ADS vehicle safety features. Similarly, the lack of integration between different DSM systems hinders comparative analyses and insights into their relative performance and reliability.

Finally, the study's reliance on smart watches for physiological measurements introduces inherent limitations in accuracy compared to medical-grade devices. The absence of validation studies to assess the accuracy and reliability of the smartwatch-based measurements underscores the need for caution when interpreting the study's findings. Future research endeavors should prioritize rigorous validation studies to ensure the integrity and validity of the physiological data collected. Additionally, to assess individual differences, it is important to capture a baseline per participant to interpret the results more accurately.

Overall, while acknowledging these limitations, the study's findings offer valuable insights into the performance and usability of DSM systems in real-world driving scenarios. By addressing these limitations and incorporating them into future research endeavors, we can advance our understanding of DSM technology and its role in enhancing safety and well-being for safety operators and other road users.

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