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Ensuring the Safe Operation of Automated or Partially Automated Locomotives: The Role of Driver State Monitoring Systems

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14. ABSTRACT
States of reduced operator alertness, such as fatigue and inattention, are well-known factors contributing to railway accidents and safety incidents. However, more effective solutions are needed to mitigate their impact. Driver state monitoring (DSM) systems can potentially play a mitigatory role, as these systems use cameras and sensors to continuously observe operator behavior to detect likely signs of fatigue, distraction, or inattentiveness, and provide visual or audible warnings to the operator if a change in operator state is detected. While various DSM systems are available and in use by the automotive industry (e.g., GMC Super Cruise, Ford Blue Cruise), these systems must be evaluated for their applicability in the rail environment and potentially modified to suit the control tasks of locomotive engineers. The Federal Railroad Administration (FRA) sponsored the Virginia Tech Transportation Institute to identify DSM systems for further testing in an in-cab rail setting to address challenges and find solutions to enhance their effectiveness. The team evaluated and demonstrated the potential of DSM technologies so that, with further refinement, DSM systems could be implemented to reduce human error and improve locomotive engineer performance. This research was conducted from 2022 to 2024 using FRA's Cab Technology Integration Laboratory (CTIL) high-fidelity, full-sized locomotive simulator.

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Executive Summary

States of reduced operator alertness, such as fatigue and inattention, are well-known factors contributing to railway accidents and safety incidents. However, more effective solutions are needed to mitigate their impact. Driver state monitoring (DSM) systems can potentially play a mitigatory role, as these systems use cameras and sensors to continuously observe operator behavior to detect likely signs of fatigue, distraction, or inattentiveness, and provide visual or audible warnings to the operator if a change in operator state is detected. While various DSM systems are available and in use by the automotive industry (e.g., GMC Super Cruise, Ford Blue Cruise), these systems must be evaluated for their applicability in the rail environment and potentially modified to suit the control tasks of locomotive engineers.

The Federal Railroad Administration (FRA) sponsored the Virginia Tech Transportation Institute to identify DSM systems for further testing in an in-cab rail setting to address challenges and find solutions to enhance their effectiveness. The team evaluated and demonstrated the potential of DSM technologies so that, with further refinement, DSM systems could be implemented to reduce human error and improve locomotive engineer performance. This research was conducted from 2022 to 2024 using FRA's Cab Technology Integration Laboratory (CTIL) high-fidelity, full-sized locomotive simulator, located at the Volpe National Transportation Systems Center in Cambridge, MA.

An effective DSM system in a rail cab environment would continuously monitor locomotive engineer state and performance and provide warnings if fatigue or inattention was detected. As automation becomes more prevalent in the rail cab and locomotive control systems, a fully integrated DSM system could activate some form of automated control (e.g., apply brakes to slow locomotive, or bring it to a complete stop) to prevent incidents or accidents associated with the onset of fatigue and/or inattention.

The research team first completed a comprehensive technology scan to provide insight into the current state of DSM technologies, including the availability, capabilities, and limitations of vehicle-based features that monitor driver state and their potential applicability in a rail cab environment. DSM systems currently in use in the automotive industry use complex algorithms to determine the onset of fatigue or inattention prior to warning the driver about the change in driver state. Ideally, a rail version of the system would function in the same way in a rail environment, although the specific criteria used to determine what constitutes a high-risk period of fatigue or inattention would likely be different for rail versus automotive due to the difference in performance requirements and control tasks.

Researchers selected two candidate DSM technologies – a fixed camera-based system (i.e., SmartEye) and a wearable eye tracking system (i.e., ETVision) – for further testing and assessment in a simulated rail environment using FRA's CTIL locomotive simulator. The team recruited nine passenger locomotive engineers to participate in the study. All the participants completed the simulator scenario using the SmartEye DSM system, with five of the participants also wearing the ETVision eye tracking glasses. The DSM systems captured continuous data during the entire simulated scenario, which was designed to induce fatigue and inattention.

The SmartEye camera-based system showed potential for detecting locomotive engineer fatigue; however, the single fixed camera struggled to capture accurate data due to locomotive engineers frequently moving in their seat or alternating between sitting and standing, particularly as fatigue

set in. This movement caused the camera to lose sight of their face and eyes, diminishing data quality during critical moments. A multi-camera setup could resolve these issues and improve data accuracy but would increase costs, limiting widespread adoption. Additionally, poor pupil and gaze tracking caused by camera distance and positioning may have contributed to erroneous inattention event detection.

The ETVision eye tracking glasses also showed potential for detecting locomotive engineer fatigue using measures such as blink frequency and eyelid position. However, the system also struggled with reliable pupil tracking, affecting its ability to detect inattention. For instance, one participant experienced a complete loss of pupil tracking for five minutes, rendering gaze detection ineffective. The system's wearable design allowed greater movement around the cab but often compromised data quality due to the glasses shifting position, leading to loss of pupil or eyelid detection. Additionally, the system requires precise calibration across the field of view, posing challenges for real-world use.

User acceptance was higher for the SmartEye DSM system due to its non-intrusive design, requiring no interaction from locomotive engineers. However, camera-based systems may raise privacy concerns, as users fear potential management reprisals if recorded engaging in prohibited behaviors. In contrast, user acceptance of the ETVision system was lower, primarily because the glasses were uncomfortable to wear and needed to be tightly secured to prevent slipping.

While these DSM systems showed promise in some respects, there were numerous issues with each system that impacted data quality and the resulting fatigue and inattention measures. Any DSM system is only as good as the data it collects. While a system may show promise and/or positive results in a highly controlled environment, in a real-world scenario where continuous high-quality data is critical to reliable and accurate measures and output, the issues identified during this project would be problematic. Relying on a DSM system to provide a minute-to-minute accurate assessment of driver state requires high-quality data with very minimal instances of data loss, which neither of these DSM systems could provide in their current form.

1. Introduction

From June 2022 to December 2024, the Federal Railroad Administration (FRA) sponsored Virginia Tech Transportation Institute (VTTI) to investigate the applicability and functionality of driver state monitoring (DSM) technologies in an in-cab rail environment to determine challenges and potential solutions to improve DSM system use.

1.1 Background

The operating environment in the rail industry demands that locomotive engineers remain consistently alert and attentive over extended periods. These conditions are often characterized by monotony interrupted by bursts of high activity or critical events requiring immediate responses (Edkins & Pollock, 1997). Compounding these challenges, irregular work and rest schedules often result in poor sleep quality and duration, further impacting alertness. While increased automation in locomotive cabs is generally intended to reduce workload and enhance safety, it can unintentionally worsen alertness and attention issues. By shifting the human operator from an active control role to a more passive supervisory position, automation places greater emphasis on monitoring the system and intervening when necessary (Parasuraman et al., 1996). Research consistently demonstrates that humans struggle with tasks requiring sustained attention over long periods. Consequently, increased monitoring responsibilities can lead to significant alertness and attention challenges, as well as "out-of-the-loop" performance problems, where operators lose awareness or understanding of the automated system's state.

DSM technologies use sensors in the vehicle to determine when drivers might be distracted, drowsy, fatigued, or otherwise inattentive. These driver states are widely acknowledged and recognized as being detrimental to the safe operation of all modes of transportation, including locomotives, light vehicles, trucks, buses, and aircraft. Therefore, detecting when drivers or operators are distracted, fatigued, or inattentive offers opportunities to reduce hazards and mitigate the associated consequences.

Recently, as the automotive industry pushes forward with more advanced driving automation systems, DSM systems have become more widely incorporated in consumer and fleet vehicles. Leading safety agencies such as the National Transportation Safety Board (NTSB) and the European New Car Assessment Program recommend the use of DSM systems, also known as driver monitoring systems, in vehicles equipped with advanced driving automation systems.

Automated systems designed under incremental levels of automation still require human supervision for safe operation. It is therefore important to have a system that helps a driver maintain attention and focus so they can monitor automated systems and keep human control authority over the vehicle should automation fail or initiate incorrect actions. Driver monitoring systems have the potential to detect levels of alertness in the driver and provide warnings or possibly initiate control actions. For this reason, DSM systems can be beneficial for all forms of automated or partially automated transportation, including locomotives.

While DSM technologies are currently available and in use by numerous automobile manufacturers (e.g., GM’s Super Cruise and Tesla’s Autopilot), systems that work in an automobile may not work effectively in a locomotive. In addition, control tasks vary greatly between motor vehicles and locomotives. To develop an effective DSM system for rail, the differences in parameters between the two need to be understood and addressed.

DSM systems can also use various approaches. For example, some DSM systems are camera based, while others are sensor based; some are fixed mounted systems, while others are wearable devices. Each of these DSM types has pros and cons, which may make them more or less suitable for use in a rail cab environment.

1.2 Objectives

A range of vehicle-based DSM technologies currently exist; however, they have not been assessed for usefulness in a rail environment and potentially adapted/modified to accommodate the control tasks of a locomotive engineer. The goal of this project was to identify candidate DSM systems for further testing in an in-cab rail environment to determine challenges and solutions to improve effectiveness.

The primary objectives of this project include:

- Review the capabilities and limitations of currently available DSM technologies to provide a complete picture of technologies from the automotive sector that may be adapted for rail.
- Identify two candidate DSM technologies and conduct initial pilot testing to ensure these systems work in a controlled environment.
- Investigate the applicability and functionality of the two candidate DSM technologies in an in-cab rail environment.
- Provide FRA with an evaluation of the candidate DSM systems, including challenges and potential solutions to improve system effectiveness, and determine the most appropriate and effective method for monitoring locomotive engineer alertness.

1.3 Overall Approach

The research team conducted a comprehensive technology scan to develop a complete and up-to-date assessment of the state of DSM technologies, including the availability, capabilities, and limitations of vehicle-based features that monitor driver state and their potential applicability for use in a rail cab environment. Two candidate DSM technologies were then selected for further testing and assessment in a simulated rail environment. Initial pilot testing was conducted at VTTI using a desktop simulator to verify the functionality and effectiveness of the technologies under different conditions and scenarios. The final assessment of the candidate DSM systems was conducted using FRA's Cab Technology Integration Laboratory (CTIL) high-fidelity, full-sized locomotive simulator, located at the Volpe National Transportation Systems Center in Cambridge, MA. The DSM systems continually captured data during a simulated scenario designed to induce fatigue and inattention. This allowed the team to examine how well the DSM systems identified locomotive engineer fatigue and inattention across the trip and explore how well the DSM was able to discern varying levels of alertness.

1.4 Scope

The candidate DSM systems were assessed in a highly controlled environment using the CTIL locomotive simulator to ensure that all participants experienced identical study conditions. Nine locomotive engineers were recruited to complete the study. All participants completed the simulator scenario using the SmartEye DSM system, with five of the participants also wearing the ETVision eye tracking glasses during completion of the scenario.

1.5 Organization of the Report

This report is organized into the following sections:

- Section 2 provides an overview of available DSM technologies
- Section 3 presents the method for the CTIL simulator study
- Section 4 examines the study results
- Section 5 discusses these results and presents concluding remarks

2. Review of DSM Technologies

In the automotive context, there are multiple methods for assessing and monitoring driver state to detect driver fatigue or distraction. However, not all these methods will translate effectively to a rail environment. Currently available DSM technologies essentially fit into one of three groups of products: camera-based technologies, wearable devices, and other sensor solutions.

2.1 Camera-Based Technologies

Most camera-based DSM technologies use eye-tracking methods and computer-vision-based techniques to track a user's eyes and head position, allowing the system to determine the direction of their gaze. In automotive applications, these systems are often designed to monitor whether drivers are looking at critical areas (e.g., the road ahead) or potential distractions (e.g., the infotainment system). Additionally, they can assess driver fatigue by analyzing eye closure patterns. A common metric for these eye patterns is "percentage of eye closure" (PERCLOS), which measures the proportion of time a driver's eyes remain closed over a given interval; higher values often indicate drowsiness (Dinges & Grace, 1998; Sommer and Golz, 2010).

Under optimal conditions, camera-based DSMs can accurately pinpoint a driver's gaze to specific objects within the vehicle cabin, often within a few inches. This precision, however, requires calibration using a 3D model of the vehicle's interior. With advancements in machine learning, these systems are also capable of identifying undesirable behaviors (e.g., eating, reading, or using a cellphone) which can compromise safety (Li et al., 2020; Masood et al., 2020). However, despite their capabilities, camera-based DSM systems face limitations. For example, Wayland (2019) found that camera-based systems are negatively affected by certain lighting conditions or when the sun is at certain angles relative to the driver. Additionally, their effectiveness is constrained by the camera's field of view, making them unreliable if the driver's face is even partially obstructed or out of frame. This challenge may be particularly pronounced in a rail cab environment, where locomotive engineers may move beyond the coverage of a single camera. A potential solution would be to deploy multiple cameras to cover all critical areas of operation, although this would likely increase the cost of the DSM system (i.e., single camera vs. multiple cameras).

Another concern is privacy. These systems rely on constant video capture, which can raise objections from users wary of being continuously monitored. For instance, similar concerns have been noted in the trucking industry, where drivers often resist the installation of cameras in their vehicles (Adler, 2022). Thus, while camera-based systems demonstrate promise at detecting and alerting drivers to periods of fatigue or inattention, these technologies will require use considerations, and research and development work.

2.2 Wearable Devices

Wearable technologies such as glasses, headbands, and wristbands are designed to be versatile, comfortable, and minimally intrusive, making them suitable for industries like trucking, mining, and construction. These devices monitor various physiological indicators to enhance safety by detecting and mitigating fatigue.

Glasses equipped with sensors monitor eye and eyelid movements, measuring parameters like the speed and extent of eyelid opening and closing. Data are collected up to 500 times per second, enabling the calculation of variables such as drowsiness. Metrics like the Johns

Drowsiness Scale (JDS) (Johns et al, 2006) or PERCLOS are used to determine fatigue levels. When high fatigue is detected, auditory alerts notify the wearer, and safety managers can receive real-time notifications, including emails or text messages, if a driver is deemed as high risk of fatigue. However, glasses must be worn continuously, which some users find uncomfortable. Interchangeable lenses are available for varying light conditions, but sudden lighting changes may render the glasses unsuitable, potentially leading drivers to remove them.

Wristbands typically use actigraphy to monitor sleep quality and duration, while also measuring biometrics like heart rate, stress, and body temperature. Advanced algorithms not only detect fatigue but can also predict fatigue with high accuracy (Russell et al., 2016). Vibrating alerts notify wearers of critical fatigue levels. Wristbands must be worn continuously for sleep tracking, and typically require a subscription to a mobile app to sync sleep data and access personalized risk assessments. These insights, however, may be available only to the wearer.

Headbands employ electroencephalogram (EEG) technology, the gold standard for monitoring vigilance (Zhang et al., 2017; Zhou et al., 2018) and detecting driver drowsiness (Hu et al., 2013; Sikander and Anwar, 2019; Hu and Lodewijks, 2020). They provide early fatigue detection and real-time feedback through auditory and visual alerts. Fatigue alerts are sent directly to the driver but may also be shared with safety managers using cloud-based analytics platforms for monitoring purposes. Headbands can be worn alone or integrated into standard headwear. Like other wearables, they must be worn continuously, kept charged, and cleaned regularly for optimal performance.

Despite their benefits, wearable DSM devices have limitations, including user comfort, the need for continuous usage, battery life, and dependency on supporting infrastructure (e.g., mobile apps). Wearables are also typically standalone devices and are not integrated into the vehicle, making it challenging to provide real-time monitoring, as there is no link between driver state and performance of the driving task.

2.3 Vehicle-Based Sensor Solutions

Vehicle-based performance measures are used as an indicator of fatigue and inattention using sensors in various parts of the vehicle. Sensors in the steering assembly can be used to assess driver attention using the steering angle sensors (Hermannstädter & Yang, 2013) to calculate the roughness of steering input patterns by the driver. The system continuously compares subsequent driving patterns to a baseline using a statistical analysis of steering correction errors. If the difference in driving patterns reaches a certain level, the system determines that the driver's attention is reduced and provides an audible and visual alert to the driver. Other examples include lane position and variation, lane departures, and speed maintenance, all of which may be impacted by the loss of alertness while driving.

Monitoring drivers under automated or partially automated control is more complex, however, because the vehicle is performing aspects of the driving task that may otherwise be used to predict driver state under manual control. For example, monitoring based on steering angle sensors is no longer applicable if the driver is not required to touch the steering wheel. Similarly, lane position and variation could be controlled by lane centering/lane keeping systems and adaptive cruise control could maintain vehicle speed. Control tasks in a locomotive are vastly different to a motor vehicle and do not necessarily require continuous operator input, unlike steering a motor vehicle. There may be other control-based inputs associated with locomotive operation that could be used to assess driver state, although a combination of data sources would likely be more reliable and accurate.

Radar sensors can also be used in vehicles for monitoring driver's movements and vital signs such as heart rate (HR) and breathing rate (BR). Radar can penetrate clothing and other materials, allowing it to detect subtle chest movements associated with breathing and heartbeat, even when the driver is partially obscured. Numerous studies have demonstrated that a decrease in BR and HR is a sign of a drowsy driver (Siddiqui et al., 2021; Kyo & Chan, 2021). These signals can also be combined with eyeblink and/or head movement signals to obtain a more reliable assessment of driver drowsiness. Similarly, various radar signals, such as head movements and arm gestures, may be useful for detecting driver distraction, which could then trigger alerts or warnings to the driver. Radar sensors provide a higher level of privacy by not directly capturing images and/or video of the driver's facial features, which could make radar a more appealing method of driver monitoring compared to camera-based systems. Radar signals are also unaffected by variations in lighting conditions and could be used in situations with varying light levels.

2.4 Selection of DSM Technologies for Further Evaluation

DSM systems rely on various measures to assess changes in driver state, with each measure often tailored to a specific condition. For example, gaze direction (i.e., where a driver is looking) is critical for identifying distraction but less relevant for detecting fatigue, which focuses more on metrics such as eye closure and blink duration. Some DSM systems infer gaze direction using head movements (i.e., head pose) to identify distraction or inattention. However, research shows that drivers using cell phones often move their eyes independently of their head, making head pose an unreliable indicator unless combined with eye-tracking technology (Seeing Machines, 2018). Therefore, while not all DSM systems track eye movements, the accurate and reliable detection of distraction and inattention requires both head pose and eye tracking to reliably assess gaze direction. For fatigue detection, DSM systems also primarily use eye-related measures, such as eye closure and blink duration, rather than gaze direction.

These factors were carefully considered during the selection of the two candidate DSM technologies for further evaluation. The review process incorporated a range of criteria, including availability, key features, effectiveness, and practicality within the rail industry. Ultimately, the two most critical selection factors were cost (i.e., affordability for potential future implementation) and usability. Usability was assessed based on a human factors evaluation, which determined whether the systems could effectively measure fatigue and inattention in locomotive engineers without requiring extensive additional development. The two selected DSM systems, both featuring eye-tracking capabilities, were the SmartEye camera-based system and ETVision eye-tracking glasses.

3. Method

3.1 Participant Recruitment

Researchers recruited nine passenger locomotive engineers from the Boston/Cambridge, MA, area to participate in the study. Criteria for inclusion in the study included:

- Current passenger locomotive engineer
- Current valid U.S. driver's license
- Comfortable reading, writing, and speaking English
- Normal or corrected to normal vision in both eyes
- Normal or corrected to normal hearing
- No past or current serious medical conditions
- No history of stroke, head or brain injury, epilepsy, seizures, blackouts, migraines, or severe headaches
- No untreated sleep disorders, such as sleep apnea or narcolepsy
- Does not experience motion sickness or simulator sickness (if known)

3.2 CTIL Simulator

FRA's CTIL is a full-size locomotive simulator that can be reconfigured and equipped with new technologies to assess the resulting impact on human performance. For this study, the simulator cab was configured with a passenger locomotive control panel (Figure 1) and used computerized graphics of segments of the Northeast Corridor

Figure 1. Interior of CTIL Simulator, modified Siemens ACS 64 console

The simulator scenario was customized to enhance characteristics that would induce fatigue in the participants. The selected route was divided into two segments of the Northeast Corridor, Northbound (milepost 51.22 to 6.24 from Newark, DE to Newark, NJ), and Southbound (milepost 5.6 to 51.22 from Newark, NJ to Newark, DE). Time to travel each segment in the simulator was approximately 2 hours at a track speed of 80 mph with 8 temporary speed restrictions (i.e., 4 in each segment) ranging from 10 mph to 30 mph. Additionally, 8 trackside obstructions, such as debris on the tracks (e.g., tree branches or a shopping cart) or vehicles/trespassers near the tracks, were added to the scenario. Participants were instructed to report these abnormal events as they would during normal operations. The scenario included no stopping at stations or signals and each temporary speed restriction would have signage posted two miles in advance of the restricted section. The point where the temporary speed restriction started was marked with a yellow sign showing an "S" and the end of the speed restriction was designated by a green sign showing an "R". Finally, to maximize fatigue, the simulator was customized to reflect a late-night scenario with headlights providing illumination of the tracks and trackside scenery, while the cab interior was lit by a single overhead light. Overall, the goal was to create a scenario whereby the locomotive engineer would experience a long, uneventful run requiring continuous monitoring but little active engagement with the controls. Figure 2 shows an example of the interior of the cab and a temporary speed restriction sign of 45 mph.

Figure 2. CTIL cab interior and forward view of the tracks

3.3 DSM System Set Up

The two DSM systems were set up in the CTIL simulator to capture continuous data during the entire scenario. One was a camera-based device and the other was a wearable eye tracking device.

3.3.1 SmartEye DSM System

The SmartEye DSM system for this project used a single camera, although the system is scalable up to eight cameras allowing for 360-degree tracking. Infrared lights on either side of the camera illuminate the subject's face and eyes, which enabled tracking in low ambient light conditions. As shown in Figure 3, the SmartEye system was installed in the CTIL simulator above the locomotive control panel and was relatively small and unobtrusive. The single camera faced the locomotive engineer, who was seated at the control panel, and was calibrated prior to each study session to best capture the face and eyes of the participant.

Figure 3. **SmartEye DSM system set up in the CTIL simulator**

The SmartEye system tracks a variety of facial features (Figure 4) and performs calculations to provide an estimate of where the subject is looking and the state of their eyes (e.g., closed, open).

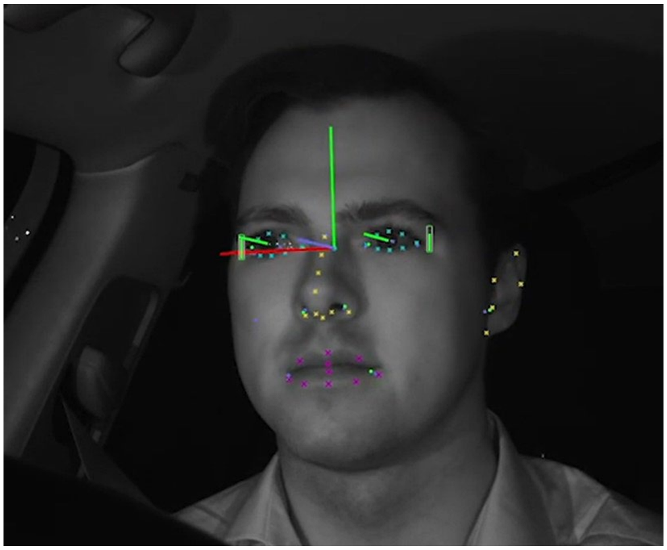

Figure 4. **Facial features and tracking measures used by the SmartEye system**

The system recorded four primary tracking measures:

- Head pose, which is the rotation and position of the head
- Eyelid opening, which is a measurement of the eyelid opening for each visible eye
- Estimated gaze, which is a gaze vector for each visible eye and is combined with the designated environmental model to provide an estimation of where the subject is looking
- Precise gaze, which uses the pupil calculated from cornea reflection (i.e., glint) and the designated environmental model to provide a precise gaze location for each eye

To determine driver drowsiness and inattention, each tracking measure is given a quality score by the SmartEye system for each data point recorded, ranging from 0 to 1. Researchers then evaluated the certainty of driver state estimates provided by the system. For instance, if head pose tracking quality is low then it is unlikely that finer grain estimates of gaze direction/target are accurate. The same is true for precise gaze measures, which use pupil tracking to enable better gaze direction/target estimates.

3.3.2 ETVision Eye Tracking System

The ETVision eye tracking system from Argus Science resembles a pair of eyeglasses and includes two eye cameras, infrared light sources, scene camera, and microphone (Figure 5). This system provides precise binocular eye measurement, pupil diameter, blink detection, and eyelid position measurement. Similar to the SmartEye system, ETVision also uses corneal reflection to identify the pupil and determine point of gaze with respect to the scene camera image.

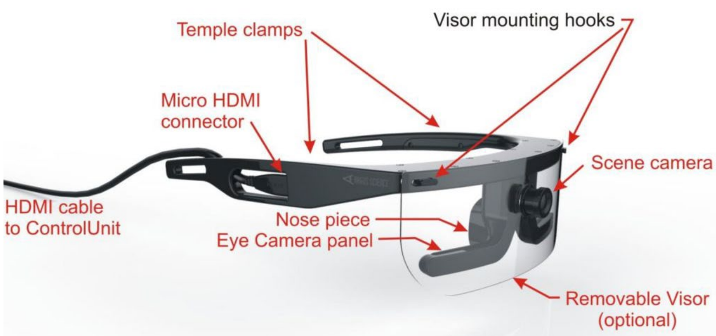

Figure 5. ETVision eye tracking glasses

Figure 6 shows an example image of the left and right eye, with each pupil successfully identified by the cameras. Underneath the images of the eyes is the view from the scene camera on the front of the glasses that highlights the point of gaze.

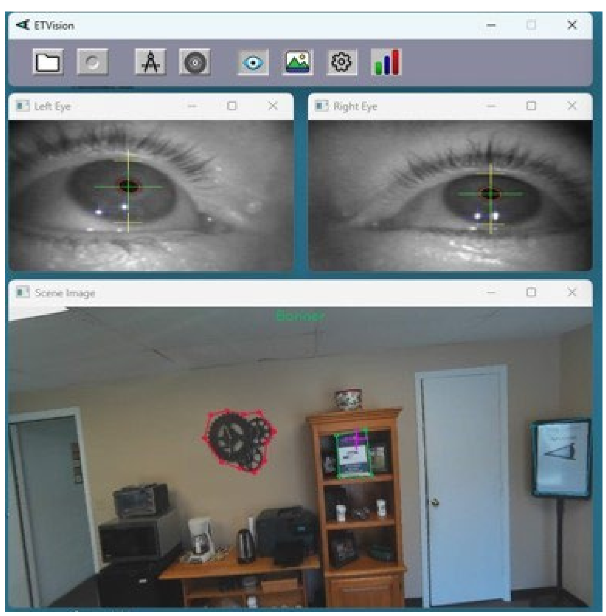

Figure 6. Example images collected by the ETVision system

The ETVision glasses were fitted and calibrated to each participant just prior to the start of the simulator scenario. Although the glasses design allows for more freedom of movement than the fixed camera system, the glasses must be kept firmly in place to remain aligned with the eyes. If the glasses slide down the nose or are knocked out of alignment, the quality of the data is impacted.

3.4 Procedure

Locomotive engineers recruited to participate in the simulator study arrived at the Volpe Center at 7 am. They were escorted to the CTIL simulator where a researcher presented the consent form and explained all the associated procedures. Once the consent form was signed and the participant was ready to start, they were seated in the CTIL cab and the SmartEye system was calibrated for the best view of their eyes and face in the seated position. Five of the participants were also fitted with the ETVision eye tracking glasses, which were used in combination with the SmartEye system to maximize the amount of data obtained from the participants. The glasses were fitted to the participant's head and calibrated for optimal eye position within the camera view for each eye. Once the DSM systems were calibrated and recording, the simulator scenario was started and the participant completed a short practice trip that took approximately 15 minutes to familiarize themselves with the controls and the expectations and requirements for the session. After completion of the practice trip, any final necessary adjustments were made to the DSM systems and the session commenced.

4. Results

4.1 SmartEye DSM System

Initial analysis of the SmartEye data focused on data quality metrics, which is an indicator of the suitability of this style of DSM system (i.e., single, fixed camera) to the in-cab rail environment. The measures of fatigue and inattention are then presented and interpreted with the data quality issues in mind.

4.1.1 Data Quality Metrics

Figure 7 shows the percentage of each session that subjects were at or above a certain quality level for head pose. Ideally, subjects' head pose tracking data should be at a high-quality level for a high percentage of the trip. If each subjects' data points are closely grouped and at a high percentage level (e.g. Subject 101), then this indicates that head pose tracking was working well for this subject. Those instances where the red (>0.80) and purple lines (>0.90) drop indicates the system was less able to track the subjects' facial features, which reduces data quality and the ability to provide alerts or other countermeasures for undesirable behavior. Figure 7 indicates the SmartEye system was confident about subjects' head positions for at least 85 percent of all trips with all subjects, although one subject (i.e., Subject 204) showed low quality head pose tracking for more than 5 percent of the session.

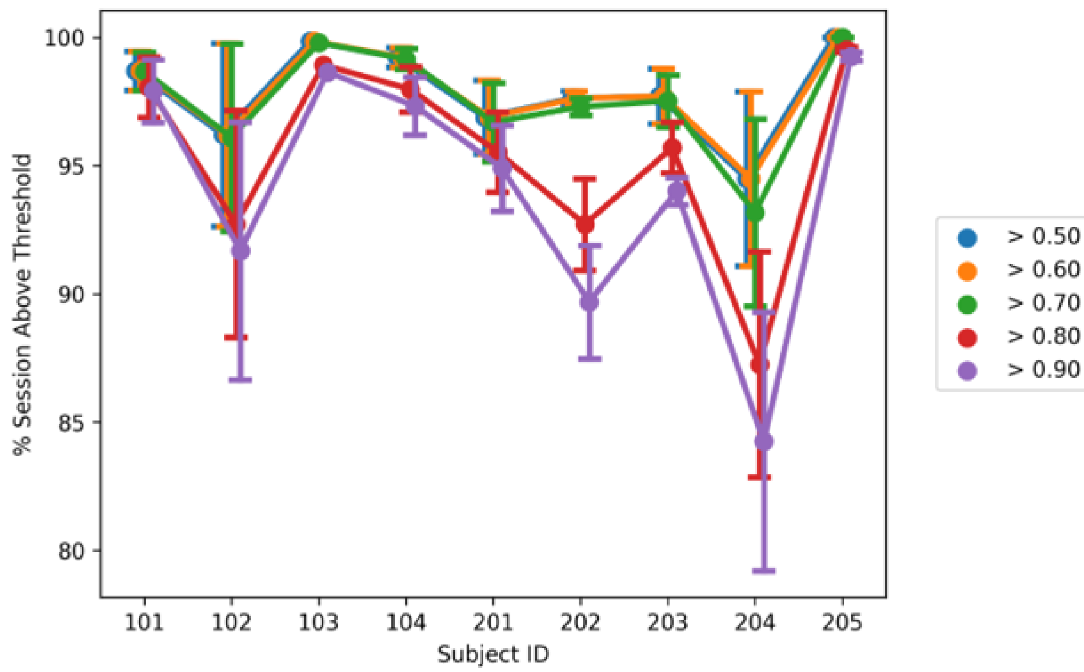

Figure 7. Percent of session above quality threshold – head pose tracking

Like above, Figure 8 shows the percentage of each session that subjects were at or above a certain quality level for eyelid tracking. These results highlight a clear gap in tracking quality between subjects who were wearing the ETVision glasses (i.e., Subjects 201 to 205) and those who were not (i.e., Subjects 101 to 104). Participants who were not wearing the eye tracking glasses during their session had much higher percentages of their sessions at very high-quality thresholds, typically 0.9 or greater quality for more than 95 percent of the session. There are two possible explanations for this outcome. Either the ETVision glasses obscured markers of the eyelid that the SmartEye camera needed for high quality eyelid tracking, or the eyelid markers were overexposed due to the additional infrared lighting provided by the two systems being used in combination.

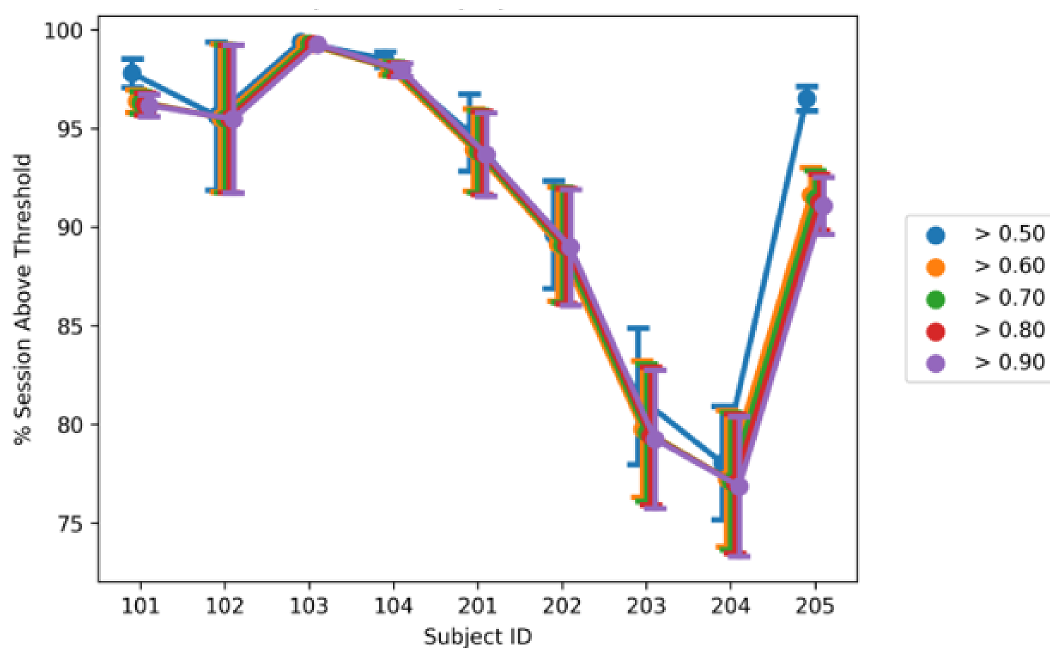

Figure 8. Percent of session above quality threshold – eyelid tracking

As seen in Figure 9, data quality for pupil detection and precise gaze tracking was considerably worse than head pose and eyelid data quality.

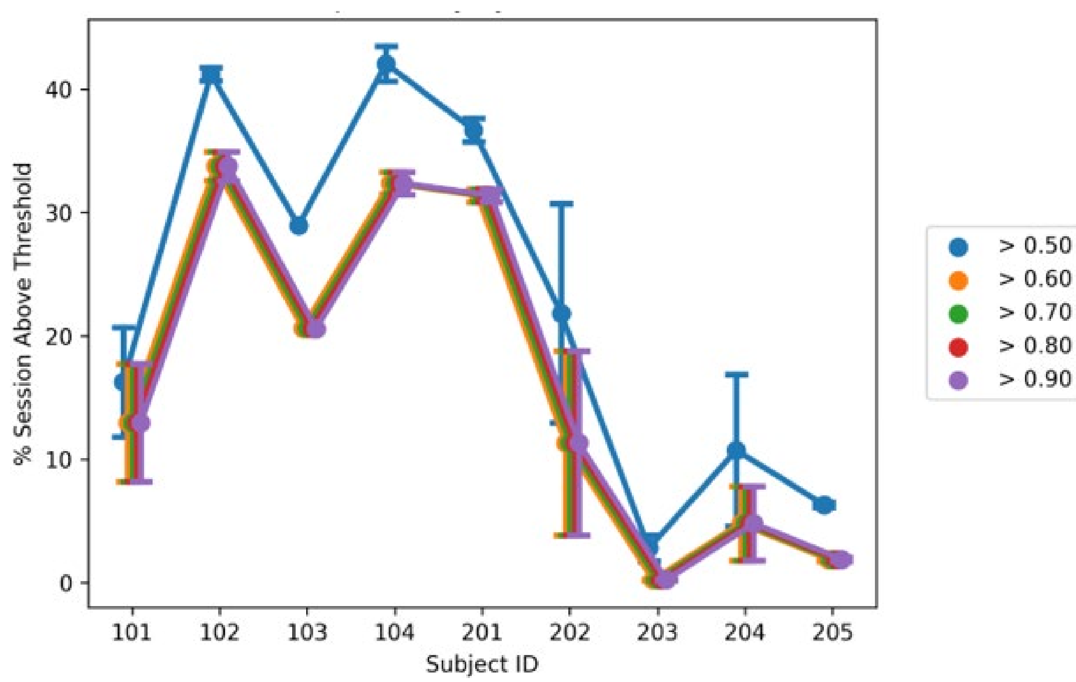

Figure 9. Percent of session above quality threshold – pupil tracking

Pupil tracking was generally of low quality for greater than 50 percent of the session for every subject. As with eyelid tracking, data quality was typically worse for those wearing the ETVision glasses, but not uniformly so (e.g., data quality for Subject 101 was generally lower than Subject 201). Poor pupil tracking would subsequently diminish the quality of gaze tracking, as gaze tracking relies on pupil position and head pose to estimate where a subject is looking. There are several potential reasons for poor pupil tracking quality. For those also wearing the ETVision glasses, there may have been interference from using the two systems together. The subject may have moved further away from the SmartEye camera or leaned back in their seat after calibration had been completed, resulting in the camera being too far from the subject to accurately identify the pupil from surrounding markers. It is also possible that subjects positioned their body in a way that made identifying the pupils difficult.

The quality of gaze estimation data is provided in Figure 10. Although there is greater variation in the percentage of each session at each quality level, the gaze tracking quality is still generally poor across all subjects, making it difficult to confidently estimate where subjects were looking for large portions of the sessions. It is highly likely the quality of the gaze tracking data was negatively impacted by the same factors that affected the quality of the pupil tracking data.

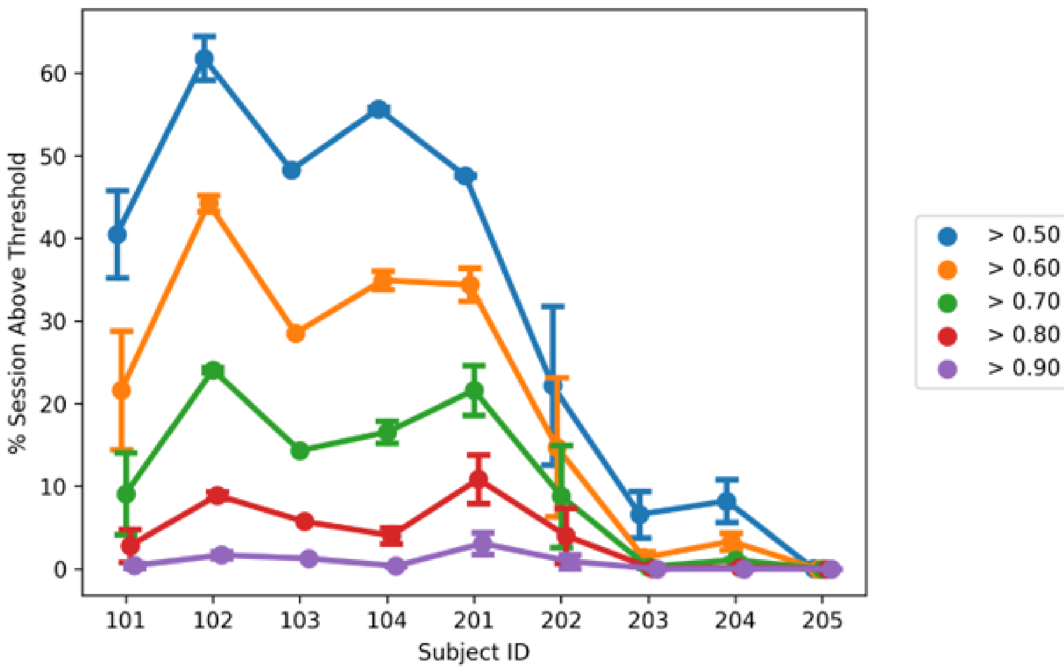

Figure 10. Percent of session above quality threshold – gaze estimation

4.1.2 Measures of Fatigue and Inattention

High quality and continuous head pose tracking data is essential for the SmartEye system to provide accurate measures of fatigue and inattention. Indicators of fatigue include head pose and eyelid tracking, with measures based on the distance between the upper and lower eyelid, long durations of the eyes being closed, and the occurrence of blinks. Poor head pose data means the system is not tracking the subject's face effectively, which in turn reduces the likelihood that good quality eyelid, gaze, and pupil tracking data are being collected. All these measures combine in different ways to allow the system to calculate fatigue and inattention measures; thus, the less accurate the components, the less accurate the overall measures. The following should be interpreted with that in mind, particularly for the inattention measures that are largely based on pupil and gaze tracking (i.e., the poorer quality tracking data that were collected).

As discussed in the previous section, the quality of the head pose data was high for 95 percent of the session for most subjects; however, there were instances where data quality was poor, and the system failed to effectively collect data. Figure 11 shows the duration of these poor-quality head pose events for all subjects.

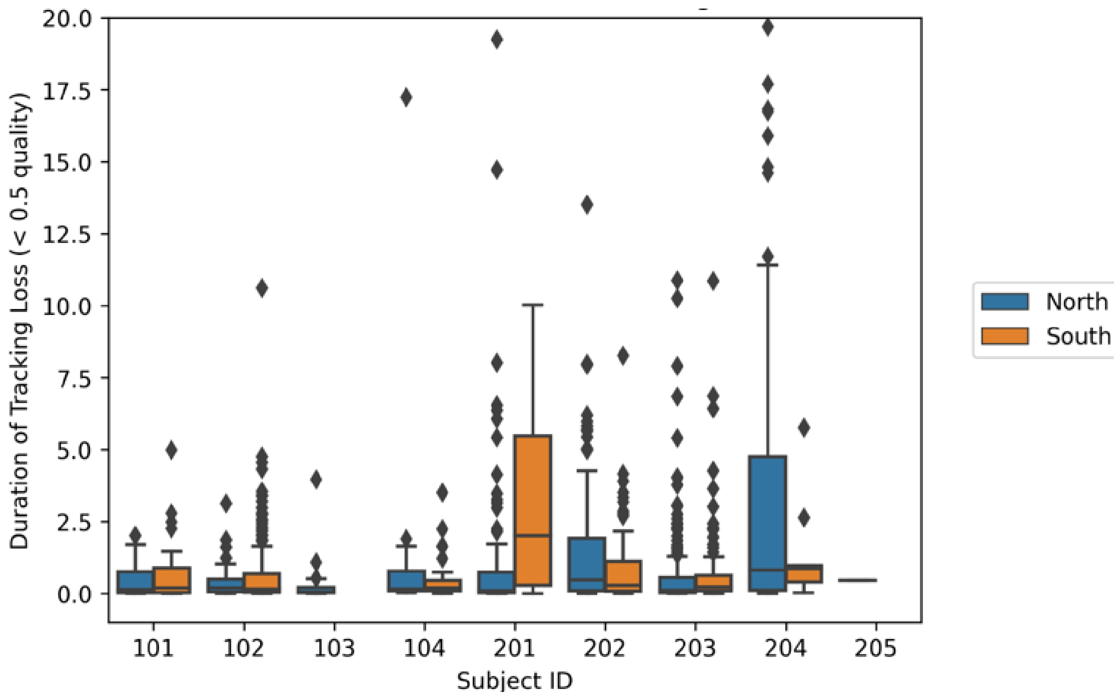

Figure 11. Distribution of poor head pose tracking durations

These events provide insight into how long poor head pose data quality could be expected to last. It is worth noting certain subjects (e.g., Subjects 201 & 204 North) recorded many outliers that contributed largely to the overall percentage of time the SmartEye system was not effectively tracking a subject's face, although this is not well reflected by the boxplot percentiles.

Table 1 shows the maximum duration of these poor head pose tracking events for each subject by the travel direction of the session (i.e., northbound and southbound). The SmartEye DSM system recorded relatively long poor tracking quality events for several subjects, the longest of which lasted over 4 minutes. These events would prevent the DSM system from providing accurate information related to driver state for long periods of time. However, a critical factor that should not be overlooked is that these periods of poor tracking quality may be indicative of a much more serious issue. For instance, if the DSM system cannot detect a subject's face for an extended period, it is possible that it is not a failure of the tracking system but could be that the subject is no longer visible (e.g., they have left the cab or have become incapacitated and fallen out of view). Unfortunately, if this were the case, the SmartEye DSM system alone would not be capable of distinguishing this event from genuine tracking failures in real time.

Table 1. Maximum durations of poor tracking events by subject and session

Subject	Condition	Travel Direction	Poor Tracking Quality Duration (s)
101	SmartEye	North	56.74
		South	164.31
102	SmartEye	North	3.13
		South	267.3
103	SmartEye	North	3.97
		South	-
104	SmartEye	North	17.24
		South	59.1
201	SmartEye & ETVision	North	30.75
		South	118.19
202	SmartEye & ETVision	North	12.515
		South	140.55
203	SmartEye & ETVision	North	138.07
		South	10.89
204	SmartEye & ETVision	North	21.75
		South	5.77
205	SmartEye & ETVision	North	0.47
		South	-

Table 2 shows the number of events where subjects had their eyes closed for longer than 5 seconds and 10 seconds, respectively. There were also gaps of varying lengths in the DSM system data, where tracking quality was poor.

Table 2. Eyes closed events longer than 5 and 10 seconds

Subject ID	Eyes Closed > 5s	Eyes Closed > 10s
101	2	0
102	1	0
103	0	0
104	4	2
201	4	1
202	2	0
203	9	0
204	15	2
205	2	0

Figure 12 shows the distribution of eye closure event durations, for all cases where subjects had their eyes closed for longer than 1 second. Long eye closures may be indicative of fatigue and drowsiness, or even microsleeps. Practically speaking, if subjects' eyes are closed then they are not able to identify potential imminent threats and respond quickly and effectively. Items above the red line in Figure 12 highlight instances where the subjects had their eyes closed for 10 seconds or more. In cases such as these, a warning from the DSM system would be helpful to alert the subject to their fatigued state with the goal of mitigating a potentially dangerous situation.

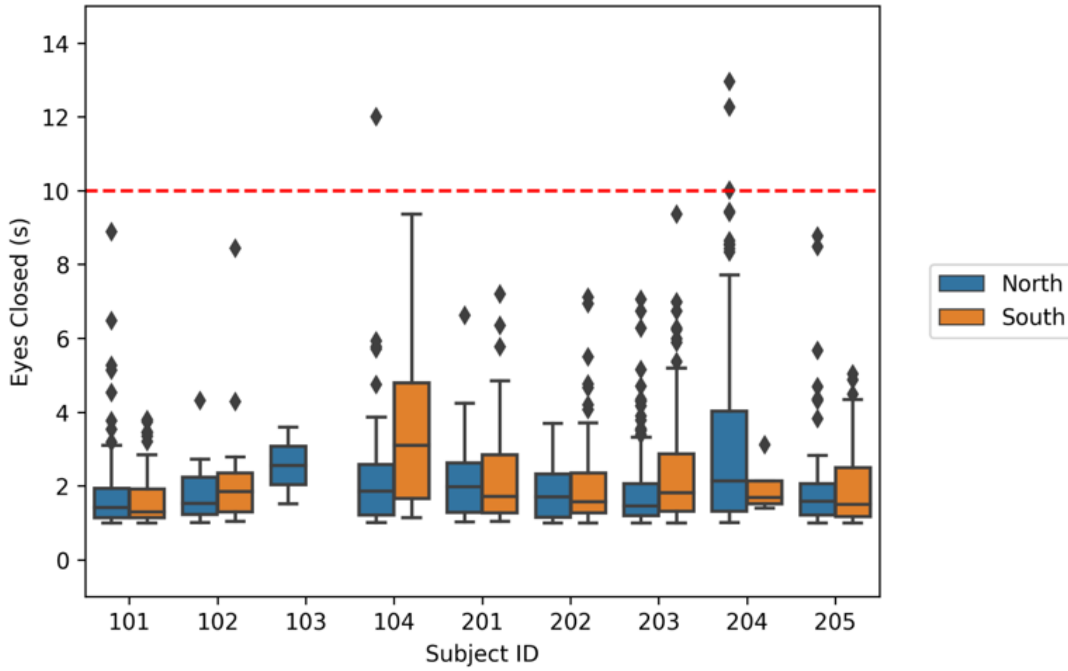

Figure 12. Distribution of eyes closed event durations

Considering the poor-quality gaze and pupil tracking data discussed earlier, the SmartEye DSM system used estimated gaze direction and the environmental model developed for the simulated rail cab to provide output related to inattention measures (i.e. the subject was not looking ahead at the tracks). These inattention events were identified and the duration of each event calculated. Table 3 shows the number of inattention events that were longer than 5 and 10 seconds, respectively.

Table 3. Inattention events longer than 5 and 10 seconds

Subject ID	Inattention Events > 5s	Inattention Events > 10s
101	4	0
102	2	1
103	0	0
104	13	5
201	18	8
202	50	12
203	98	21
204	43	17
205	4	0

What is immediately obvious is the much larger number of inattention events longer than either 5 or 10 seconds than there are fatigue events (i.e., eyes closed). Again, this difference may be due to the low quality inattention data or it is possible that the participants struggled with the low workload and boring scenario and displayed a higher degree of inattention to the task.

Figure 13 shows the distribution of these event durations. These inattention events are generally short in duration, often less than 2.5 seconds long. However, outliers shown above the red line in the figure highlight a large number of events that are longer than 10 seconds.

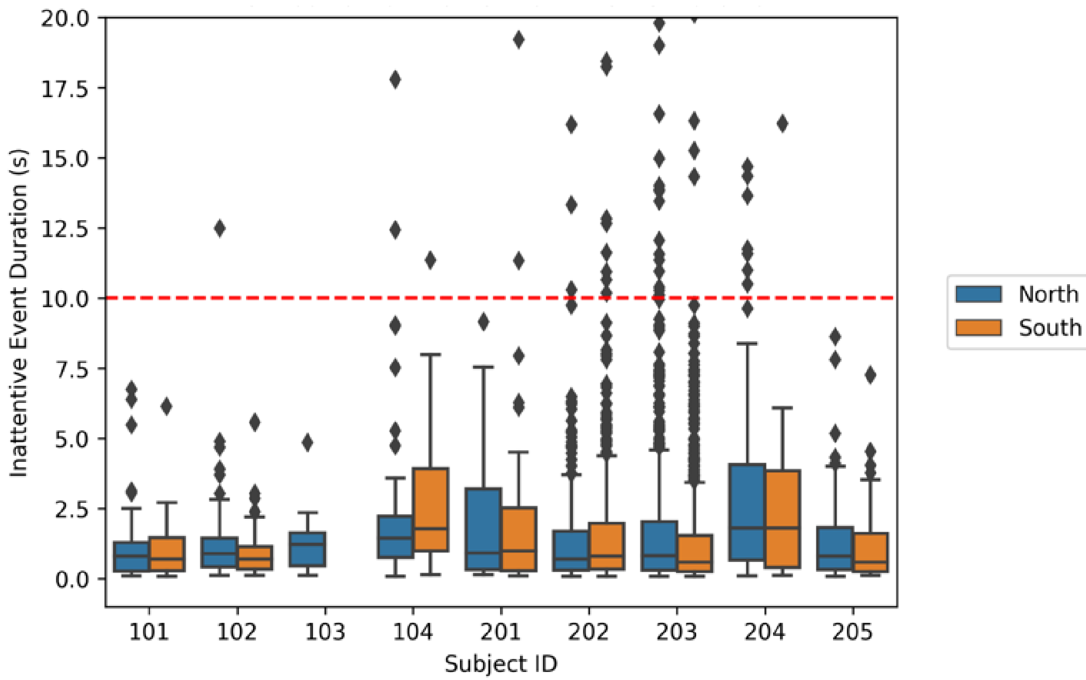

Figure 13. Distribution of inattention events durations

The maximum duration of inattention events for each subject and session are shown in Table 4. It is clear that some subjects had very long inattention events that were recorded in the data (e.g., 2.5 minutes). Again, these event durations should be evaluated with the generally low gaze and pupil tracking data quality in mind. It is entirely possible that these events are an artifact of the poor data quality that was observed for some subjects.

Table 4. Maximum inattention event durations by subject and session

Subject	Condition	Travel Direction	Maximum Event Time (s)
101	SmartEye	North	6.74
		South	6.14
102	SmartEye	North	12.49
		South	5.57
103	SmartEye	North	4.85
		South	-
104	SmartEye	North	17.79
		South	61.55
201	SmartEye & ETVision	North	52.72
		South	60.65
202	SmartEye & ETVision	North	16.19
		South	154.13
203	SmartEye & ETVision	North	143.51
		South	106.49
204	SmartEye & ETVision	North	81.27
		South	8.63
205	SmartEye & ETVision	North	7.25
		South	-

4.2 ETVision Eye Tracking System

Initial analysis of the ETVision data focused on data quality metrics, which is an indicator of the suitability of this style of DSM system (i.e., wearable eye tracking glasses) to the in-cab rail environment. Associated measures of fatigue are then presented and interpreted with data quality issues in mind.

4.2.1 Data Quality Metrics

The primary data quality output of the ETVision system is a set of binary outcomes that indicate whether certain landmarks, such as the pupils or corneal reflections, are recognized. Quality assessment focused on pupil detection, which allows the best comparison to the SmartEye system. Table 5 shows the percentage of time that *either* pupil was detected by the ETVision system, broken down by subject and session. As expected, pupil tracking varied by session and subject; however, the ETVision system successfully tracked at least one pupil for a large portion of each session. The exception was Subject 204, whose northbound trip recorded less than 68 percent of the trip with pupil tracking. Additionally, entire north and southbound portions of three sessions were unavailable for analysis due to issues during data collection (e.g., ETVision laptop froze and had to be rebooted).

Table 5. Percentage of time ETVision tracked either pupil

Subject ID	Session	% Either Pupil Tracked
201	North	*N/A*
	South	91.89
202	North	*N/A*
	South	85.68
203	North	88.82
	South	83.84
204	North	67.69
	South	*N/A*
205	North	89.31
	South	98.95

Table 6 shows the maximum duration of pupil tracking loss for one subject was almost 5 minutes, meaning neither pupil was able to be tracked for that amount of time. These instances would eliminate the ability of the ETVision glasses to estimate where a subject was looking, although some measures such as eyelid closure could potentially still be useful if accuracy was maintained. As shown in Figure 14, the average duration of loss of pupil tracking was generally very short, although there were instances of longer duration.

Table 6. Number of pupil tracking loss events and maximum duration

Subject ID	Tracking Loss Events > 5s	Tracking Loss Events > 10s	Maximum Tracking Loss (s)
201	3	0	7.1
202	9	2	52.3
203	24	6	54.3
204	33	5	290.4
205	0	0	4.2

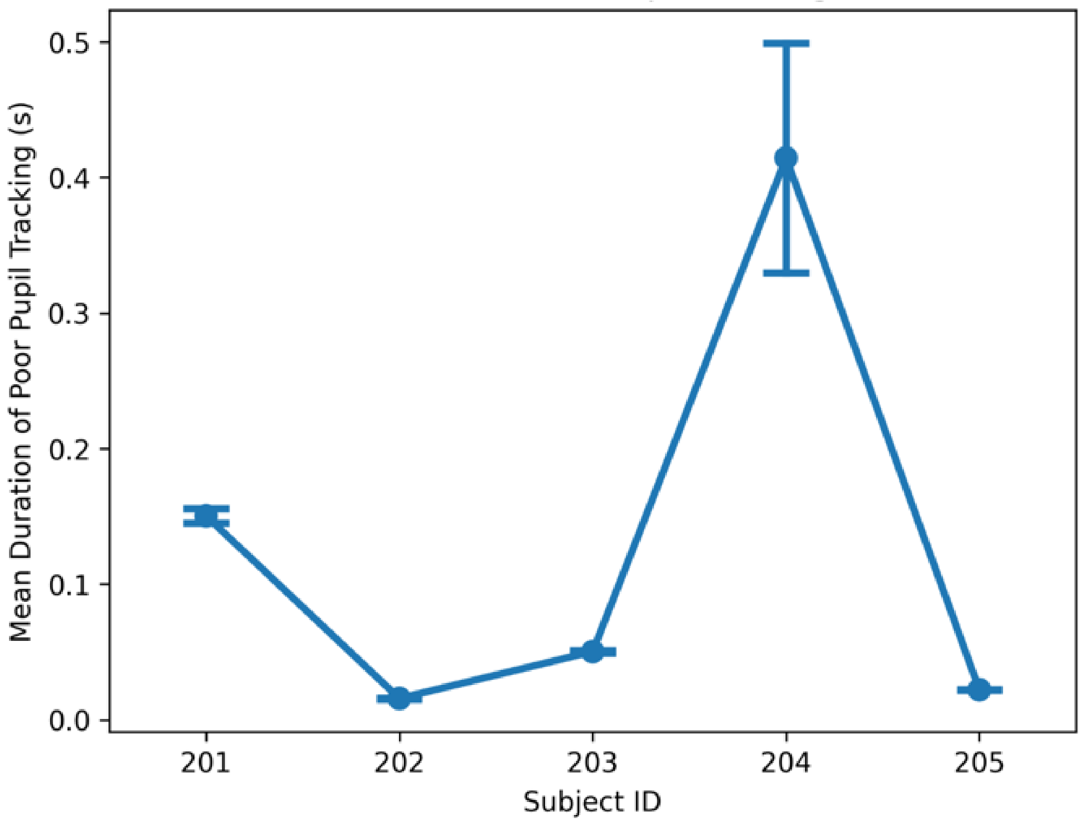

Figure 14. Mean duration of pupil tracking loss events

4.2.2 Measures of Fatigue

The ETVision system provides several measures associated with eye closure, such as the occurrence of blinking and estimated position of upper and lower eyelid. Combined, these measures can be used to identify long eye closures by calculating the distance between the upper and lower eyelid positions while blinks occurred. A threshold for eye closure was developed by calculating the 15th percentile of the distance between upper and lower eyelid positions during the occurrence of blinking. This percentile level was determined empirically by observing videos of the eyes during blinks and comparing these with the data. Since the eyelid position data is quite noisy, a rolling average was applied to help smooth out rapid changes in position common to routine eye movements not associated with closed eye events.

Once these metrics of eye closure and thresholds were developed, the ETVision data were processed to identify all events where the eyes were closed for longer than 1 second (i.e., like the SmartEye analysis). Figure 15 shows the distribution of eye closures longer than 1 second for each subject. Data points above the red dashed line indicate eye closures that were greater than 10 seconds. It is important to note that to represent the scale effectively, extreme outliers have been removed from the figure. Table 7 shows the maximum duration of these outlier events, along with counts of eye closure events longer than 5 and 10 seconds in duration, respectively.

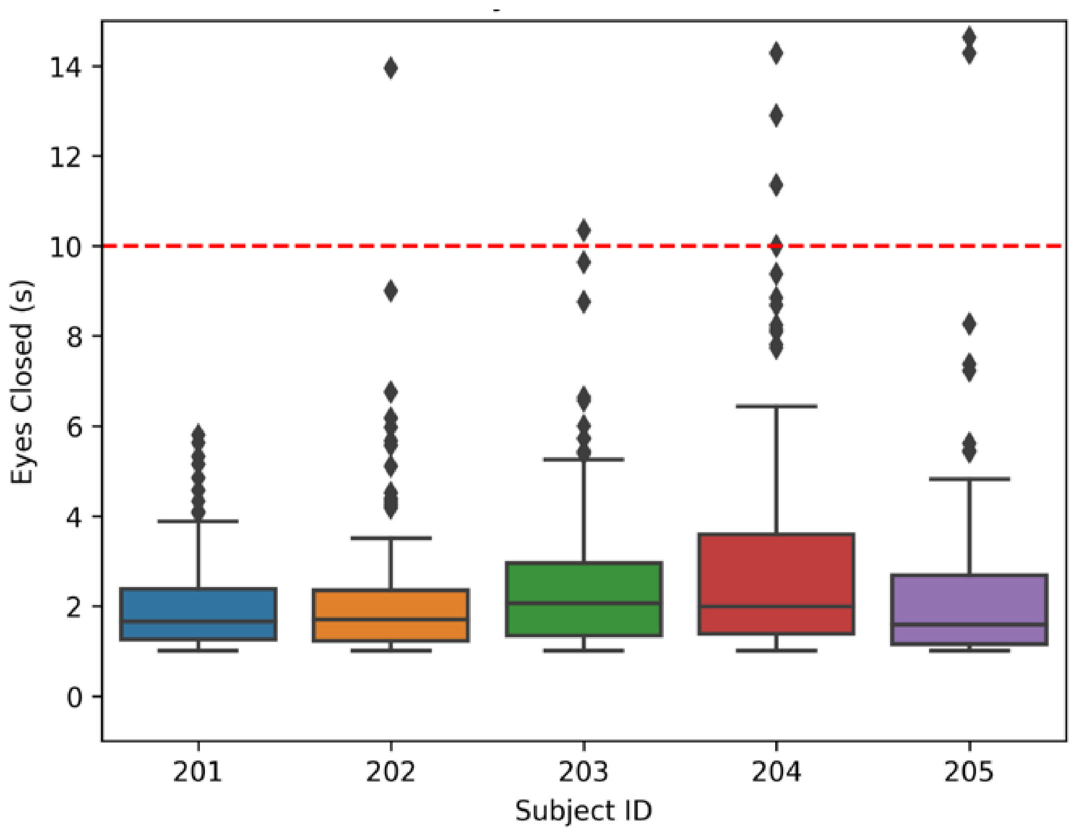

Figure 15. Distribution of eyes closed event durations

Table 7. Eye closure event counts and maximum duration

Subject ID	Eyes Closed Events > 5s	Eyes Closed Events > 10s	Maximum Duration Eyes Closed (s)
201	4	0	5.8
202	9	2	*198.9**
203	13	1	10.3
204	25	3	14.3
205	14	8	46.1

An example of misclassification by the ETVision system is evident in the results presented in Table 7. An eye closure event over 3 minutes in duration was detected for Subject 202; however, after reviewing the associated video, it was determined to be a false positive event likely caused by movement of the glasses, which resulted in a loss of eye tracking. The yellow crosshairs on the image of the right eye in Figure 16 (highlighted by green arrows) indicate the correctly detected upper and lower eyelid. As can be seen in the image of the left eye in Figure 16, these crosshairs (highlighted by red arrows) are not accurate since the lower eyelid is no longer visible. Thus, like the SmartEye system, real time estimates of eye landmark positions cannot always be relied upon for accuracy.

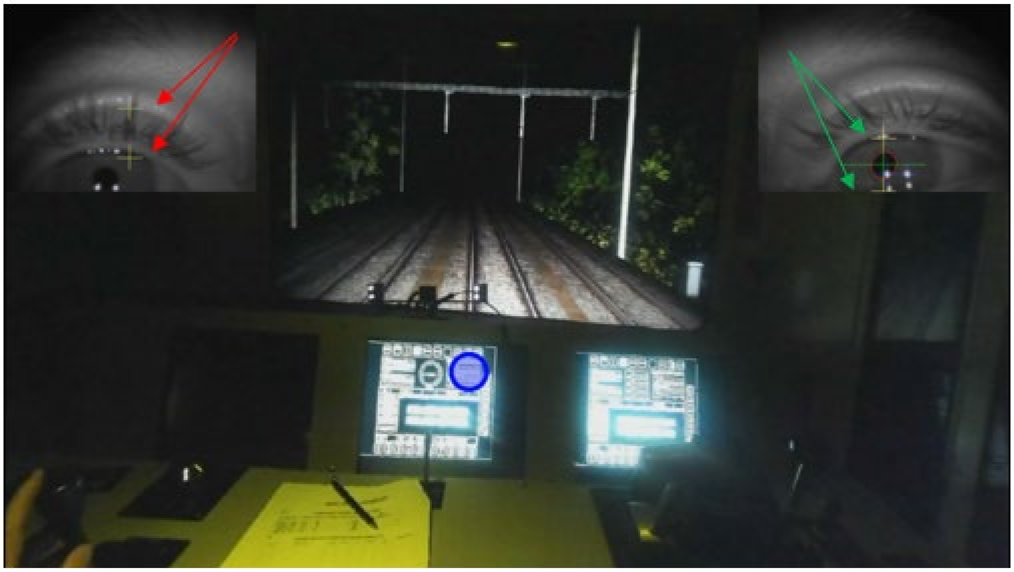

Figure 16. Screen capture of false positive long eye closure event

5. Discussion & Conclusions

Researchers investigated two DSM systems in an in-cab rail environment to determine their applicability and functionality for monitoring locomotive engineer fatigue and inattention. While both systems functioned somewhat effectively overall in the rail cab, each was found to have several difficulties during data collection that impacted the quality of the data collected and the associated analysis derived from the output.

The SmartEye system is a fixed camera-based system that can potentially detect fatigue in locomotive engineers. Unfortunately, the single camera system used in this research was not suited for the rail cab, as locomotive engineers move around too much for a single fixed camera to capture accurate data. For example, initial set up of the system prior to data collection required the locomotive engineer to be seated at the control panel and look straight ahead. The locomotive engineers rarely stayed seated for the entire duration of the simulator session, and the camera lost sight of their face and eyes when they stood at the controls. Additionally, moving around the cab and switching between sitting and standing is more likely to occur once fatigue sets in, as locomotive engineers try to stay alert, so loss of data during these times would be especially detrimental to the usefulness of the system. A multi-camera system would solve this problem and greatly improve data quality; however, adding extra cameras adds to the cost of the system and may make it too expensive for widespread implementation.

Upon initial examination of the results, it may appear that the SmartEye system would be useful for detecting periods of inattention due to the large number of events identified that were longer than 10 seconds. When assessing these systems, however, it is critical to consider the quality of the data used to identify these events. The poor quality of the pupil and gaze detection and tracking likely contributed to the large number of long events, with the distance between the camera and the locomotive engineer's face and eyes causing problems, which were exacerbated when they leaned back in the chair or stood at the controls. As mentioned above, a multi-camera system may improve data quality, although camera placement to improve inattention measures would need to be tested. It is also possible that the participants struggled with the low workload and boring scenario and displayed a higher degree of inattention to the task. Anecdotal evidence based on discussions with the participants after the study session indicated the simulator scenario was extremely boring and numerous participants struggled to stay alert and focused, which was the goal when designing the scenario. Thus, despite the poor quality of pupil and gaze detection and tracking, the SmartEye system may still have been effective at identifying overt and obvious periods of inattention. However, higher-quality data could enhance its ability to detect more subtle instances of inattention that require more detailed and precise measurements.

The ETVision system is a wearable eye tracking system that fits the wearer like a pair of eyeglasses. While this system showed some potential for detecting fatigue in locomotive engineers based on the occurrence of blinks and associated eyelid position, it had difficulty with reliable and accurate pupil tracking which would impact detection of inattention. For example, pupil tracking was lost entirely for one participant for roughly 5 minutes, which rendered the system ineffective for gaze detection for that period. As demonstrated by the example of a false positive long eye closure event, the ETVision system was susceptible to poor quality data issues, largely attributable to movement of the glasses resulting in loss of pupil and/or eyelid detection. While the wearable glasses design allowed for more freedom of movement around the rail cab, this movement often negatively impacted the data quality. The ETVision system also required specific calibration to various points around the field of view, which would be problematic for real-world implementation.

User acceptance of the SmartEye system was high as the locomotive engineers did not have to interact with the system at all and the camera was small and unobtrusive. However, camera-based systems may raise privacy concerns among users. User acceptance of the ETVision system was considerably lower than the SmartEye system due to the discomfort of wearing the glasses, which need to be firmly secured to the user's face to prevent the glasses moving around and/or slipping down the nose.

There were several limitations in this study to consider when interpreting the associated data and results. The main limitation was the small number of participants included in the study. The study was essentially a pilot test for the two DSM systems in a rail cab environment, therefore nine participants were deemed sufficient for this purpose. A more thorough evaluation and assessment prior to any proposed implementation of a DSM system would require a greater number of participants. The results also seem to indicate that the two DSM systems interfered with each other for the five participants who used the ETVision system in addition to the SmartEye system, possibly due to the additional IR lights on the glasses interfering with the IR lights from the camera. Regardless, use of a single DSM system per data collection session would be ideal in future testing.

While the DSM systems explored in this study demonstrated potential in certain areas, several key issues with each system significantly impacted the quality of the data collected, which in turn affected the accuracy and reliability of fatigue and inattention assessments. These systems, though promising in controlled environments, faced challenges when applied to real-world scenarios. Continuous, high-quality data is essential for any DSM system to provide reliable and precise evaluations of a driver's state, particularly for minute-to-minute monitoring. Unfortunately, the systems tested in this project struggled with maintaining data quality, experiencing frequent data loss and inaccuracies that would undermine their effectiveness in practical applications.

In environments where constant, uninterrupted data collection is crucial for making real-time decisions about operator safety, the inability of these systems to consistently capture high-quality data would present significant problems. Thus, while the systems may work well under ideal conditions, the identified shortcomings suggest that they are not yet suitable for real-world deployment in an in-cab rail environment, where data integrity and accuracy are paramount for reliable fatigue and inattention detection. For these systems to be truly effective in the rail industry, improvements would be needed to reduce data loss and enhance the overall quality of the data being collected.

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Abbreviations and Acronyms

ACRONYM	DEFINITION
ADS	Automated Driving System
BR	Breathing Rate
CTIL	Cab Technology Integration Laboratory
DMS	Driver Monitoring System
DSM	Driver State Monitoring
EEG	Electroencephalogram
FRA	Federal Railroad Administration
HR	Heart Rate
IR	Infrared
JDS	John's Drowsiness Scale
NTSB	National Transportation Safety Board
PERCLOS	Percentage of Eye Closure
PTC	Positive Train Control
VTTI	Virginia Tech Transportation Institute