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Assessing the Feasibility of Vehicle-based Sensors to Detect Drowsy Driving

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14. ABSTRACT

1.1 Drowsy driving is a significant contributor to death and injury crashes on our Nation's highways, accounting for more than 80,000 crashes and 850 fatalities per year. The successful detection of drowsiness is a crucial step in implementing mitigation strategies to reduce the cost to society of drowsy driving. Building upon prior research in detecting impairment from alcohol and distraction, the goal of this research was to determine the extent to which alcohol impairment algorithms could detect drowsiness and distinguish it from alcohol impairment. Data were collected from seventy-two participants during daytime (9 a.m. - 1 p.m.), early night (10 p.m. – 2 a.m.), and late night (2 a.m. - 6 a.m.) sessions to provide data for algorithm testing and refinement. Driving data indicated a complex relationship between driving performance and conditions associated with drowsiness: compared to daytime session, driving performance improved during the early night session, before degrading during the late night session. This non-linear relationship between continuous time awake, subjective assessments of drowsiness and driving performance has the potential to complicate the early detection of drowsiness. Drowsiness, as indicated by unintended lane departures, occurred in all sessions and demonstrated a transient nature. Algorithms based on lane position and steering wheel data, which can be obtained inexpensively, were best at predicting drowsiness related lane departures. Alcohol detection algorithms were not successful in detecting drowsiness but could be retrained to do so. Rather than one algorithm being generalized to detect multiple impairments, these results indicate that specialized algorithms might co-exist and allow one to detect and differentiate alcohol and drowsy-impaired driving. These findings provide a better understanding of the relationship between impairment from alcohol and drowsiness and lay the foundation for detecting and differentiating among impairment from alcohol, drowsiness, fatigue and drugs.

15. SUBJECT TERMS
Alcohol, Algorithm, Driver Impairment Scenario Design, National Advanced Driving Simulator

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EXECUTIVE SUMMARY

The most notable findings from this study include:

- Algorithms based on driving performance measures could detect impairment due to drowsiness.
- Algorithms designed to detect alcohol-impaired driving were not well suited to detecting drowsiness-impaired driving.
- The time scale for detection of impairment from drowsiness must be shorter than for alcohol impairment, due to the transient nature of drowsiness.
- Performance-based detection algorithms have the potential to outperform more traditional methods such as percentage of eye cloSure (PERCLOS), at a lower cost.

Background

Drowsy driving is a significant contributor to death and injury crashes on our Nation's highways accounting for more than 80,000 crashes and 850 fatalities per year. Recent research using data from the 100-car naturalistic study found that drowsy driving contributed to 22 percent to 24 percent of crashes and near-crashes observed. According to the National Sleep Foundation's 2009 annual Sleep in America survey, 28 percent of drivers had driven drowsy at least once per month in the past year. Of those who drove while drowsy, 28 percent have fallen asleep. The rate of drowsy driving and the severity of the resultant crashes give clear cause for concern and research continues to be needed to help reduce the numbers of lives lost due to drowsy driving. Previous research in detecting alcohol impairment showed that algorithms based on driving performance metrics could reliably tell the difference between an impaired driver from an unimpaired driver based on a signature pattern of lane position and steering. Algorithms such as these could be implemented as vehicle-based safety systems to detect impairment from drowsiness.

Objectives

This report describes efforts completed in Phase 1 of the Driver Monitoring of Inattention and Impairment Using Vehicle Equipment (DrIIVE) program to develop and assess algorithms for the detection of drowsy driving. It begins with the application of alcohol detection algorithms to the drowsiness impairment. Specific objectives include:

- Evaluate previously developed algorithms designed to detect alcohol impairment for their ability to detect drowsiness.
- Determine if algorithms designed to detect alcohol impairment can be generalized to detect both alcohol and drowsiness.
- Determine if algorithms can distinguish between impairment caused by alcohol and drowsiness.
- Determine if real-time algorithms can reliably detect drowsiness in advance of a drowsiness-related mishap, and do so better than event-based algorithms.

Method

Data were collected from 72 participants in the National Advanced Driving Simulator on three drives over two visits: one daytime drive between 9 a.m. and 1 p.m.; two nighttime drives with an early night drive between 10 p.m. and 2 a.m. and a late night drive between 2 a.m. and 6 a.m. Drivers were divided into equal groups by age (21 to 34, 38 to 51, and 55 to 68) and gender. The participants drove a scenario representative of a nighttime drive home from an urban area for a total drive time of approximately 35 minutes. The drives started with an urban segment composed of a two-lane roadway through a city with posted speed limits of 25 to 45 mph with signal-controlled and uncontrolled intersections. A suburban segment followed that consisted of a four-lane divided expressway with a posted speed limit of 70 mph. The drives continued with a rural segment composed of a two-lane undivided road with curves, ending with a ten-minute long drive on a section of straight rural roadway. Drivers' control inputs, vehicle state, driving context, and driver state were captured in representative driving situations, with precise control and in great detail.

Results

The objectives were addressed with two broad sets of analyses. The first focused on whether drowsiness affected performance. The second focused on detection of impairment. These analyses show the simulator and scenario to be sensitive to drowsiness, and that algorithms can detect drowsiness-related impairment.

Driving data indicated that a complex relationship exists wherein driving performance improves with low levels of drowsiness in the early night session before degrading in the late night session. This non-linear relationship between continuous time awake, subjective assessments of drowsiness and driving performance has the potential to complicate the early detection of drowsiness. Drowsiness, as indicated by unintended lane departures, occurred in all conditions and highlights the transient nature of the impairment from drowsiness. Alcohol detection algorithms were not successful in detecting drowsiness but could be retrained to do so. Rather than one algorithm generalized to detect multiple impairments, these results indicate that specialized algorithms might co-exist and allow one to detect and differentiate alcohol and drowsy-impaired driving.

Recommendations and conclusions

This study demonstrates the feasibility of detecting drowsiness with vehicle-based sensors. Results show that the differences in the manifestation of alcohol and drowsiness impairment do not allow for a single algorithm to detect both types of impairment; however similar algorithms trained independently may be successful. To detect impairment due to either alcohol or drowsiness, a more complex approach is necessary where separate algorithms are combined to work with each other. These results suggest promise in a vehicle-based approach to impairment detection including multiple types of impairment.

Future research should focus on examining distraction related impairment to evaluate the extent to which distraction can be detected when drivers are impaired from alcohol or drowsiness, and the extent to which impairment from alcohol, drowsiness and distraction can be distinguished. Then other types of impairments may also be considered, such as drugs and age-related cognitive decline.

Additional research should evaluate the extent to which existing impairment detection algorithms are capable of detecting impairment from medications or illicit drugs. Many over the counter medications are known to produce drowsiness; however, because these medications produce a more uniform level of drowsiness compared to the transient nature of the natural onset of drowsiness, this type of impairment should be tested to determine if the algorithms developed to detect drowsiness as part of this research would detect driving impaired by medications or illicit drugs.

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1 BACKGROUND

Exact counts of the number of crashes caused by drowsiness are hard to obtain due to the use of varying methodologies. The Gallup organization surveyed drivers and estimated that during the 5 years prior to 2002 as many as 1.35 million drivers may have been involved in drowsy-driving-related crashes (Royal, 2003). A National Highway Traffic Safety Administration report of crash report data from 2005 to 2009 attributed 83,000 crashes per year and 886 fatal crashes per year to drowsy, fatigued, or sleeping drivers. Over the 5-year period these causes resulted in 5,021 fatalities. Similar variability in research methods, driver populations, and findings is seen for the percentage of drowsy driving crashes. The 100-car naturalistic driving study found that drowsy driving contributed to 22 percent to 24 percent of crashes and near-crashes observed (Klauer et al., 2006). In a report to Congress, NHTSA stated that 3.2 percent of crashes were related to actual sleep (NHTSA, 2008). An estimated 1 percent of all large-truck crashes, 3 to 6 percent of fatal heavy-truck crashes, and 15 to 33 percent of fatal-to-the-truck-occupant-only crashes have been attributed to driver fatigue as a primary factor (Knipling & Shelton, 1999). Although the methodologies result in different estimates, all point to a significant problem.

According to the National Sleep Foundation's 2009 annual Sleep in America survey, 28 percent of drivers had driven drowsy at least once per month in the past year. Of those that drove while drowsy, 28 percent have fallen asleep (NSF, 2009). A survey conducted in 2003 found that 37 percent of drivers have nodded off for at least a moment or fallen asleep while driving at least once in their driving careers, while 8 percent of them had done it in the last 6 months. Of those encountering an episode of nodding off, 58 percent of drivers were on a multilane interstate highway, and 92 percent of them were startled awake and of those who were startled awake, 33 percent wandered into another lane or shoulder, 19 percent crossed the centerline and 10 percent ran off road (Royal, 2003). Drowsy driving is not only common in the United States, it was found that one in five Canadian drivers have admitted to nodding off or falling asleep at least once while driving (Beirness, 2005) and that driver fatigue contributes to at least 9 to 10 percent of crashes in the United Kingdom (Maycock, 1997).

Clearly, there is cause for concern about the rate of drowsy driving and the resultant crashes, injuries and fatalities. Research continues to be needed to develop technological approaches that will help reduce the numbers of lives lost due to drowsy driving. The present aim is to extend Impairment Monitoring to Promote Avoidance of Crashes using Technology or IMPACT, a program of research into detecting alcohol-impaired driving based primarily upon vehicle-based measures to the domain of drowsy driving (Lee et al., 2010). IMPACT has developed alcohol detection algorithms for all drivers (general algorithms) and algorithms that take into account individual driving differences (individualized algorithms). This work explores how well the previously developed algorithms that detect impairment from alcohol are able to detect drowsiness, and how to best to modify those algorithms, if necessary, to detect both. The algorithms that were previously developed to detect alcohol impairment were effective at levels comparable to the Standardized Field Sobriety Test in 8 to 25 minutes. One algorithm used logistic regression of standard speed and lane-keeping measures; a second used decision trees and a broad range of driving metrics that were grounded in cues NHTSA has suggested police officers use to identify alcohol-impaired drivers; a third used support vector machines and the standard deviation of lane-keeping.

To better place these algorithms in the context of existing research, four research questions must first be addressed:

- Can algorithms designed to detect alcohol impairment and distraction also detect drowsiness?
- Can algorithms designed to detect alcohol impairment be generalized to detect both alcohol and drowsiness?
- Can algorithms distinguish between alcohol and drowsiness-related impairment?
- Do real-time algorithms perform better in detecting drowsiness in advance of a drowsiness-related mishap?

The following sections describe what has been learned from previous research that can help to inform this project.

Terminology:

While this project focuses on studying drowsy drivers as opposed to fatigued drivers, it should be noted that while reviewing the literature, the words fatigue and drowsiness were often used interchangeably. For example, the recent NHTSA Traffic Safety Facts on Drowsy Driving defined a drowsy driving crash as one "in which the driver was reported as drowsy, sleepy, asleep, or fatigued" (NHTSA, 2011). For the purpose of this research, drowsy is defined as instances where the driver wishes to sleep, and fatigued as instances where the driver wishes to cease working (driving). In reviewing the open literature, while an author may have used the term fatigued, the keywords of the publication generally included drowsiness or related physiological and cognitive indices of drowsiness, such as attentional resources, vigilance, or effort. This was also true in the reverse, as authors that used the term drowsiness had key words that included fatigue, inattention, fatigued driving, and sustained attention. Fatigue and drowsiness can co-occur. However, in the following review of literature, careful attention was paid to ensure that when articles concerning fatigue were reviewed, the fatigue symptoms and methodology were indicative of a study of drowsy driving. All studies solely of physical fatigue were excluded from the review. Exclusion of all articles that used the term fatigue, however, would have produced a review that does not yield a full understanding of the behavioral indicators of drowsy driving and the environments in which those indicators are found. For the purposes of this review discussion, fatigue can be interpreted as synonymous with drowsy driving.

1.1 Scenario Characteristics

The difficulty of different driving scenarios or situations may depend upon whether a driver is impaired, and if so, the type of impairment. Alcohol impairment is generally the most understood due to the precision of its measurement (breath or blood alcohol concentration), specific legal limit, and its consequent use as a comparison for other types of impairment research. However, different types of impairment manifest in different ways, and just because a driver may find a scenario challenging when impaired with alcohol, does not necessarily mean that a drowsy driver will find it challenging. This section describes why certain scenarios may be more challenging to drowsy drivers than others. The characteristics of such scenarios that are difficult for drowsy drivers can be categorized as ones that affect either endogenous (internal) or exogenous (external) contributors to drowsiness. Circadian variation, time on task, and lack of sleep are considered endogenous whereas scenario characteristics represent exogenous factors (Thiffault & Bergeron, 2003). These authors demonstrated that unpredictable roadside scenery can disrupt the deleterious effects of an otherwise monotonous driving environment. Their findings suggest that “monotony may exacerbate the impact of late night driving, whilst overloaded roadside environments may generate arousal levels that counteract this effect” (p. 382). Similarly, straight road conditions are more challenging to drowsy drivers than curved roads (Matthews & Desmond, 2002).

Overall, these studies suggest that the most challenging driving situation for a drowsy driver would be a long, low demand, predictable driving environment with little driver intervention required. A scenario with a long rural straightaway, little interaction with other traffic and no curves would be consistent with the evidence presented. Additionally, this would suggest that roads with few changes in the surrounding roadway environment such as buildings and signage would also prove more challenging to a drowsy driver. Such situations that come towards the end of a drive are likely to place a greater demand on a drowsy driver because drowsiness tends to increase as time on task increases.

1.2 Reliable and Sensitive Vehicle-Based Indicators

Although there are many measures of driver fatigue and drowsiness, those that are commonly studied are generally perceptual, biological, physiological, or performance based. Vehicle-based indicators of drowsy driving have been less prevalent among studies assessing driver drowsiness or fatigue, and their associated effects on performance. However, simple functions of driving performance such as steering wheel movements, lateral shifts, standard deviation of lane position, and frequency of line crossings and have all been used to measure the effects of drowsiness on driving performance

A review article by Liu, Hosking, and Lenne (2009) summarizes the effects on driving performance measures of driver drowsiness or fatigue based on 17 studies published in peer-reviewed journals in which at least one objective vehicle-based measure was reported. Overall, the reviewed literature indicated an increase in lane departures with increased drowsiness. Moreover, the average standard deviation of lane position (SDLP) and mean absolute value of steering wheel angle and standard deviation of steering wheel movements were shown to increase with drowsiness. It was noted that the current body of knowledge also associates drowsiness with increases in standard deviation in speed and variation in speed from the speed limit, but not consistently. The authors also point out that the research does not present analyses of time histories as the basis of determining drowsiness, but instead focuses on overall averages across entire test periods. This research provides a foundation for focusing the review of indicators of drowsy driving.

Steering wheel movements and the resultant heading error have shown to be reliable indicators of drowsiness. A review of literature related to fatigued and drowsy driving by Barr et al. (2003) found changes in steering behavior are associated with a “driver’s state of impairment.” Platt (1963) and Safford and Rockwell (1967) found that reduced driver capabilities were associated with an increase in steering reversal rates. Matthews and Desmond (2002) categorized steering reversals into three levels; fine (<2 degrees), medium (2-10 degrees), and coarse (>10 degrees). This is similar to the categories defined by Wilson and Greensmith (1983) that defined fine steering reversals as those less than 2 degrees and course steering reversals as those greater than

12 degrees. It was assumed that coarse reversals reflect reactive responses to lateral drift while fine, and even medium reversals reflect controlled activity (Matthews & Desmond 2002; Mackie & Miller, 1978). One of the most prevalent measures of drowsy driving throughout the literature is SDLP. Liu et al. (2009) point out that there are variations of this measure that index different aspects of driver performance. Precision is defined as the ability of the driver to maintain straight driving, independent of their location within the lane or with respect to the center of the lane. On the other hand, bias is defined as the driver's ability to accurately track the center of the lane. While both of these variations are used in the literature as measures of standard deviation of lane position, it is recommended that they be reported as separate measures (Liu et al., 2009). For the purposes of this report, SDLP will be defined as the deviation from the center of the lane unless otherwise noted.

Many researchers have shown that SDLP increases with increased drowsiness. Arnedt et al. (2001) showed that hours of wakefulness are predictive of changes in SDLP. Their research found that 19 and 22 hours of wakefulness resulted in SDLPs that were consistent with impaired performance at .05 grams per deciliter and .08 g/dL blood alcohol concentration (BAC), respectively. Using a time on task approach and partial sleep deprivation, Otmani et al. (2005) found that SDLP was greater with partial sleep deprivation than with normal sleep, and that it increased over the course of a 90-minute drive. The partial sleep deprivation condition that used moderate sleep restriction during the night prior to the driving session consisted of approximately 12 hours of wakefulness in the 16-hour period before driving. Subjects were allowed to sleep only from 3 to 7 a.m. with driving occurring during the "post-lunch dip period between 2 and 4 p.m." Another type of study examining the effects of caffeine by De Valck and Cluydts (2001) showed that SDLP was sensitive to both the effects of hours of sleep and caffeine: increased SDLP with less sleep, and decreased SDLP after using caffeine. It should be noted, however, that SDLP is also affected by substances such as alcohol and distraction as documented in the IMPACT program (Lee et al., 2011a), and the Distraction Detection and Mitigation Through Driver Feedback (Lee et al., 2011b) final reports. While this metric may facilitate multiple impairment detection, it may not be very useful for distinguishing among them.

Inappropriate line crossings (lane departures) also increase with drowsy driving. Philip et al. (2005) found that the number of inappropriate line crossings, defined as crossing one of the lateral highway lane markers, increased for sleep-deprived drivers as opposed to well-rested drivers. Speed control is another measure where research has shown differences. This measure has not been reported as often as have lateral control measures; however, a number of researchers have found it to be sensitive to the effects of drowsiness. Arndt (2001) also found that speed variability increased with hours of wakefulness. Specifically, he found greater variability after 20 hours of wakefulness than after 16 hours; however, when comparing the effect of alcohol, the effect of hours of wakefulness is less than the effect of alcohol at the .08 g/dL BAC. De Valck and Cluydts (2001) showed that deviation from the speed limit increased with less sleep, but decreased when using caffeine under these conditions.

Overall, it appears that there are potentially several diagnostic vehicle-based indicators of drowsiness with lateral control measures the most promising. Across the studies reviewed by Liu et al., the most sensitive and reliable indicator appears to be lateral vehicle control, specifically SDLP.

1.3 Current Algorithms

This project builds from the detection of impairment due to alcohol intoxication, and compares the performance for alcohol detection and drowsiness detection algorithms to correctly identify episodes of drowsy driving based upon a protocol of prolonged wakefulness. First, consider the methods currently proposed for detecting alcohol impairment. A review of the literature indicates that the primary focus of algorithm development to detect alcohol impairment has been on interlock systems. This includes approaches such as the currently deployed breath-based alcohol detection, and newer technologies such as sniffers to detect the presence of breath-alcohol from the driver (Nissan, 2011), transdermal ethanol detection (Webster, 2007) and tissue spectrometry (Ridder et al., 2008). Lee et al. (2010) demonstrated three algorithms that use vehicle control measures such as variability in lane position and speed to predict impairment from alcohol above the legal limit. These algorithms were implemented to detect impairment from alcohol by considering driving performance over a period of similar driving demand (event). Performance metrics primarily included lane keeping and speed control, which were combined to predict impairment.

Several contrasts can be observed between algorithms that are sensitive to alcohol impaired and drowsy driving. Whereas algorithms to detect alcohol have been validated by directly measuring BAC, there is no corollary measure of drowsiness. Instead, drowsiness research has primarily focused on eye behavior such as PERCLOS, or brain activity (Dinges, Mallis, Maislin, & Powell, 1998). When considering driving data that could indicate impairment, the alcohol detection algorithms focused on changes in variability of lane keeping and speed control. However, research indicates that the safety degradations associated with drowsiness may not be present at lower levels of drowsiness (Fairclough & Graham, 1999). In this study, while near lane crossings were more common for drivers drowsy from partial sleep deprivation (only 4 hours of sleep the preceding night), those with full sleep deprivation (no sleep the preceding night) had more frequent actual lane crossings. Both groups of drowsy drivers had a lower steering wheel reversal rate than did control drivers or drivers under the influence of alcohol. In general, this suggests a need to look beyond events directly relevant to safety to detect drowsiness (Fairclough & Graham, 1999). This conclusion is born out of the approaches used in several drowsy driver detection algorithms that focus not only on vehicle performance measures, but also on driver input measures. (Tijerina et al., 1999; Mattsson, 2007).

As the goal of this literature review is to inform the choice of algorithms for comparison to algorithms from Lee et al. (2010), the following sections focus on presenting typical examples of the various approaches that have been attempted. For the purposes of this review, approaches are described in terms of a broad grouping of algorithms that seek to identify similar signatures of drowsiness. The approaches discussed in this review include driver-based, vehicle-based, and combination algorithms.

When algorithm *accuracy* is reported, it is defined as the total correct classifications (hits and correct rejections) relative to all classifications (hits, misses, false alarms and correct rejections). *Specificity* is defined as the ratio of correct rejections to the total number of instances where no drowsiness was present (false alarms + correct rejections). *Sensitivity* is defined as the ratio of hits to the total number of instances where drowsiness was present (misses + hits). The following sections relate the algorithms compared in this study to those found in the literature. Additional details on the algorithms can be found in Appendix A.

1.3.1 **Driver-Based Algorithms**

The first approach to detecting drowsy driving focused on observing ocular measures of driver drowsiness rather than its manifestation in driving performance. In 1998, NHTSA published an evaluation of several approaches for detecting drowsy drivers based on monitoring the driver (Dinges, Mallis, Maislin, & Powell, 1998). The authors identify these systems as "operator-centered, in-vehicle, [and] fatigue-monitoring technologies (p. 16)," which seek to measure behavioral manifestations of drowsiness. This study examined several different approaches comparing algorithm predictions to performance lapses. It found that PERCLOS was the most reliable indicator of drowsiness in terms of consistent classification. Head position, blinks, and electroencephalograms (EEGs) were found to be less generally applicable across drivers. This effectiveness is likely associated with its general construct validity: measuring when the driver's eyes are closed is a very effective way of identifying when drivers are falling asleep. While reliable, it may provide identification too late to prevent a crash. Additionally, the authors suggest that to improve successful identification of drowsy drivers, a combination of two generally well performing algorithms that complement each other may work best. This approach helps deal with issues associated with a particular algorithm having difficulty with a particular individual. The redundancy of a second algorithm provides a method for detecting drowsiness when individual differences prevent the primary algorithm from working well. This approach was developed in IMPACT (Lee et al. 2010) for alcohol impairment, but in the evaluation, the primary algorithms succeeded often, preventing evaluation of the secondary algorithms.

With increasing video processing capabilities, new approaches to identifying driver drowsiness have emerged that can take into account more complex facial information. Ji et al. (2004) propose an approach that uses a variety of facial information including: head pose, gaze movement, PERCLOS, and facial expression to provide an estimate of level of fatigue. This approach is reliant on being able to extract the information from the video of the driver, and systematically combine the information to predict drowsiness. The facial expression method used is a "feature-based facial-expression-analysis algorithm," that focuses on the driver's eyes and mouth. They report that current work focuses on detecting yawning. Overall, the authors successfully detected drowsiness by comparing a composite measure of fatigue with response time across a variety of drivers of different ages, genders and ethnicities. They report robust, reliable and accurate results; however, specific details concerning their algorithm's performance across individual drivers, and specific metrics such as sensitivity and specificity were not provided in the paper. Thus, it is difficult to gauge the effectiveness of their particular approach.

1.3.2 **Vehicle-Based Algorithms**

Evaluations of vehicle-based performance measures have shown varying degrees of success. Based upon the findings described about the sensitive indicators of drowsiness above, it is not surprising that many of the efforts to predict impairment focus on lateral control.

Wierwille et al. (1996) proposed a vehicle-based approach to estimate PERCLOS (ePERCLOS) through a combination of measures of steering wheel activity, lane position, and lateral velocity over a three-minute window. This study builds upon the prior successful use of PERCLOS to predict decrements in performance associated with drowsiness (Wierwille et al., 1994). The advantage of this approach is that it does not necessitate the verification of drowsiness; however, this is gained at the risk of misclassifying, if the PERCLOS algorithm fails to accurately capture the actual state of the driver. Using this approach, Wierwille reported a classification accuracy of 96 percent in a simulator study. Tijerina et al. (1999) evaluated this algorithm's reliability in a study with 8 drivers on the road. They found similar results with a reported classification accuracy of 89 percent, indicating that the simulator research transferred well to on-road prediction of PERCLOS.

Tijerina et al. (1999) also evaluated options for improving the performance of a modified, ePERCLOS algorithm. Their approach, BEST ePERC, uses only lane exceedances or excursions (proportion of time out of lane) and variance in lane position to predict PERCLOS and drowsiness. This approach resulted in fewer false alarms, but also fewer true positives than the original.

In a master's thesis, Mattsson (2007) examined the ability of lane position measures to accurately predict drowsiness. A variety of measures of lane position were evaluated and included in a multi equation algorithm with the algorithm selected based upon the data available. The author evaluated the algorithm's performance against drivers' self-reported drowsiness on the Karolinska Sleepiness Scale (KSS). The algorithm was designed to predict KSS values greater than 8 (8 or 9), and proved most accurate when predicting either a reported sleepiness of 8 or 9 on the nine point scale.

Another approach focused on steering wheel behavior to predict when a driver was drowsy. King et al. (1998) described three types of functions that were used to develop the fatigue prediction: time-based, frequency-based, and phase-based. For example, one time-based measure, amplitude duration squared theta, uses the durations found between pairs of consecutive crossings of zero steering wheel angle (i.e., steering reversals). Two phase-based predictors were based on the relationship of the steering wheel angle to its velocity. These predictors were the most successful at detecting periods of fatigue, which was identified through video review on straight road segments of those evaluated. This algorithm has not been extended to work on curves or turns.

1.3.3 Combination Algorithms

More recently, efforts have been made to combine driver-based and vehicle-based performance measures in algorithms that predict drowsiness. One approach that is currently under development is PERCLOS+. This algorithm merges PERCLOS over a 3-minute window with lane deviations over a 1-minute window (Hanowski, Bowman, Alden, Wierwille, & Carroll, 2008a) to classify level of drowsiness.

An approach under development in the European Community is the "System for effective Assessment of driver vigilance and Warning According to traffic risK Estimation" (AWAKE) project (AWAKE, 2010). This program is aiming for an algorithm that provides at least 90 percent accuracy with less than a 1 percent false alarm rate. The algorithm proposed uses eye lid data, steering wheel grip and lane keeping, to classify the level of drowsiness as awake, may be drowsy, or drowsy. No detailed descriptions of the algorithm or results are currently available.

1.3.4 Recommendations

Existing drowsy driving detection algorithms can serve as benchmarks or points of comparison in the evaluation of the effectiveness of the IMPACT algorithms for the detection of drowsy driving. To warrant implementation and study, comparison algorithms must meet several criteria: They must be (1) sufficiently detailed and feasible to implement, (2) supported by evidence of their effectiveness, and (3) include different approaches using both individualized and generic algorithms.

Based on the criteria for this research, the most promising comparison algorithms for implementation are two related to PERCLOS (PERCLOS and PERCLOS+), and the steering behavior algorithm (King et al., 1998). Unlike many drowsiness detection algorithms, these algorithms meet the established criteria particularly related to sufficient detail for implementation. Additionally, they provide a driver-based, vehicle-based and combination algorithms focused on continuous detection of drowsiness that complement the event-based algorithms for detection of alcohol impairment that will be evaluated from the prior IMPACT work.

PERCLOS uses video of the driver's face to determine the proportion of time that the driver's eyes are more than 80 percent closed over a particular time window, sometimes as small as 1 minute. This algorithm is highly effective at identifying drowsy driving using a model of the individual's eyes to accurately detect proportion of eye closure. It is detailed sufficiently in the literature, generally accepted, and available commercially in many eye tracking systems including FaceLab.

PERCLOS+ combines vehicle-based measures and PERCLOS to identify drowsy drivers. The data needed to support this algorithm are easily accessible within the simulation environment. Early results show promise, although published data on the overall analysis of algorithm performance is not yet available (Hanowski, Bowman, Alden, Wierwille, & Carroll, 2008b). This algorithm appears to use the combined data sources to improve the sensitivity and robustness of the PERCLOS algorithm.

King et al. (1998) proposed a purely vehicle-based algorithm using steering inputs that does not consider direct data about the drowsy driver state, such as eye closures. It has the potential to detect drowsiness relatively early because it considers degradation in steering control before it results in degraded lane keeping, such as lane departures used in the PERCLOS+ algorithm which risks misses if the driver is able to avoid departing the lane. Sufficient detail is available to implement the algorithm, as well as access to the data required to make the algorithm work. Another advantage is that it does not rely on PERCLOS, unlike the other two algorithms that will be compared to the IMPACT algorithms.

Other potential algorithms that were considered were not included for a variety of reasons. EEG-based algorithms have been found to be less reliable than the PERCLOS approach and would have required additional equipment and integration, The ePERCLOS algorithm appears similar in effectiveness to other algorithms, such as Mattsson (2007) and King et al. (1998), and is based on PERCLOS. The facial expression algorithm (Ji et al., 2004) did not provide sufficient details to implement and would likely have required additional hardware and software. Although they are not a promising algorithm input, because of the close association of EEG with sleep, EEG-based metrics are used in conjunction with other measures to identify drowsiness.

One of the aims of this effort is to consider the individualization of algorithms in predicting impairment. Individualization can be regarded in terms of measurement or in terms of thresholds. Individualization of measurement largely focuses on differences in how driver-based measures are captured, such as facial features or eye models. Individualization in thresholds for classification has been less used. Individualization of the threshold requires sufficient data in both the impaired and non-impaired state to properly train, which is difficult in a short experimental session, as well as on a road where driver state is difficult to accurately ascertain. For this reason, the focus was on selecting at least one algorithm that individualizes based upon driver features, while including other algorithms for which individualization of thresholds is feasible.

Three algorithms PERCLOS, PERCLOS+, and steering behavior were selected as the comparison algorithms. The PERCLOS and PERCLOS+ algorithms, both use individualization in their models of eye closure. The PERCLOS and steering behavior algorithms, both lend themselves to individualization of the thresholds, at which drivers are classified as drowsy.

2 DATA COLLECTION METHODS

Data were collected from drivers both while alert and while drowsy, during representative driving scenarios in a high-fidelity driving simulator. The following sections summarize the data collection methods: participant population, simulator and sensor suite, experimental design, procedure, and dependent variables.

2.1 Participants

Seventy-two participants[1] completed three drives: one during the daytime, one when moderately drowsy, and another when severely drowsy. The drivers were healthy men and women from three age groups (21to34, 38 to 51, and 55 to 68 years old). Each possessed a valid State-issued driver's license. Participants were paid $250 for completing all study sessions. Pro-rated compensation was provided for participants who did not complete the study.

Participants were recruited from the NADS Participant Database, Internet postings, and referrals (see Appendix B for recruitment material). An initial telephone interview determined eligibility for the study. Applicants were screened for health history, current health status (see Appendix C), and whether they were a morning or evening person (Adan & Almirall, 1991) (see Appendix D). To eliminate potential participants that were very awake during the overnight data collection periods, applicants with scores on the morning/evening scale less than 12 out of 30 were not eligible for participation. Those with scores indicating that they were an early morning person were not excluded. Pregnancy, disease, sleep disorders, or evidence of substance abuse resulted in exclusion from the study. Applicants taking prescription medications that cause or prevent drowsiness were also excluded from the study.

In particular, the criteria required that participants were licensed and drove at least 10,000 miles per year for the past 2 years, had no restrictions on their driver's license except for vision, were not currently taking illegal drugs or medications that cause or treat drowsiness, and had no warning signs for obstructive sleep apnea (Brown et al., 2009). They also had to live within a 30-minute drive to the National Advanced Driving Simulator (NADS), be able to participate after 7 p.m., stay awake overnight without sleeping, abstain from caffeine consumption after 12 p.m. on the day of overnight visit, and abstain from driving during the day following the overnight visit. In addition, participants needed to have sleep patterns that include going to bed and waking up at approximately the same time every day, not use any special equipment to drive, such as pedal extensions, hand brake or throttle, spinner wheel knobs, or other nonstandard equipment, and not have participated in distraction or alcohol and driving studies conducted at the NADS. Additional details on participant enrollment can be found in Appendix E.

2.2 Simulator and Sensor Suite

The NADS is located at the University of Iowa's Oakdale Campus. It consists of a 24-foot dome in which an entire car is mounted (see Figure 1). All participants drove the same vehicle—a 1996 Malibu sedan. The motion system on which the dome is mounted provides 400 square meters of horizontal and longitudinal travel, and ±330 degrees of rotation. Each of the three front projectors has a resolution of 1600 x 1200; the five rear projectors have a resolution of 1024 x

[1] A total of 103 participants were enrolled.

768. The edge blending between projectors is 5 degrees horizontal. The NADS produces a thorough record of vehicle state (e.g., lane position) and driver inputs (e.g., steering wheel position), sampled at 240 Hz.

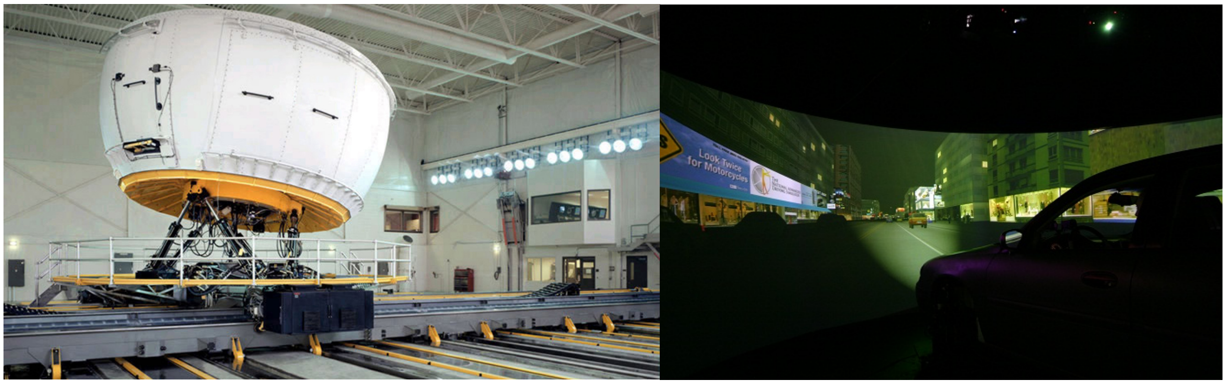

Figure 1. Representation of NADS driving simulator (left) with a driving scene from inside the dome (right).

The cab was equipped with a Face Lab 5.0 (Seeing Machines, Canberra, Australia) eye-tracking system that was mounted on the dash above the steering wheel. The worst-case head-pose accuracy was estimated to have RMS error of 5 degrees. In the best case, where the head was motionless and both eyes were visible, a fixated gaze may be measured with an estimated error of 2 degrees. The eye tracker records data at a rate of 60 Hz. The cab was also equipped with a Seeing Machines Driver State Sensor (DSS) V3.4.260101, a single-camera system that was used for head tracking. The installation of the cameras is shown in Figure 2.

Figure 2. Face Lab cameras mounted in the Malibu cab with a separate head tracking system mounted between them.

The driver's seat was configured with a set of 14 seat sensors that provide posture data. This included six on the base of the seat with three running along each side, and eight on the back of the seat with four running along each side. Data from these sensors were collected at 60 Hz. They were not used for any of the drowsiness detection algorithms, but were needed for a distraction detection algorithm that will be examined in future research.

The study also used the B-alert X-10 to collect EEG data from F3,Fz, F4, C3, Cz, C4, P3, POz, and P4 and heart rate data (Advanced Brain Monitoring, 2011). These signals were used to generate proprietary metrics of task engagement, distraction, drowsiness, and workload to help validate the effectiveness of the experimental manipulations and will also be available for future research.

Additional sensors were used to ensure that participants followed the procedure. An Alco-Sensor IV (Intoximeters Inc., 2011) breath-alcohol-testing instrument was used to measure participants' breath alcohol concentration (BrAC). The hand-held sensor uses a fuel cell to determine BrAC. The system was checked at least every other day for calibration and recalibrated using an approved dry gas standard. A Motionlogger Actigraph (Ambulatory Monitoring Incorporated, 2009) was used to measure participants' activity level to determine when participants were sleeping for the two days prior to each visit.

2.3 Driving Scenarios

The scenarios were largely the same as those that were used in the IMPACT study (Lee et al., 2011). This scenario was selected as the starting point for the scenario for this study in order to provide continuity with prior driver impairment research examining alcohol and distraction. By keeping the driving environment and the driving events largely constant, it allows for future comparisons and algorithm development in Phase 2 of this research which will examine alcohol-impairment, distraction and drowsiness.

Each drive included three connected nighttime driving segments. The drives started with an urban segment composed of a two-lane roadway through a city with posted speed limits of 25 to 45 mph, as well as signal-controlled and uncontrolled intersections. An interstate segment followed that consisted of a four-lane divided expressway with a posted speed limit of 70 mph. After a period in which drivers followed the vehicle ahead, they made lane changes to pass several slower-moving trucks. While on the expressway, a CD changing task, consistent with that used in the IMPACT study.[2] The drives concluded with a rural segment featuring a two-lane undivided road with curves onto a gravel road. In a difference from the IMPACT study, the final segment of the drive included an extension of the original gravel roadway from IMPACT, and then a 300-second straight paved roadway. These three segments mimicked a drive home from an urban parking spot to a rural location via an interstate. Scenario events (driving segments with turns, signals, curves, interstate truck following, a dark rural road, etc.) in each of the three segments combined to provide a representative trip home of approximately 35 minutes, in which drivers encountered situations that might be encountered in a real drive. Throughout the urban section, a series of potential hazards required drivers to scan the roadside. These hazards

[2] It should be noted that there was a tradeoff in presenting the CD task between temporary arousal of the driver that might lessen the drowsiness effects, and the ability to compare back to the alcohol data and in the future to begin to examine the interaction between drowsiness and distraction. It was decided that consistency with previous data ws more important.

included pedestrians, motorbikes, and cars entering and exiting the roadway. These hazards had paths that would cross the driver's path if they were to remain on their initial headings. There was an instance where a pedestrian crossed the driver's path well in front of the driver. Scenario events are summarized in Appendix F, Table 4. The differences from IMPACT are the extension of the drive to include additional time on the gravel roadway, a transition back to a paved road, and a ten minute drive on a straight roadway to end the drive instead of pulling into a driveway, as in the IMPACT scenario. These changes were implemented to improve sensitivity of the scenario to the effects of drowsiness, as discussed in Section 1.1, by adding a segment of drive that is most likely to be problematic for drowsy divers while maintaining the ability to compare back to prior data.

Each participant drove the simulator three times, once in a daytime alert condition, once in a moderately drowsy condition and once in a more severe drowsy condition. All three drives were completed with nighttime visual scene. Three scenarios with varied scenario event orders (but the same scenario events) were used to minimize learning effects from one drive to the next. Each of the three scenarios had the same number of curves and turns, but their order varied. For example, the position of the left turn in the urban section varied so that it was located at a different position for each drive. Additionally, the order of the left and right rural curves varied between drives. The scenario specification in Appendix F provides additional details concerning the differences among the three scenario event sequences.

2.4 Experimental Design and Independent Variables

A 2 x 2 x 3 x 3 mixed-design exposed 12 groups of participants to three drowsiness levels in two different orders. Between-subject independent variables were: age group, gender, and order of the drowsy and alert drives. The within-subject independent variables were drowsiness: (daytime) alert, (nighttime) moderate drowsiness and (nighttime) severe drowsiness, with two nighttime drowsiness sessions blocked into one visit, such that the moderate drowsy drive preceded the severe drowsy drive. The blocking of these two drives conforms to the natural pattern of increased drowsiness across an evening and is consistent with other prior studies looking at drowsiness in which repeated performance measures are collected across a single session. Although this blocking does have the potential to introduce a confound, this method was chosen to most closely replicate the natural process of increased drowsiness and because it avoids potential confounds associated with different amounts of continuous time awake if the overnight drives occurred separately.

2.4.1 **Age and Gender**

The choice of age range was made to match the data previously collected with alcohol impaired drivers in the IMPACT project. Three factors motivated the choice of the age ranges in that study. The first factor was that only those who could legally drink in Iowa would be included. Therefore, enrollment in the study was restricted to those 21 or older. The second factor was that to the extent practical, the entire spectrum of adults who drink and drive should be included, which motivated including the older age group. The third factor was that the age ranges should be uniform, with equal spacing between them. Thus, each group had a range of 14 years. Both male and female drivers were included in the study.

2.4.2 **Drowsiness**

The choice of the daytime alert and drowsy conditions was designed to provide data that are clearly differentiated. The daytime alert drive occurred during the morning (nominally) alert period between 9 a.m. and 12 noon. The nighttime drowsy drives began between 10 p.m. and 1 a.m. (moderately drowsy) and 2 a.m. and 5 a.m. (severely drowsy). The severely drowsy condition occurred after at least 18 hours of continuous wakefulness. The order of the daytime alert and nighttime drowsy conditions was counterbalanced to partially avoid confounding from learning effects.

2.5 Procedure

Following a screening visit, each driver participated in three data collection sessions; two occurred during the night visit, which was separated by at least 3 days from the day visit. This differs from IMPACT, in which the three visits were 7 days apart. Order of visits (alertness sequence) and assignment to a scenario event sequence were counterbalanced across participants as shown in Table 1. A summary of the study procedures is found in Appendix G.

Table 1. Participants assigned to each alertness sequence and scenario sequence

		Age					
		21-34		38-51		55-68	
		Gender		Gender		Gender	
Alertness Sequence[1]	Driving Scenario Sequence[2]	Male	Female	Male	Female	Male	Female
1	1	2	2	2	2	2	2
1	2	2	2	2	2	2	2
1	3	2	2	2	2	2	2
2	1	2	2	2	2	2	2
2	2	2	2	2	2	2	2
2	3	2	2	2	2	2	2
Total		12	12	12	12	12	12

Note. [1]Alertness sequence 1 = Alert, Drowsy; 2 = Drowsy, Alert.
[2]Driving Scenario Sequence 1 = Scenario A, B, C; 2 = Scenario B, C, A; 3 = C, A, B.

2.5.1 Screening Visit

On study Visit 1 (screening), each participant first gave informed consent to participate in the study and received a copy of the signed informed consent form (see Appendix H). They then provided urine samples for the drug screen and, for females, the pregnancy screens. The drug screen was a 10-panel test for amphetamines, methamphetamines, benzodiazepines, cocaine, marijuana, methadone, phencyclidine (PCP), barbiturates, tricyclic antidepressants, and morphine/opiates. Any other medications were reported by participants. Measurements of blood pressure and heart rate were then made. Cardiovascular measures within acceptable ranges (systolic blood pressure = 120 ± 30 mm Hg, diastolic blood pressure = 80 ± 20 mm Hg, heart rate = 70 ± 20 bpm) and a negative BrAC confirmed eligibility for the study. Eligible participants then completed a demographic survey that included questions related to crashes, moving violations, driver behavior, and driving history (see Appendix I). They viewed an orientation and training presentation (see Appendix J) that provided an overview of the simulator cab and the in-cab CD changing task they would be asked to complete while driving. Participants then completed an approximately 8-minute practice drive that included making a left-hand turn, driving on two- and four-lane roads, and practicing the CD changing task. They received recorded audio navigational instructions to guide them through the route. Appendix K describes the in-cab protocol that was administered. After the drive they completed a wellness survey that asks questions about how they felt (see Appendix L). If the survey indicated a propensity for simulator sickness based on total score greater than 35 or nausea scores greater than 40, the participant was ineligible to continue. If still eligible, the participant was fitted with a B-Alert cap and electrodes, and completed an EEG baseline procedure.

Two days prior to Visit 2, participants were given an activity monitor (Actigraph) that they were instructed to wear until Visit 3. It recorded periods of activity and sleep prior to their study visits. Participants also were instructed to keep a written activity log (see Appendix M) during this period to provide more details about activities that could affect their alertness.

2.5.2 Daytime-Alert Visit

Participants were asked to not ingest any caffeine on the days when they underwent their daytime alert condition. They drove themselves to the facility. Upon arrival, the activity monitor and activity log were collected and data uploaded and recorded. In addition to the activity log that the participants brought with them, they completed a survey that asked questions about their sleep and food intake over the past 24 hours, (see Appendix N). The monitor and log data were reviewed to ensure that the participants had a normal night's sleep (at least 6 hours) the preceding night. Their BACs were checked to ensure that they were not under the influence of alcohol (BAC of zero). Participants who did not meet the sleep or BAC requirements were dropped from the study. Participants were then fitted with the wireless B-Alert cap and electrodes to record their EEGs and heart rates. The participants then entered the simulator and eye tracking calibrations were completed.

Prior to beginning the drive, the participants also completed a questionnaire about their current sleepiness level, the Stanford Sleepiness Scale (Hoddes et al., 1973) (see Appendix O), and a version of the Psychomotor Vigilance Test or PVT (Cognitive Media Iowa City, IA) based on the Psychomotor Vigilance Task (Wilkinson & Houghton, 1982). This version of the PVT displayed a target to which the participant responded as quickly and accurately as possible by a button press. Although the duration of the PVT is generally 10 minutes, more recent research has supported the use of shorter duration tasks (Loh et al., 2004). This version of the test was implemented on an iPad, and provides both a 5 and 10-minute version for use at different times in the procedure. The participants drove through the simulation scenario after completing the 5-minute PVT in the vehicle.

Following the drive, participants were again administered the Stanford Sleepiness Scale), the wellness survey, PVT, plus a Retrospective Sleepiness Scale (See Appendix P) and a simulator realism survey (see Appendix Q). The Retrospective Sleepiness Scale required subjective judgments of drowsiness at specified scenario locations. The B-Alert cap was then removed. If the participants had not already completed their nighttime-drowsy visit, the activity monitor and activity log were returned to them and they were reminded of their next appointment.

2.5.3 Nighttime-Drowsy Visit

Participants were instructed to restrict beverage consumption to water after 12 p.m. on the day of their overnight visit, to minimize caffeine intake. They were provided with a list of items to avoid that contained caffeine including coffee, tea, soda, vitamin water, energy bars, energy drinks, and foods with chocolate. On nights when participants underwent their nighttime drowsy condition, they were picked up at their homes after having eaten dinner, and transported to the simulation facility to arrive around 7 p.m. Upon arrival, the activity monitor and activity log were collected and data recorded. While the data were being recorded, the participants completed sleep and food intake surveys. The activity monitor and log data were reviewed to ensure that the participants had a normal night's sleep (at least 6 hours) the preceding evening and did not take any naps during the day. If a participant indicated that the monitor was worn and the data were not recorded, only the log was used to determine if the participant was eligible to continue. If a participant indicated that the monitor was taken off or not worn, he or she was dropped for non-compliance to the protocol. Participants' BAC was checked to ensure that they were not under the influence of alcohol. Participants who did not meet the sleep or BAC requirements were dropped from the study and returned home. Each participant's caffeine intake was reviewed in the activity log and again in the sleep and intake log. If caffeine was consumed after noon on the day of the overnight drive, the participant was either rescheduled or dropped from the study. Participants were assigned to simulator drive times based on their waking times; therefore, based upon their survey responses and the activity logs, the participant who had awakened the earliest was selected to drive first and so on. Participants were then fitted with the B-Alert monitoring device.

A variety of activities were provided to keep participants awake including activities on an iPad, reading, playing computer games, etc. They were monitored to ensure they did not fall asleep or converse with other participants. If participants began to fall asleep, they were engaged by a researcher to keep them awake. The participants completed the Stanford Sleepiness Scale every 30 minutes until they drove. One hour prior to their drive, they were taken to a private room to wait. They completed a PVT at this time, and also at 30 minutes prior to the drive. Participants were escorted to the simulator between 10 p.m. and 1 a.m. for their first drives. Once in the simulator, eye tracking calibration procedures were performed, and the B-Alert electrode connection was verified. Before starting the drive, the participants completed a PVT and Stanford Sleepiness Scale. After the drive, participants completed the Stanford Sleepiness Scale, a Wellness Survey, a PVT, and a Retrospective Sleepiness Scale.

Participants were then escorted back to a separate waiting area where TV, movies, reading, computer games, etc. were available. A Stanford Sleepiness scale was administered every 30 minutes until their next drive. One hour prior to their second drive times, participants were again taken to a private room to wait. They completed a PVT one hour prior to the drive and also at 30 minutes prior to the drive. Participants were escorted to the simulator between 2 a.m. and 5:30 a.m. for their second drives. Once in the simulator, eye-tracking calibration procedures were performed, and the B-Alert connection was verified. Before starting the drive, the participants completed a PVT and Stanford Sleepiness Scale. After the drive, participants completed Stanford Sleepiness Scale, a Wellness Survey, a PVT, a retrospective sleepiness scale, and a realism survey. The B-Alert system was then removed. If the participants still needed to return for their daytime-alert visit, the activity monitor and activity log were returned to them, and they were reminded of their next appointment. At the end of their third visit, participants were given a debriefing survey, (see Appendix R) and paid $250. Then the participants were given the debriefing statement (see Appendix S) and driven home.

2.6 Dependent Variables

The dependent variables differed across the 22 distinct scenario events that comprised the three segments of the drive. The primary measures were lane position (mean, standard deviation, departures), speed (deviation from limit, standard deviation), steering (reversals, heading error), lateral acceleration (maximum, jerk rate), eye closure (blinks), head position (standard deviation). The scenario specification describes the dependent variables for each scenario event (see Appendix F). Potential intervening variables and their mitigation are discussed in Appendix T.

2.6.1 Data Verification and Validation

The data reduction began with verification of the raw input data. The data was then aggregated as needed to support sensitivity analyses and algorithm development and testing. The process concluded with validation of metrics that summarize the data.

Verification concerns the process of ensuring that the raw data accurately reflected the state of the vehicle, driver, and roadway. Scenario event errors, database flaws, and measurement noise all may contribute to spurious raw data that would need to be removed before they are transformed into measures of driver behavior. Several automatic data checks combined with manual visualizations identified these issues. The verification procedures included verifying that all the variables in the raw data contain values, and that the file was of the expected size. The integrity of each variable was assessed on three factors: whether the values lie within the expected range, whether the values vary in a meaningful manner, and whether the variation in the values was continuous. These three indicators were automatically assessed or revealed in a plot of the data.

Validation concerns the process of ensuring that the summary measures accurately reflect the driver behavior or vehicle performance of interest. Measures based on aggregating measures at the sample level (across scenario events, drives, or people) might fail to reflect the underlying population differences in behavior due to such issues as differences in the distribution of the data, or the presence of data that differs in significant ways from the rest of the sample. Data visualization techniques provide a useful tool for addressing challenges to the validity of such summary measures by examining them in the context of the time history and distribution of the data. Data were visualized by superimposing the summary measures over the raw data with a reference point, such as the posted speed limit, to roughly assess whether the underlying calculations are correct and in fact capture the behavior of interest, as opposed to separate types of behavior that might otherwise have been combined.

In the following chapter, data will be reviewed and analyzed to assess the sensitivity of the measures to the drowsiness manipulation. This chapter will include an analysis of PERCLOS, metrics derived from EEG and heart rate, driving performance measures, PVT, and self-reports of sleepiness. The analysis will focus on documenting patterns of performance that differentiate the three levels of drowsiness over the drive. The analysis will also consider the how well measures taken outside the drive, (PVT, self-reported sleepiness, and hours of wakefulness) predict measures obtained during the drive.

3 LEVEL OF DROWSINESS AND DRIVING PERFORMANCE

3.1 Drowsiness of Participants

Table 2 reports the cumulative time awake (CTA, in minutes) for the three drowsiness conditions: day, early night, and late night. As expected, the greatest CTA was measured in the late night condition (1,230 min), followed by the early night condition (1,001 min), and the day condition (222 min).

Table 2. Average cumulative time awake by drowsiness condition

	Day				Early Night				Late Night			
	N	*M*	*SD*	Median	*N*	*M*	*SD*	Median	*N*	*M*	*SD*	Median
CTA	72	223	73	214	72	1,001	53	995	72	1,230	51	1,228

Table 3 reports the SSS scores that were obtained pre-drive, post-drive, and the averages for the three drowsiness conditions. The SSS has a range of 1 to 7 with 1 feeling active, vital, alert or wide awake and 7 being no longer fighting sleep, sleep onset soon having dreamlike thoughts. The average sleepiness score for the day drive was 2.35. The average sleepiness score for the early night and late night drives were 3.77 and 5.19, respectively. Thus, the highest level of sleepiness was measured for the late night drive, followed by the early night drive and the day drive. Note that in some cases the scale was not administered, resulting is some missing data.

Table 3. Average Stanford Sleepiness Scale scores by drowsiness condition

	Day				Early Night				Late Night			
Measurement	*N*	*M*	*SD*	Median	*N*	*M*	*SD*	Median	*N*	*M*	*SD*	Median
Pre-drive	68	1.8	.8	2.0	69	3.4	1.2	3.0	72	5.0	1.3	5.0
Post-drive	71	2.9	1.2	3.0	68	4.1	1.3	4.0	71	5.4	1.3	6.0
Average	68	2.4	.9	2.0	65	3.8	1.2	4.0	71	5.2	1.2	5.5

Table 4 reports the pre-drive, post-drive, and average for the psychomotor vigilance test (PVT) across the three drowsiness conditions. The average PVT reaction time for the day drive was 382 ms. The average PVT reaction time for the early night and late night drives was 404 ms and 445 ms, respectively.

Table 4. Average psychomotor vigilance reaction times (ms) by drowsiness condition

	Day				Early Night				Late Night			
Measurement	*N*	*M*	*SD*	Median	*N*	*M*	*SD*	Median	*N*	*M*	*SD*	Median
Pre-drive	72	371	44	364	72	397	53	386	72	430	62	419
Post-drive	72	394	52	387	72	412	58	414	72	460	74	448
Average	72	382	46	379	72	404	52	400	72	445	62	441

Table 5 reports the correlations between CTA, SSS average, and PVT reaction time average. Pearson correlations ranged from .394 to .949. (all significant at the .01 level). The pattern of correlation sizes indicates that CTA-SSS and CTA-PVT correlations varied in size. This suggests that measures of sleepiness did not vary solely as a function of time awake since last sleep, but potentially also as a function of time of day, circadian rhythms, and possibly the participants' level of arousal during the entire test session at the NADS.

Table 5. Pearson correlations between testing drowsiness condition (time of day) and selected measures of sleepiness

Measure	1	2	3	4
1. Drowsiness Condition				
2. Cumulative Time Awake (CTA)	.95			
3. Stanford Sleepiness Scale (Pre/Post Average)	.73	.69		
4. Psychomotor Vigilance Test (pre/Post Average)	.43	.39	.47	

3.2 Driver Adaptation to Scenario Events With Repeated Exposure

The effect of repeated exposure was examined for lane deviation, mean speed, and speed deviation to determine if there was a systematic change across sessions. Analyses of variance with alpha level set at .05 were used to determine whether there were reliable differences as a function of session. No efforts were made to control for the family-wise Type I error. There were 12 scenario events for which lane deviation showed a significant difference across sessions. Only the gravel rural extension showed a pattern of improved performance across visits. There were 10 scenario events for which average speed showed a significant difference across scenario events. For all but one of those scenario events, there was an increase in average speed; however, the increase in average speed was less than 4 mph, at its greatest. There were 6 scenario events for which speed deviation showed a significant difference across visits. For all but one of those scenario events, there was a decrease in variability across visits. Twenty-one of the 28 significant differences were associated with short scenario events lasting approximately 30 seconds or less. For 60 of the 75 comparisons, there was not a significant pattern of learning observed. Overall most scenario events across these variables did not demonstrate a systematic learning effect or adaptation by the driver across visits. More detail can be found in Appendix U.

3.3 Effect of Drowsiness on Driving Performance Across Roadway Conditions

3.3.1 Analysis of Variance

A 2 x 3 x 3 between-between-within ANOVA was performed on each of the three composite measures for lane deviation, average speed and speed deviation. The composite scores were calculated by averaging the *z* scores of each measure across the scenario events and by re-standardizing the mean into a T-score ($M = 50$, $SD = 10$). Additional details on the individual scenario events and the composite measure can be found in Appendix V. Between-subjects independent measures were gender and age group (21 to 34, 38 to 51, 55 to 68). Within-subjects independent measure was drowsiness condition (day, early night, and late night).

3.3.1.1. Lane Deviation Composite Scores

The mean lane deviation composite scores by drowsiness condition, age group, and gender are shown in Table 6. Mauchly's test of sphericity was not significant, indicating that no adjustment to the degrees of freedom was required. Drowsiness condition produced a statistically significant main effect $F\ (2, 132) = 15.22$, $p < .001$, partial $\eta^2 = .19$. As shown in Figure 3, lane deviation composite scores varied as a function of drowsiness condition $F\ (1, 66) = 9.28$, $p < .01$, partial $\eta^2 = .12$. As shown in Table 7, lane deviation was not statistically different between the day and the early night conditions, and between the day and late night conditions. It was, however, statistically different between the early night and the late night conditions.

Table 6. Lane deviation composite score by drowsiness condition, age group, and gender

Age Group	Gender		Day	Early Night	Late Night
21-34	Females	*M*	50.43	48.62	53.68
		N	12	12	12
		SD	9.64	7.82	9.96
	Males	*M*	46.84	44.47	51.66
		N	12	12	12
		SD	9.86	7.68	10.98
	Total	*M*	48.63	46.54	52.67
		N	24	24	24
		SD	9.71	7.87	10.30
38-51	Females	*M*	52.21	49.24	52.96
		N	12	12	12
		SD	13.11	14.29	16.81
	Males	*M*	50.73	48.87	52.57
		N	12	12	12
		SD	10.16	8.11	13.60
	Total	*M*	51.47	49.06	52.77
		N	24	24	24
		SD	11.50	11.36	14.96
55-68	Females	*M*	49.52	48.14	53.32
		N	12	12	12
		SD	5.29	7.40	7.51
	Males	*M*	48.70	47.43	50.63
		N	12	12	12
		SD	7.47	6.82	7.46
	Total	*M*	49.11	47.78	51.97
		N	24	24	24
		SD	6.34	6.97	7.45
Total	Females	*M*	50.72	48.67	53.32
		N	36	36	36
		SD	9.66	10.04	11.74
	Males	*M*	48.76	46.92	51.62
		N	36	36	36
		SD	9.12	7.57	10.69
	Total	*M*	49.74	47.79	52.47
		N	72	72	72
		SD	9.38	8.87	11.18

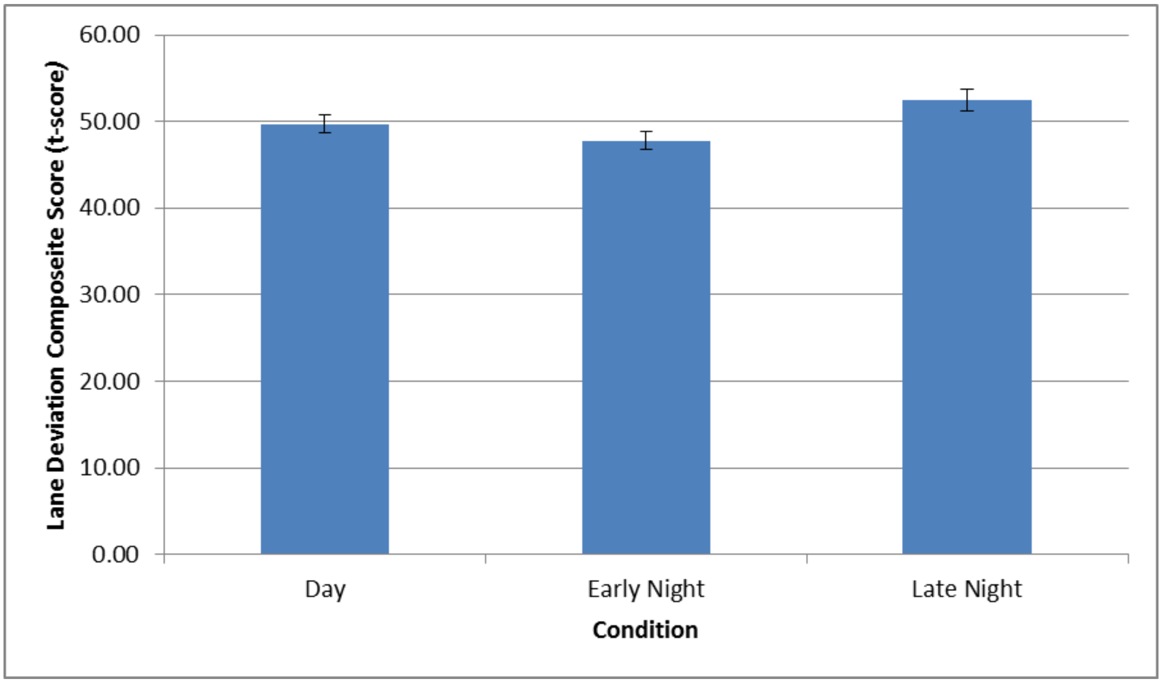

Figure 3. Lane deviation composite score as a function of drowsiness condition. Error bars represent standard error.

Table 7. Post-hoc Lane Deviation Comparisons

Comparison		Mean Difference	Std. Error	Significance	99.9% Confidence Interval for Difference	
					Lower Bound	Upper Bound
Day	Early night	1.95	.77	No	-.97	4.87
Day	Late Night	-2.73	.90	No	-6.13	.66
Early night	Late night	-4.67	.88	Yes	-8.00	-1.35

Note. Pairwise comparisons were conducted with α=.001.

3.3.1.2. **Average Speed Composite Scores**

The mean speed composite scores by drowsiness condition, age group, and gender are shown in. Mauchly's test of sphericity was statistically significant, and the Greenhouse-Geisser adjustment was used to adjust the degrees of freedom.
Drowsiness condition produced a statistically significant main effect, $F\ (1.64, 107.99) = 13.19$, $p < .001$, partial $\eta^2 = .17$. As shown in Figure 4, average speed composite scores varied as a function of drowsiness condition.

As shown in Table 9, there was a statistically significant difference in average speed between the day and the early night conditions, but not between the day and late night conditions and between the early night and late night conditions.

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3.4 Robustness of Metrics with Respect to Age, and Gender

3.4.1 Lane Departure Composite Scores

Although there was a significant effect of drowsiness condition on lane deviation, there were no effects for lane deviation relative to age and gender. There were no interactive effects between age and gender with drowsiness condition.

3.4.2 Average Speed Composite Scores

There was one effect on average speed relative to age. There was a significant main effect of age, F (1, 66) = 16.08, p < .001, partial η^2 = .33.

Figure 5 shows that there was a statistically significant difference in average speed between the 21-to-34 and the 55-to-68 age groups, but not between the 21-to-34 and the 38-to-51 groups and the 38-to-51 and 55-to-68 age groups. There were no interactive effects between age and gender with drowsiness condition.

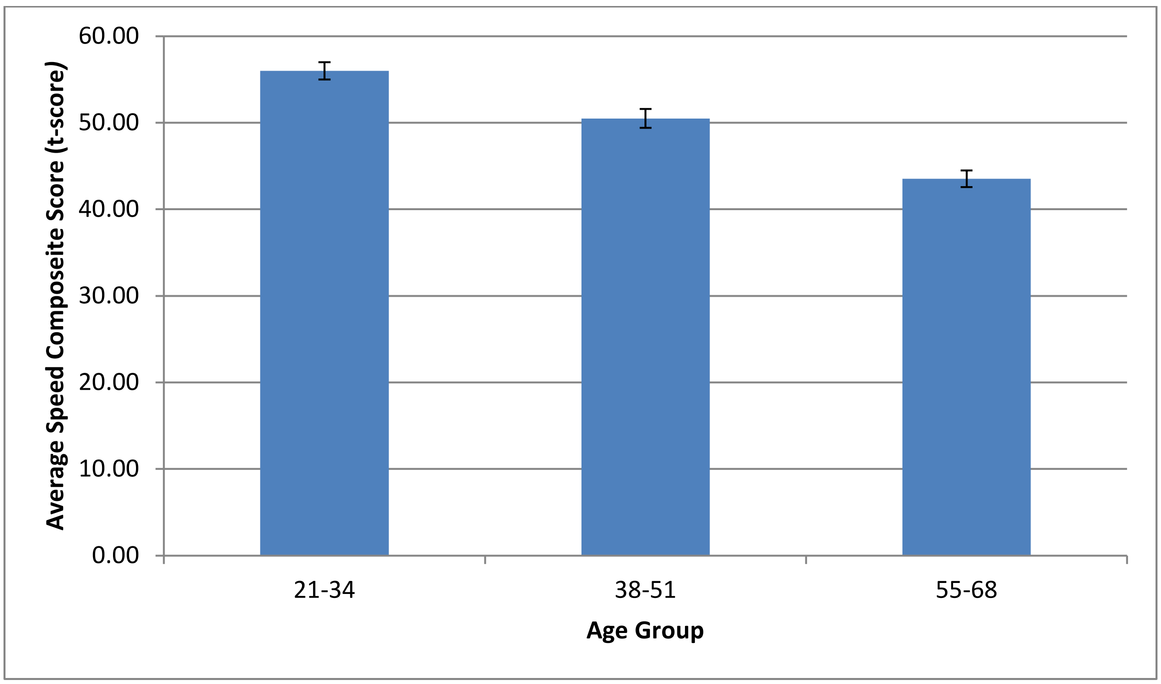

Figure 5. Average speed composite score as a function of age group. Error bars represent standard error.

distraction in that the onset of symptoms may be relatively sudden and transient. Drowsiness may induce gaze concentration similar to distraction. Drowsiness would be expected to share some features with alcohol impairment as they both impact the CNS; indeed, the performance under the two types of impairments have been equated in several studies (Williamson & Feyer, 2000; Dawson, Drew, & Reid, 1997; Arnedt et al., 2001).

The NHTSA distraction detection and mitigation project (Lee et al., in review) considered visual and cognitive distraction. Four algorithms were implemented and evaluated for this project. Only one of the four was designed to detect cognitive distraction, which is included in this study because cognitive distraction may share characteristics of drowsy driving, namely a lack of active visual scanning of the forward scene signified by gaze concentration.

A truly general algorithm could help protect drivers from impairments not anticipated by the designer. This is a motivating factor in adapting proven alcohol and distraction algorithms for application to drowsiness in this study.

We considered algorithms applied at three distinct timescales, summarized in Table 12. The utility of an algorithm varies according to its timescale, with long range approaches being appropriate for post-drive evaluation, medium range ones appropriate for moderately spaced countermeasures, and short range for the detection of safety-critical situations.

Table 12. Three levels of algorithm timescale

Timescale	Description	Period	Indicators
Long range	Whole drive	~30 minutes	Stanford Sleepiness Score; Condition
Medium range	Event-based	~1-6 minutes	Retrospective Sleepiness Score
Short range	Real-time	~60 seconds	Drowsy lane departures

The previous NHTSA study of alcohol (Lee et al., 2010) produced three algorithms that were sensitive to differences between the baseline condition and two BACs (.05 and .10 g/dL). These algorithms were based on logistic regression, boosted decision trees, and support vector machines (SVMs). Various measures of driver performance, environmental demand, and event type were used as inputs to the algorithms; and they were trained and tested on simulator data. The BAC classifications were grouped by scenario event because driver behavior during a yellow light dilemma, for instance, could vary considerably from that observed during highway driving. A decision tree algorithm with boosting was able to detect impairment with greater accuracy than the other candidates: support vector machines and logistic regression. For this reason, the event-based decision tree algorithm is one of the candidates evaluated in the current work to detect drowsiness.

Additionally, the current project has developed a real-time algorithm to detect drowsiness that was trained and testing using data from the IMPACT study and applied to the drowsiness data. The new algorithm uses a Bayesian network to model the conditional probabilities associated with several driving performance measures.

Table 13. Impairment Detection Algorithm Summary

Label	Algorithm	Source	Impairment	Timescale
PC	PERCLOS	(Dinges, Mallis, Maislin, & Powell, 1998)	Drowsiness	Medium
PC+	PERCLOS+	(Hanowski, Bowman, Alden, Wierwille, & Carroll , 2008)	Drowsiness	Medium
SB	Steering-Based	(King, Mumford, & Siegmund, 1998)	Drowsiness	Short
EEG	EEG	NHTSA DRIIVE	Drowsiness	Short
DT	Decision Tree	NHTSA IMPACT	Alcohol, Generalized	Medium
MDD	Multi-Distraction Detection	NHTSA distraction detection and mitigation	Distraction	Short
TLC	Time-to-lane-crossing	NHTSA DRIIVE	Drowsiness	Short
SRF	Steering random forest	NHTSA DRIIVE	Drowsiness	Short
BN	Bayes net	NHTSA DRIIVE	Alcohol, Generalized	Short

A summary of the various algorithms is given in Table 13. Each of these algorithms was developed to detect a specific impairment, with several being developed specifically to detect drowsiness. This study assesses whether any of the alcohol-specific algorithms can also detect drowsiness as well as those developed specifically to detect drowsiness, and therefore offer promise as general algorithm that can detect and distinguish a wide range of impairments.

4.4 Algorithm performance criteria

Assessing algorithm performance depends on comparing the classification (i.e., drowsy or alert) to the actual state of the driver. The actual state of the driver is sometimes referred to as the ground truth, and is ideally indicated by a "gold standard" measure that provides an unambiguous indicator of the driver state. Such a gold standard is difficult to define for drowsiness. Arguably a clinical EEG record scored by a sleep expert is the gold standard indicator of drowsiness, but it was not possible to obtain this indicator for

Can algorithms designed for alcohol impairment detection be generalized to work well for both alcohol and drowsiness? Alcohol algorithms that have been retrained on drowsy driver data or new algorithms that include variables appropriate for drowsiness should be more accurate in detecting drowsiness than specialized alcohol detection algorithms, but may also be less accurate in detecting alcohol impairment if alcohol and drowsiness do share symptoms.

Can algorithms distinguish between alcohol and drowsiness-related impairment?

Do real-time algorithms perform better in detecting drowsiness in advance of a drowsiness-related mishap? Event-based algorithms, such as the decision tree algorithms previously used to detect alcohol impairment, may be less likely to have a high AUC value six seconds before the onset of a drowsiness-related mishap compared to a real-time algorithm.

4.6 Evaluation method

4.6.1 Algorithms

Impairment detection algorithms can be characterized by the timescale over which they operate, and the timescale over which impairment indicators are expected to vary. Table 12 and Table 13 above present three distinct timescales that the algorithms use. The timescale assignments in Table 13 are not fixed. One may accumulate short or medium range algorithm outputs over a longer timeframe for a post-drive review for instance. Alternatively, one may attempt to sample medium range algorithms more often for real-time prediction, though the accuracy may suffer.

Other dimensions that separate the algorithms are the types of inputs they use (physiological or driving performance) and how the inputs are combined. Beyond these dimensions, some algorithms may be parametrically modified to become more general, perhaps by simply changing a parameter threshold. Alternatively, the more complicated alcohol algorithms may be retrained to a dataset obtained from drowsy driving, or a combined dataset consisting of both drowsy and alcohol impairments. Table 14 again lists the impairment detection algorithms that were used in this study, this time with inputs and outputs described.

Most of the algorithms produce a binary classification, making it the common basis for comparison between all the algorithms. In cases where an algorithm outputs something other than a binary output, the categorical or continuous outputs were mapped to a binary classification. Binary classifiers were obtained from more complex ones by setting thresholds. The details of obtaining a binary classification for drowsiness are given in the next chapter.

For each algorithm in Table 14, a binary output was created if one did not exist. Then the accuracy, PPP, AUC, and timeliness of each algorithm were calculated. These data were organized into two datasets: one based on scenario events and the other based on fixed windows of time with some percentage of overlap.

5 ANALYSIS OF ALGORITHM PERFORMANCE

This chapter describes algorithms and their ability to detect driver drowsiness. Similar algorithms have been developed to detect alcohol impairment (Lee et al., 2010) and distraction, and the central aim of this study is to assess how well these techniques can be used to detect drowsiness. The degree to which similar algorithms can detect both alcohol impairment and drowsiness, and the degree to which such algorithms can differentiate the two impairments, depends on the profile of the impairment over time and the particular manner in which the impairment influences driver behavior. Specifically, the impairment of alcohol is relatively constant over a period of 20 to 30 minutes and strongly influences lane keeping performance, whereas drowsiness might vary considerably over this period and might influence other elements of driving performance. These underlying differences in the profiles of impairment demonstrate the demands of developing algorithms to detect impairment. This study addresses the understanding of the demands of drowsiness detection by addressing the following questions:

- Can algorithms designed to detect alcohol impairment or distraction also detect drowsiness?
- Can algorithms designed to detect alcohol impairment be generalized to detect both alcohol and drowsiness?
- Can algorithms distinguish between alcohol and drowsiness-related impairment?
- Do real-time algorithms perform better than event-based or post-drive algorithms in detecting drowsiness in advance of a drowsiness-related mishap?

In order to answer these questions, several types of drowsiness measurement are used throughout the chapter. Each has its own merit and appropriate usage. SSS is a scale from one to 8 where one is alert and 8 is asleep. It was collected both pre and post-drive through a survey. The retrospective sleepiness scale (RSS) uses the same scale as SSS, and is administered via survey, but is an estimate from a continuous time measurement over the course of the drive. The psychomotor vigilance test (PVT) is an active memory test known to correlate with drowsiness. A 5-minute PVT was administered before and after each drive. A video review of lane departures was conducted to obtain a good quality set of truly drowsy scenario events against which to judge algorithm performance. The three timescales considered are summarized in Table 15, reproduced from Chapter 5.

Table 15. Three algorithm timescales

Aggregation	Description	Period	Indicators
Long range	Whole drive	~20-30 minutes	Post-drive SSS; Condition
Medium range	Event-based	~1-6 minutes	Event-based RSS
Short range	Real-time	~60 seconds	Drowsy lane departures

SSS ratings and PVT scores are only appropriate when considering data from entire drives, while RSS data can be used for finer grain analysis or grouped at the scenario event or drive level. Drowsy lane departures are reliable events to compare against, but are transient in nature and not associated with drives or scenario events. Note that it is difficult to standardize terminology around the word drowsiness because the standard survey instruments used in this study use the word sleepiness. Throughout this chapter the terms drowsy and sleepy are used interchangeably.

The following analyses address the research questions by first describing the distribution of drowsiness across drivers, conditions, and the drive. Drowsiness is classified here using a threshold of post-SSS rating greater than three. This distribution of drowsiness suggests algorithms used to detect alcohol impairment over the course of a 20-minute drive might perform relatively poorly, which is confirmed with an analysis of algorithms detecting impairment over the drive. The differences in the profiles of alcohol impairment and drowsiness are then used to create algorithms that detect alcohol impairment, drowsiness impairment and differentiate between the two. Real-time algorithms that aim to predict drowsiness associated with lane departures in advance of the lane departure are then considered. For that analysis, a more complex classification of drowsiness that combined SSS, RSS, PVT, and drowsy lane departures was used.

5.3 Distribution of Drowsiness across Drivers and the Drive

Unlike blood alcohol level and the associated impairment, drowsiness varies considerably across drivers and over the 35-minute drive used in this study. Figure 6 shows the ratings of sleepiness drivers made after they completed each drive using the retrospective sleepiness scale (RSS). Each line represents the ratings of a single driver. The ratings generally increase over the drive. However, these ratings fluctuate considerably from event to event, with uneventful scenario events, such as the straight rural segment, leading to higher ratings of sleepiness. The ratings generally reflect the drowsiness condition, with drivers in the late night condition tending to report higher levels of sleepiness; however, the distribution of reported sleepiness varies considerably with some drivers in the late night condition reporting lower levels of sleepiness compared to those in the daytime condition. Some drivers in the late night condition are quite alert and some in the daytime condition are quite drowsy. This pattern of impairment contrasts with that of alcohol, where BAC level is well-controlled across conditions—no drivers in the zero BAC condition were impaired by alcohol—and the BAC level was relatively constant across the drive. Assuming that BAC level reflects impairment due to alcohol, alcohol-impairment is controlled and constant across the drive. In contrast, Figure 6 shows that the drowsiness conditions induced substantial drowsiness, but that drowsiness varies considerably between drivers, within conditions, and across the drive.

Overall, there were 623 verified lane departures during the drives with 202 being classified as drowsy lane departures. The drowsy departures represented 22 percent of the daytime departures, 14 percent of the early night departures, and 51 percent of the late night departures. Figure 7 shows the frequency of drowsiness-related lane departures, with each line representing data from a single driver. The distribution of these lane departures across the conditions, drive, and drivers shares important features with the ratings of sleepiness. Like the high ratings of sleepiness, more drowsy-related lane departures occurred later in the drive, during long, uneventful segments such as the straight rural and dark rural segments. These peaks likely represent the demands of the roadway (poorly lit and relatively narrow lanes) as well as the association with higher levels of drowsiness. The frequency of lane departures varied considerably across drivers and scenario events with some drivers frequently departing their lane and others departing their lane very infrequently if at all. Similarly, during some scenario events, such as those early in the drive, drivers never departed their lane.

The pattern of drowsiness-related impairment reflected in Figure 7 has several important implications for algorithm development and evaluation, as well as for drowsiness countermeasures. Extreme levels of drowsiness and associated lane departures occur even with seemingly well-rested drivers during the daytime. Unlike alcohol (as suggested by BAC), drowsiness and its effect on lane keeping varies considerably over a drive and across drivers, making the definition of impairment challenging: impairment might not exist for a given driver within a particular scenario event even though the drowsiness condition was designed to induce impairment. Likewise, an otherwise alert driver might experience a period of extreme drowsiness; but when averaged over a drive, the mean level of drowsiness might suggest the driver was safely alert. This makes it less likely that algorithms, such as those used to detect alcohol impairment, will be able to combine event-based (medium range) information to estimate impairment over the drive.

5.4 Detecting Drowsiness With Algorithms Designed for Alcohol Impairment and Distraction

The challenge of detecting drowsiness associated with differences between drivers across the three drowsiness conditions (daytime, early night, and late night) is reflected in the relatively poor detection performance summarized in Table 11. In this table, the algorithms were assessed according to how well they differentiated the day drive from the late night drive using the metrics of AUC, PPP, and accuracy described in Section 5.2. Each algorithm was applied on a long range timescale in which classification instances were accumulated throughout the entire drive.

Not surprisingly algorithms developed to detect distraction failed to detect drowsiness—the AUC of .50 indicates the algorithm performed no better than chance. Surprisingly, algorithms designed to detect drowsiness, such as PERCLOS and those based on EEG measures also performed no better than chance. Poor performance of the algorithms reflects, in part, the drivers in the late night condition who rated themselves as alert and drivers in the daytime condition as very sleepy.

Table 17 shows algorithm performance in detecting drowsiness, as defined by drivers' ratings of sleepiness using the SSS after they completed the drive. Drowsiness is indicated by post SSS of 5 or greater and alertness by post SSS of 3 or less. In this table, In both tables the algorithm developed to detect distraction (MDD) performed very poorly. Similarly, the Bayes network trained to detect alcohol impairment also performed very poorly, and algorithms developed to detect drowsiness performed almost as poorly. Overall, these results show that algorithms developed to detect other impairments will not necessarily detect overall drowsiness as determined by SSS rating.

To assess whether algorithms developed to detect alcohol impairment perform better when they are trained to detect drowsiness, the most sensitive algorithm from the IMPACT study—a boosted decision tree using data summarized for each event— was applied to detect drowsiness. Not all measures from IMPACT that were used to train the alcohol algorithm were used in this study, so the original DT algorithm was not used. However, a direct comparison was done with a similar Bayes network algorithm; and the alcohol-trained version did not perform well on drowsiness data (see Table 16 and Table 17). A best-case analysis would consider a DT trained on drowsiness data; and this analysis is presented and showed relatively poor performance. To further tune the DT to detect drowsiness PERCLOS was added to enhance performance.

Once again, post-SSS Ratings were used to classify true drowsiness, and a long-range timescale was used. Figure 8 shows receiver operator curves (ROC) that describe the performance of the algorithms. Comparing the upper panels shows that adding driving performance variables to PERCLOS increases its sensitivity substantially. The graphs in the lower panel show that the driving performance variables and variables that describe the driving context can also be used to detect drowsiness, but less well than PERCLOS. Figure 9 shows the driving performance variables that are most indicative of drowsiness, with lateral and longitudinal acceleration (Ax_max and Ay_max), as well as normalized speed (spn_avg) and lane position (lp_avg) exerting a particularly strong influence. These results show that when trained on data from drowsy drivers the boosted decision tree algorithm can successfully detect drowsiness.

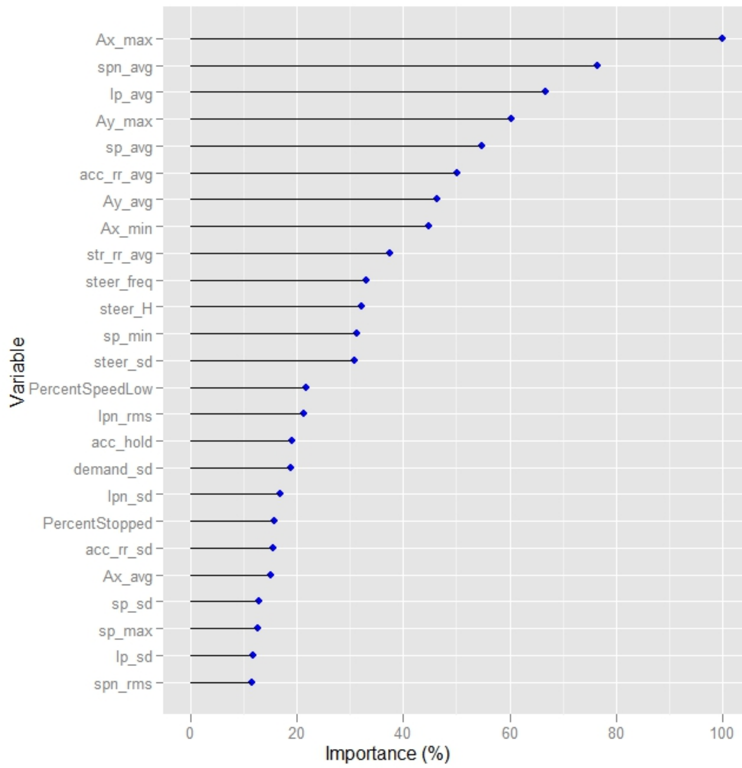

Figure 9. Relative importance of variables predicting drowsiness defined by the post-drive Stanford Sleepiness Score

If drowsiness is defined by retrospective sleepiness (RSS) ratings rather than post-drive SSS ratings a slightly different picture emerges. Figure 10 shows that boosted trees, detecting event-level measures of sleepiness, perform better than algorithms predicting drowsiness based on the post-drive Stanford Sleepiness Score. Importantly, the algorithms using the driving performance measures perform comparably to PERCLOS. Because sleepiness varied considerably over the drive, it is not surprising that algorithms predicting rated drowsiness for each scenario event performed better than those predicting drowsiness at the end of the drive.

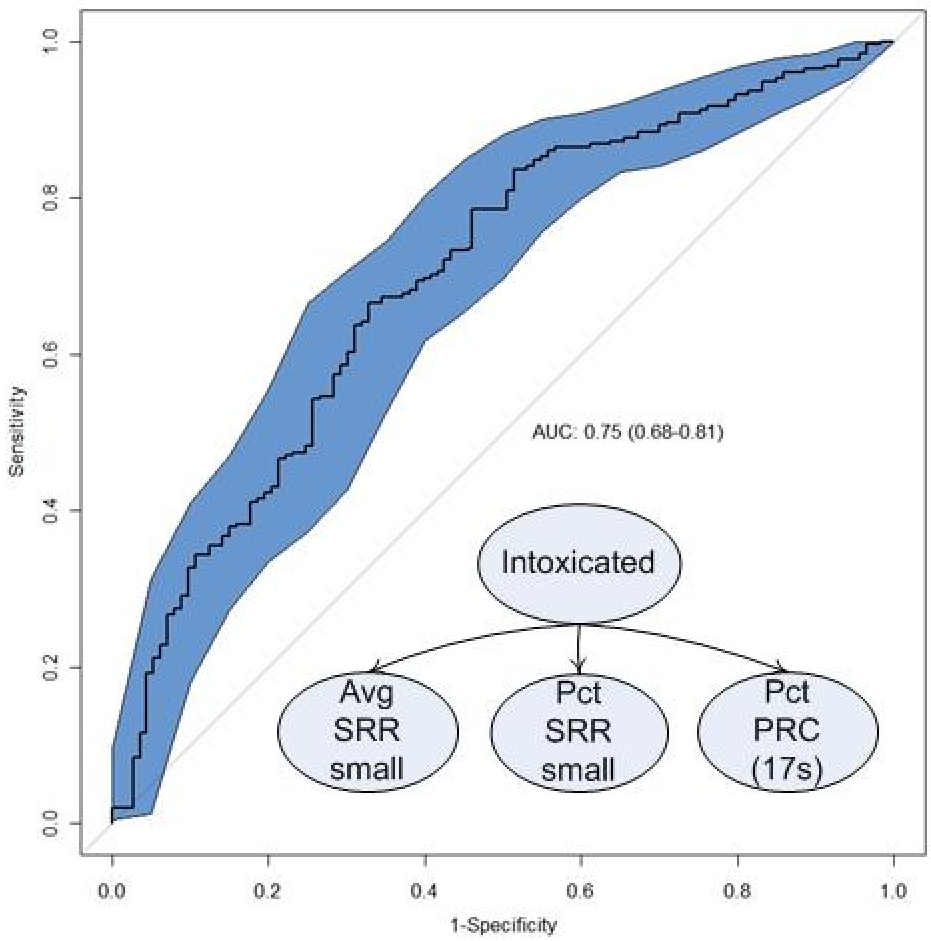

Figure 11. Performance of the Bayes network for detecting alcohol impairment

The drowsiness dataset was also amenable to this approach. The entire pool of drivers was considered rather than being restricted to verifiably awake subjects, as in the lane departure dataset. Drowsiness was selected as a binary classification, where drowsiness was defined as drives with pre and post SSS scores greater than three; and the alertness was defined as drives with pre and post SSS scores of 3 or less. Drives in which the pre and post SSS scores straddled the threshold were eliminated from the training and test set.

After examining ROC plots for all the measures using the lane departure dataset and the above classification of drowsiness, four measures were included in the drowsiness Bayes network: standard deviation of lane position (SDLP > 1), average eye closure speed (AECS > 1.2), and time to lane crossing (TLC < 6.5, TLC < 7.5), where the average, maximum, maximum, and percentage metrics were applied respectively. The model and ROC performance curve are shown in Figure 12.

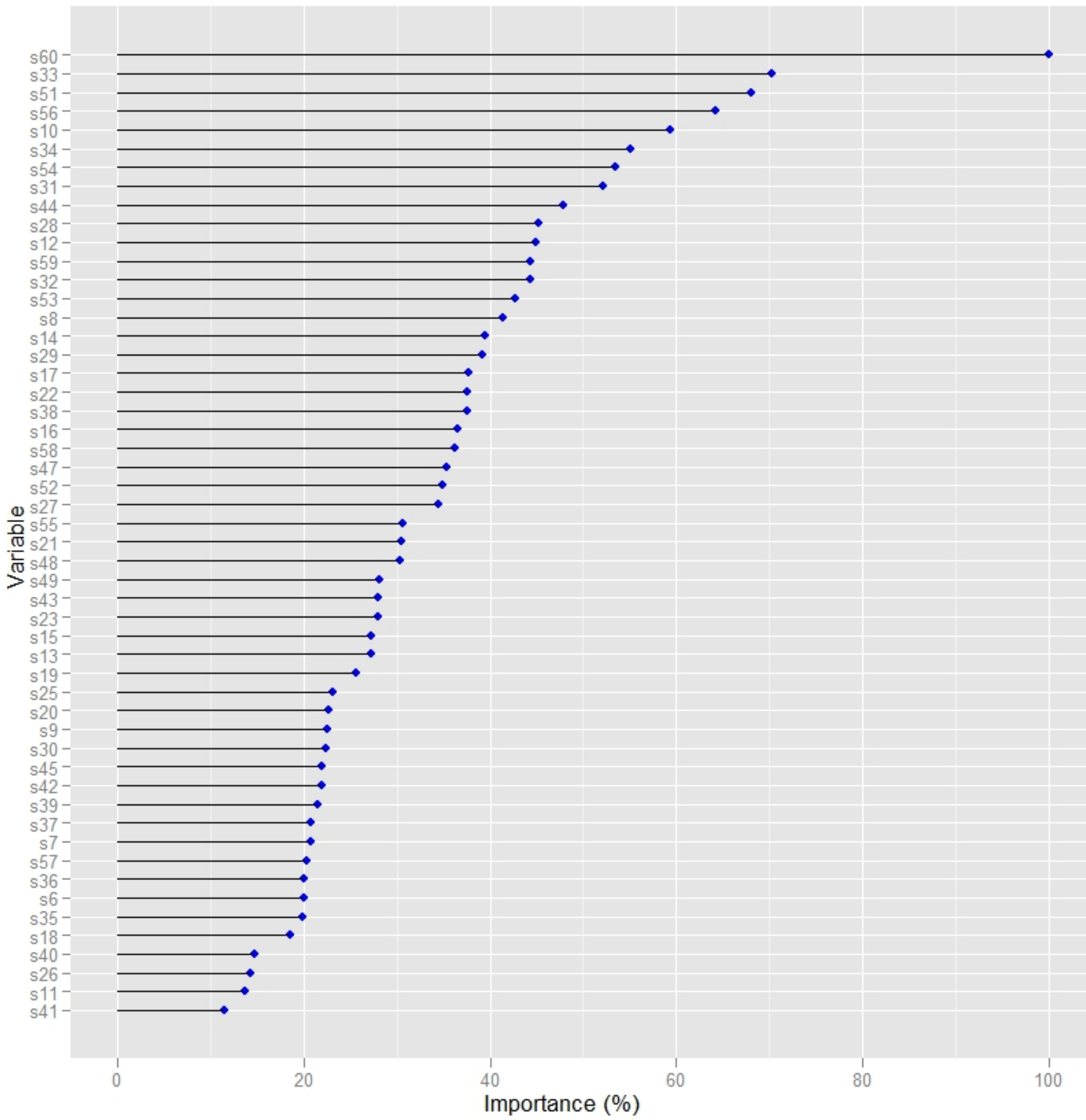

Figure 16. Variable Importance plot for 6 seconds prior classifier. Note that variables are labeled so that "s8" is the steering wheel angle 8 seconds prior to departure.

The promising performance of both the random forest applied to steering wheel position and the moving average of the TLC contrast with poor performance of PERCLOS. Figure 17 shows that PERCLOS performs only slightly above chance and markedly worse than either the TLC or steering wheel position algorithms. The accuracy of the steering models could likely be improved through data processing and filtering, as well as by combining TLC and steering wheel position information. PERCLOS might provide a useful complement to the steering and lane position algorithms because PERCLOS performs well in the ROC region associated with high specificity, where the algorithm using steering wheel movements performs relatively poorly.

Table 8. Average speed composite score by drowsiness condition, age group, and gender

Age Group	Gender		Day	Early Night	Late Night
21-34	Females	*M*	55.45	50.43	53.78
		N	12	12	12
		SD	6.73	9.44	7.94
	Males	*M*	59.15	57.82	59.32
		N	12	12	12
		SD	8.54	6.57	9.03
	Total	*M*	57.30	54.13	56.55
		N	24	24	24
		SD	7.75	8.80	8.78
38-51	Females	*M*	49.54	45.34	47.18
		N	12	12	12
		SD	9.17	11.26	11.57
	Males	*M*	56.71	51.29	52.84
		N	12	12	12
		SD	6.75	5.86	6.33
	Total	*M*	53.12	48.31	50.01
		N	24	24	24
		SD	8.69	9.29	9.57
55-68	Females	*M*	46.31	41.06	42.07
		N	12	12	12
		SD	7.14	8.00	8.53
	Males	*M*	43.71	43.02	45.00
		N	12	12	12
		SD	8.61	9.10	7.88
	Total	*M*	45.01	42.04	43.53
		N	24	24	24
		SD	7.85	8.44	8.17
Total	Females	*M*	50.43	45.61	47.67
		N	36	36	36
		SD	8.45	10.15	10.41
	Males	*M*	53.19	50.71	52.38
		N	36	36	36
		SD	10.38	9.39	9.64
	Total	*M*	51.81	48.16	50.03
		N	72	72	72
		SD	9.50	10.04	10.24

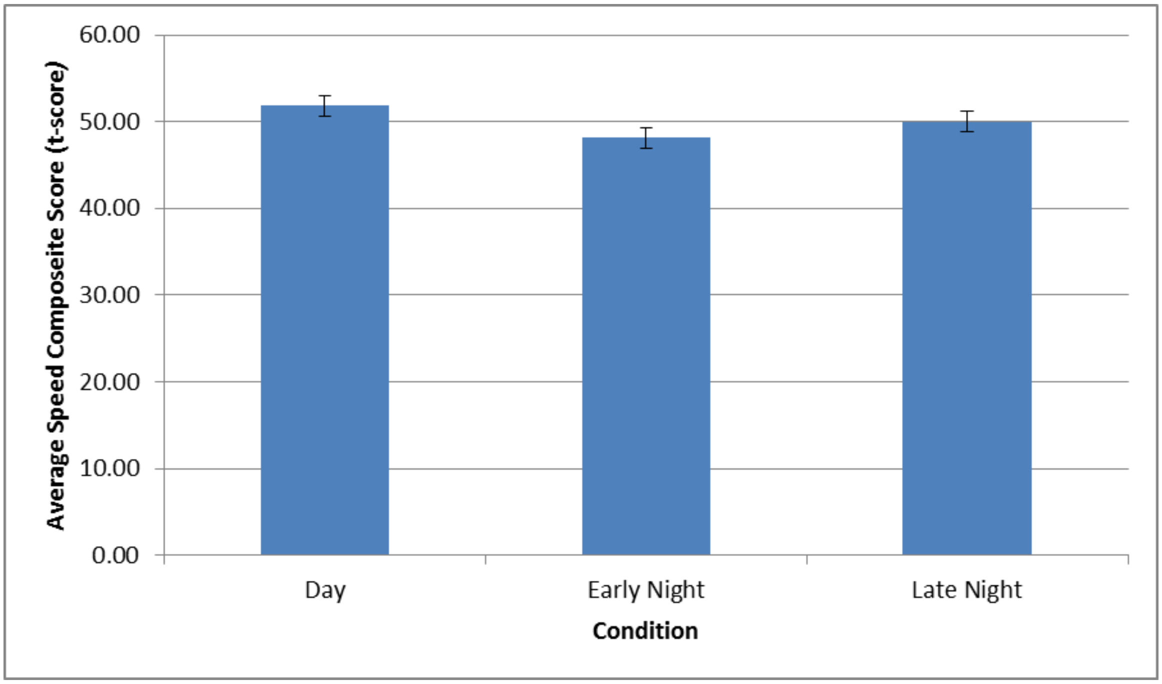

Figure 4. Average speed composite score as a function of drowsiness condition. Error bars represent standard error.

Table 9. Post-hoc comparison for average speed

Comparison		Mean Difference	Std. Error	Significance	99.9% Confidence Interval for Difference	
					Lower Bound	Upper Bound
Day	Early night	3.65	.80	Yes	.61	6.69
Day	Late Night	1.78	.78	No	-1.16	4.73
Early night	Late night	-1.87	.52	No	-3.83	.09

Note. Pairwise comparisons were conducted with α=.001.

3.3.1.3 **Speed Deviation Composite Score**

The mean speed deviation composite scores by drowsiness condition, age group, and gender are shown in Table 10. Mauchly's test of sphericity was not significant, indicating that no adjustment to the degrees of freedom was required. Drowsiness condition was not statistically significant.

Table 10. Speed deviation composite score by drowsiness condition, age group, and gender

Age Group	Gender		Day	Early Night	Late Night
21-34	Females	*M*	51.34	53.09	51.70
		N	12	12	12
		SD	11.43	15.00	10.06
	Males	*M*	44.11	45.19	48.20
		N	12	12	12
		SD	8.42	8.48	7.77
	Total	*M*	47.72	49.14	49.95
		N	24	24	24
		SD	10.49	12.58	8.97
38-51	Females	*M*	50.54	50.34	48.55
		N	12	12	12
		SD	5.97	7.49	6.82
	Males	*M*	49.17	50.86	49.71
		N	12	12	12
		SD	7.60	11.34	8.58
	Total	*M*	49.85	50.60	49.13
		N	24	24	24
		SD	6.72	9.40	7.60
55-68	Females	*M*	55.13	51.02	56.05
		N	12	12	12
		SD	14.36	12.61	9.29
	Males	*M*	49.88	47.44	47.70
		N	12	12	12
		SD	10.56	6.57	10.99
	Total	*M*	52.51	49.23	51.88
		N	24	24	24
		SD	12.61	10.00	10.83
Total	Females	*M*	52.34	51.48	52.10
		N	36	36	36
		SD	11.01	11.82	9.12
	Males	*M*	47.72	47.83	48.53
		N	36	36	36
		SD	9.07	9.07	8.99
	Total	*M*	50.03	49.66	50.32
		N	72	72	72
		SD	10.28	10.62	9.17

3.4 Robustness of Metrics with Respect to Age, and Gender

3.4.1 Lane Departure Composite Scores

Although there was a significant effect of drowsiness condition on lane deviation, there were no effects for lane deviation relative to age and gender. There were no interactive effects between age and gender with drowsiness condition.

3.4.2 Average Speed Composite Scores

There was one effect on average speed relative to age. There was a significant main effect of age, F (1, 66) = 16.08, $p < .001$, partial $\eta^2 = .33$.

Figure 5 shows that there was a statistically significant difference in average speed between the 21-to-34 and the 55-to-68 age groups, but not between the 21-to-34 and the 38-to-51 groups and the 38-to-51 and 55-to-68 age groups. There were no interactive effects between age and gender with drowsiness condition.

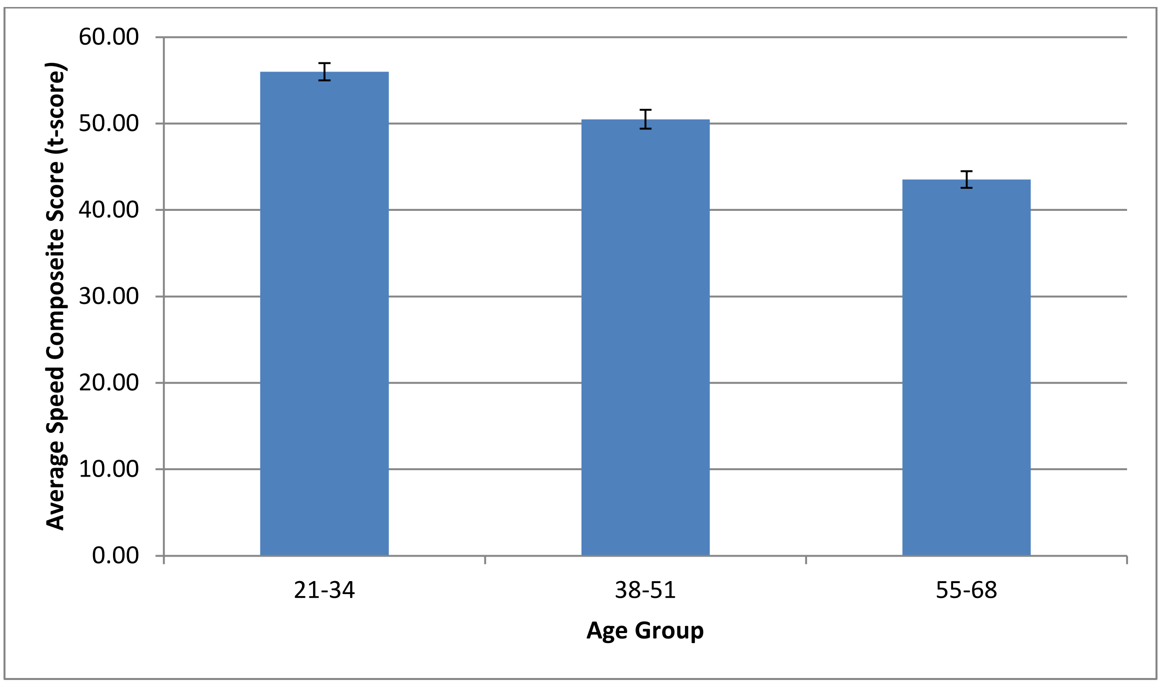

Figure 5. Average speed composite score as a function of age group. Error bars represent standard error.

Table 11. Post-hoc comparison of average speed for age

Comparison		Mean Difference	Std. Error	Significance	99.9% Confidence Interval for Difference	
					Lower Bound	Upper Bound
21-34	38-51	5.51	2.20	No	-2.83	13.85
21-34	55-68	12.46	2.20	Yes	4.12	20.80
38-51	55-68	6.95	2.20	No	-1.39	15.30

Note. Pairwise comparisons were conducted with α=.001.

3.4.3 Speed Deviation Composite Scores

There were no effects for speed deviation relative to age and gender. There were no interactive effects between age and gender with drowsiness condition.

3.5 Discussion

Drowsiness, as defined by the experimental conditions showed an effect for both lane deviation and average speed. The overall pattern of lane keeping was worse for the late night condition relative to the early night. The general pattern of the average speed was a decrease from the daytime drive to the early night drive and an increase with the late night drive, with only the difference in average speed between the early night and daytime speeds reaching statistical significance. For neither measure was there a systematic decrease in performance associated with an increase in drowsiness. The U-shaped pattern of performance indicates a more complex response to drowsiness where performance, particularly related to lane keeping, improves to a point before degrading, suggesting compensatory behavior as drivers respond to increased drowsiness. These results suggest that drowsiness does not follow a simple dose response relationship, with performance decreasing with increasing periods without sleep. However, the results also show lane keeping performance degrades the most in the situation where degraded performance is expected: late at night after a long period without sleep. The study succeeded in inducing drowsy driving.

4 ALGORITHM EVALUATION PLAN

The development of algorithms to detect drowsy driving is a topic of great interest to NHTSA and researchers around the world. Because drowsiness undermines driving safety, such algorithms could help reduce crashes and fatalities on U.S. highways. This chapter describes a process to assess algorithm effectiveness; but also considers the larger question of whether the algorithms can differentiate between drowsiness and other types of impairment detection, such as distraction and alcohol intoxication.

The algorithm development and evaluation relies heavily on previous research conducted for NHTSA concerning alcohol (Lee et al., 2010) and distraction (Lee et al., in review) impairment detection. Indeed, this study used a similar experimental protocol, scenarios, and data reduction process to maximize the opportunity for cross-study data comparisons.

This chapter describes an evaluation plan for drowsy driving detection algorithms. First algorithms that have been adapted from previous work or conceived as part of this study are described. Next, the criteria that were used to analyze algorithm effectiveness are presented, and then the steps of the evaluation are explained.

4.3 Impairment detection algorithms

This analysis considers several algorithms that have been selected for detecting drowsy driving. Some have been adopted from previous NHTSA studies, where the goal was to detect alcohol impairment and distraction (Lee et al., 2010; Lee et al., in review), while others have been added for their demonstrated sensitivity to drowsiness, such as PERCLOS and PERCLOS+ (Dinges, Mallis, Maislin, & Powell, 1998; Wierwille et al., 1994; Tijerina et al., 1999; Hanowski, Bowman, Alden, Wierwille, & Carroll, 2008). Thus, algorithms designed to detect various types of impairment were used to detect drowsiness. Assessing how algorithms tailored to detect specific impairments (i.e., alcohol, distraction, and drowsiness) perform in detecting drowsiness is one step toward assessing the degree to which a single algorithm might detect a range of impairments.

Algorithms able to detect a range of impairments are denoted as general, and those that detect single impairments are denoted as specific. A *specific* algorithm is one that has been developed to detect one type of impairment and might not be sensitive to other impairments. A *general* algorithm is designed to detect multiple types of impairment. A general algorithm may have been developed for one particular type of impairment and later expanded to fulfill a larger role. The ability of a general algorithm to succeed depends in part on the physiological and psychological similarity of the impairment mechanisms.

Alcohol acts as a central nervous system (CNS) depressant (Arnedt et al., 2001), and so one might expect drowsiness to exhibit similar influences on driving performance. In contrast, cognitive distraction loads working memory, and interferes with attention allocation, as manifested in gaze concentration (Regan, Lee, & Young, 2009). Drowsiness impacts cognitive ability and working memory as measured in psychomotor vigilance test, and results in microsleeps and more frequent eye closures. It is possible to counteract drowsiness to a certain extent with increased compensatory effort, but only up to a point (Kloss, Szuba, & Dinges, 2002). Drowsiness may share features with distraction in that the onset of symptoms may be relatively sudden and transient. Drowsiness may induce gaze concentration similar to distraction. Drowsiness would be expected to share some features with alcohol impairment as they both impact the CNS; indeed, the performance under the two types of impairments have been equated in several studies (Williamson & Feyer, 2000; Dawson, Drew, & Reid, 1997; Arnedt et al., 2001).

The NHTSA distraction detection and mitigation project (Lee et al., in review) considered visual and cognitive distraction. Four algorithms were implemented and evaluated for this project. Only one of the four was designed to detect cognitive distraction, which is included in this study because cognitive distraction may share characteristics of drowsy driving, namely a lack of active visual scanning of the forward scene signified by gaze concentration.

A truly general algorithm could help protect drivers from impairments not anticipated by the designer. This is a motivating factor in adapting proven alcohol and distraction algorithms for application to drowsiness in this study.

We considered algorithms applied at three distinct timescales, summarized in Table 12. The utility of an algorithm varies according to its timescale, with long range approaches being appropriate for post-drive evaluation, medium range ones appropriate for moderately spaced countermeasures, and short range for the detection of safety-critical situations.

Table 12. Three levels of algorithm timescale

Timescale	Description	Period	Indicators
Long range	Whole drive	~30 minutes	Stanford Sleepiness Score; Condition
Medium range	Event-based	~1-6 minutes	Retrospective Sleepiness Score
Short range	Real-time	~60 seconds	Drowsy lane departures

The previous NHTSA study of alcohol (Lee et al., 2010) produced three algorithms that were sensitive to differences between the baseline condition and two BACs (.05 and .10 g/dL). These algorithms were based on logistic regression, boosted decision trees, and support vector machines (SVMs). Various measures of driver performance, environmental demand, and event type were used as inputs to the algorithms; and they were trained and tested on simulator data. The BAC classifications were grouped by scenario event because driver behavior during a yellow light dilemma, for instance, could vary considerably from that observed during highway driving. A decision tree algorithm with boosting was able to detect impairment with greater accuracy than the other candidates: support vector machines and logistic regression. For this reason, the event-based decision tree algorithm is one of the candidates evaluated in the current work to detect drowsiness.

Additionally, the current project has developed a real-time algorithm to detect drowsiness that was trained and testing using data from the IMPACT study and applied to the drowsiness data. The new algorithm uses a Bayesian network to model the conditional probabilities associated with several driving performance measures.

Table 13. Impairment Detection Algorithm Summary

Label	Algorithm	Source	Impairment	Timescale
PC	PERCLOS	(Dinges, Mallis, Maislin, & Powell, 1998)	Drowsiness	Medium
PC+	PERCLOS+	(Hanowski, Bowman, Alden, Wierwille, & Carroll , 2008)	Drowsiness	Medium
SB	Steering-Based	(King, Mumford, & Siegmund, 1998)	Drowsiness	Short
EEG	EEG	NHTSA DRIIVE	Drowsiness	Short
DT	Decision Tree	NHTSA IMPACT	Alcohol, Generalized	Medium
MDD	Multi-Distraction Detection	NHTSA distraction detection and mitigation	Distraction	Short
TLC	Time-to-lane-crossing	NHTSA DRIIVE	Drowsiness	Short
SRF	Steering random forest	NHTSA DRIIVE	Drowsiness	Short
BN	Bayes net	NHTSA DRIIVE	Alcohol, Generalized	Short

A summary of the various algorithms is given in Table 13. Each of these algorithms was developed to detect a specific impairment, with several being developed specifically to detect drowsiness. This study assesses whether any of the alcohol-specific algorithms can also detect drowsiness as well as those developed specifically to detect drowsiness, and therefore offer promise as general algorithm that can detect and distinguish a wide range of impairments.

4.4 Algorithm performance criteria

Assessing algorithm performance depends on comparing the classification (i.e., drowsy or alert) to the actual state of the driver. The actual state of the driver is sometimes referred to as the ground truth, and is ideally indicated by a “gold standard” measure that provides an unambiguous indicator of the driver state. Such a gold standard is difficult to define for drowsiness. Arguably a clinical EEG record scored by a sleep expert is the gold standard indicator of drowsiness, but it was not possible to obtain this indicator for this study. Instead, this study used several drowsiness measures, which combined to provide ground truth indicators. The measures relied on for this purpose included the pre-drive and post-drive SSS, pre-drive and post-drive PVT, and retrospective SSS (RSS). To assess algorithm timeliness, drowsiness-related lane departures represented the ground truth indicator of drowsiness and location-matched periods of alert driving represented the ground truth indicator of alertness.

Three standard criteria were used to assess algorithm performance in detecting and distinguishing impairments: accuracy, positive predictive performance (PPP), and area under curve (AUC). Accuracy measures the percent of cases that were correctly classified, while PPP measures the degree to which those drivers that were judged to be drowsy were actually drowsy. An algorithm can correctly identify all instances of impairment simply by setting a very low decision criterion, but such an algorithm would misclassify all cases where there was no impairment. The relationship between the true positive detection rate (sensitivity) and false positive detection rate (1-specificity) is represented by the receiver operator characteristic (ROC) curve. ROC curves are presented for many of the algorithm results. AUC represents the area under the receiver operator curve, which provides a robust and simple performance measure. Perfect classification performance is indicated by an AUC of 1.0, and chance performance is indicated by .50. AUC is an unbiased measure of algorithm performance, but accuracy and PPP are more easily interpreted, so all three are used in describing the algorithms.

Beyond the standard measures of algorithm performance, this study also considered the degree to which the algorithm offers a timely detection of impairment. Timeliness is most relevant to concurrent algorithms, which run in real-time and support time-critical warnings. In contrast, post-drive algorithms aggregate data over the length of the drive to provide post-drive feedback. An intermediate approach is exemplified by the IMPACT algorithms and could be called post-*event*, or event-based. For real-time algorithms, timeliness represents a critical performance metric that is likely to be balanced by accuracy—accumulating more data generally increases accuracy but undermines timeliness. To some extent, timeliness depends on the type of algorithm—some algorithms do not provide real-time indication of impairment due to the amount of data aggregation they require.

For those algorithms designed to produce real-time alerts, timeliness, the degree the algorithm can correctly detect impairment in advance of an impairment-related mishap, is added. For this analysis, timeliness is defined as its AUC six seconds before a drowsiness-related mishap, such as a drowsy lane departure. The locations of unintentional lane departures were determined during data reduction, and drowsy lane departures were verified by video review. It was expected that real-time algorithms would provide more accurate and timely drowsiness detection compared to algorithms that aggregate data across scenario events.

4.5 Research questions and hypotheses

Can algorithms designed for alcohol impairment detection (event-based decision tree, Bayes net) and distraction also detect drowsiness? Commonalities in the physiological basis of the impairments may cause drivers' performance to degrade in similar ways.

Can algorithms designed for alcohol impairment detection be generalized to work well for both alcohol and drowsiness? Alcohol algorithms that have been retrained on drowsy driver data or new algorithms that include variables appropriate for drowsiness should be more accurate in detecting drowsiness than specialized alcohol detection algorithms, but may also be less accurate in detecting alcohol impairment if alcohol and drowsiness do share symptoms.

Can algorithms distinguish between alcohol and drowsiness-related impairment?

Do real-time algorithms perform better in detecting drowsiness in advance of a drowsiness-related mishap? Event-based algorithms, such as the decision tree algorithms previously used to detect alcohol impairment, may be less likely to have a high AUC value six seconds before the onset of a drowsiness-related mishap compared to a real-time algorithm.

4.6 Evaluation method

4.6.1 Algorithms

Impairment detection algorithms can be characterized by the timescale over which they operate, and the timescale over which impairment indicators are expected to vary. Table 12 and Table 13 above present three distinct timescales that the algorithms use. The timescale assignments in Table 13 are not fixed. One may accumulate short or medium range algorithm outputs over a longer timeframe for a post-drive review for instance. Alternatively, one may attempt to sample medium range algorithms more often for real-time prediction, though the accuracy may suffer.

Other dimensions that separate the algorithms are the types of inputs they use (physiological or driving performance) and how the inputs are combined. Beyond these dimensions, some algorithms may be parametrically modified to become more general, perhaps by simply changing a parameter threshold. Alternatively, the more complicated alcohol algorithms may be retrained to a dataset obtained from drowsy driving, or a combined dataset consisting of both drowsy and alcohol impairments. Table 14 again lists the impairment detection algorithms that were used in this study, this time with inputs and outputs described.

Most of the algorithms produce a binary classification, making it the common basis for comparison between all the algorithms. In cases where an algorithm outputs something other than a binary output, the categorical or continuous outputs were mapped to a binary classification. Binary classifiers were obtained from more complex ones by setting thresholds. The details of obtaining a binary classification for drowsiness are given in the next chapter.

For each algorithm in Table 14, a binary output was created if one did not exist. Then the accuracy, PPP, AUC, and timeliness of each algorithm were calculated. These data were organized into two datasets: one based on scenario events and the other based on fixed windows of time with some percentage of overlap.

Table 14. Impairment Detection Algorithm Inputs and Outputs.

Label	Algorithm	Inputs	Outputs
PC	PERCLOS	Eye closure	Continuous percentage Drowsy binary
PC+	PERCLOS+	Eye closure, lane departure	Drowsy categorical (low, moderate, severe)
SB	Steering-Based	Steering angle, steering rate	Drowsy binary
EEG	EEG	Scalp electrical activity	Continuous probability Drowsy binary
DT	Decision Tree	Multiple measures of driver performance	Intoxicated binary
MDD	Multi-Distraction Detection	Eye gaze location	Continuous PRC Visual binary Cognitive binary
TLC	Time-to-lane-crossing	Lane position, lane heading angle	Drowsy binary
SRF	Steering random forest	Steering wheel angle	Drowsy binary
BN	Bayes net	Multiple measures of driver performance, eye closure, eye closure rate	Intoxicated categorical (none, moderate, severe)

4.6.2 Driver data and drowsiness identification

Two datasets were created: event-based and continuous. The event-based data set follows the same format used in the IMPACT study, with the driving summarized in terms of 22- to 24-scenario events that range from about 6 to 680 seconds. The continuous data consists of driver and vehicle data recorded at 60 Hz for the entire drive. The continuous dataset was analyzed by organizing the data into time windows of a fixed time with some percentage of overlap. Each record of these datasets were coded as alert or drowsy according to three definitions: the drowsiness condition, a linear combination of PVT, pre-post and retrospective SSS, and the presence or absence of a drowsiness-related mishap. To maintain balance in the model training process, each data set was divided into equal numbers of drowsiness and alert instances.

4.6.3 Algorithm performance summary

Ten-fold cross validation was used to assess each algorithm, producing a measure of accuracy, PPP, AUC, timeliness and corresponding confidence interval for each algorithm. ROC curves were also used to summarize sensitivity and specificity graphically. In combination, these metrics were used to identify better or worse algorithms, and also to identify how they might complement each other. For example, some algorithms might not be timely, but they might be accurate. The optimal tradeoff between these factors remains an open question.

4.6.4 Algorithm generalization

Based on the results of this analysis, candidate algorithms for other target impairments were selected for adaptation to drowsy driving. The parameters were optimized for the drowsy data set, either through AUC analysis or re-training. Such changes to the parameters would undermine the ability of the algorithms to detect the impairment that they were originally designed to detect. The modified algorithms were analyzed and compared to the original ones. Potential generalizations of algorithms are considered as well. One method of generalization is simply to combine multiple specialized algorithms into one package.

5 ANALYSIS OF ALGORITHM PERFORMANCE

This chapter describes algorithms and their ability to detect driver drowsiness. Similar algorithms have been developed to detect alcohol impairment (Lee et al., 2010) and distraction, and the central aim of this study is to assess how well these techniques can be used to detect drowsiness. The degree to which similar algorithms can detect both alcohol impairment and drowsiness, and the degree to which such algorithms can differentiate the two impairments, depends on the profile of the impairment over time and the particular manner in which the impairment influences driver behavior. Specifically, the impairment of alcohol is relatively constant over a period of 20 to 30 minutes and strongly influences lane keeping performance, whereas drowsiness might vary considerably over this period and might influence other elements of driving performance. These underlying differences in the profiles of impairment demonstrate the demands of developing algorithms to detect impairment. This study addresses the understanding of the demands of drowsiness detection by addressing the following questions:

- Can algorithms designed to detect alcohol impairment or distraction also detect drowsiness?
- Can algorithms designed to detect alcohol impairment be generalized to detect both alcohol and drowsiness?
- Can algorithms distinguish between alcohol and drowsiness-related impairment?
- Do real-time algorithms perform better than event-based or post-drive algorithms in detecting drowsiness in advance of a drowsiness-related mishap?

In order to answer these questions, several types of drowsiness measurement are used throughout the chapter. Each has its own merit and appropriate usage. SSS is a scale from one to 8 where one is alert and 8 is asleep. It was collected both pre and post-drive through a survey. The retrospective sleepiness scale (RSS) uses the same scale as SSS, and is administered via survey, but is an estimate from a continuous time measurement over the course of the drive. The psychomotor vigilance test (PVT) is an active memory test known to correlate with drowsiness. A 5-minute PVT was administered before and after each drive. A video review of lane departures was conducted to obtain a good quality set of truly drowsy scenario events against which to judge algorithm performance. The three timescales considered are summarized in Table 15, reproduced from Chapter 5.

Table 15. Three algorithm timescales

Aggregation	Description	Period	Indicators
Long range	Whole drive	~20-30 minutes	Post-drive SSS; Condition
Medium range	Event-based	~1-6 minutes	Event-based RSS
Short range	Real-time	~60 seconds	Drowsy lane departures

SSS ratings and PVT scores are only appropriate when considering data from entire drives, while RSS data can be used for finer grain analysis or grouped at the scenario event or drive level. Drowsy lane departures are reliable events to compare against, but are transient in nature and not associated with drives or scenario events. Note that it is difficult to standardize terminology around the word drowsiness because the standard survey instruments used in this study use the word sleepiness. Throughout this chapter the terms drowsy and sleepy are used interchangeably.

The following analyses address the research questions by first describing the distribution of drowsiness across drivers, conditions, and the drive. Drowsiness is classified here using a threshold of post-SSS rating greater than three. This distribution of drowsiness suggests algorithms used to detect alcohol impairment over the course of a 20-minute drive might perform relatively poorly, which is confirmed with an analysis of algorithms detecting impairment over the drive. The differences in the profiles of alcohol impairment and drowsiness are then used to create algorithms that detect alcohol impairment, drowsiness impairment and differentiate between the two. Real-time algorithms that aim to predict drowsiness associated with lane departures in advance of the lane departure are then considered. For that analysis, a more complex classification of drowsiness that combined SSS, RSS, PVT, and drowsy lane departures was used.

5.3 Distribution of Drowsiness across Drivers and the Drive

Unlike blood alcohol level and the associated impairment, drowsiness varies considerably across drivers and over the 35-minute drive used in this study. Figure 6 shows the ratings of sleepiness drivers made after they completed each drive using the retrospective sleepiness scale (RSS). Each line represents the ratings of a single driver. The ratings generally increase over the drive. However, these ratings fluctuate considerably from event to event, with uneventful scenario events, such as the straight rural segment, leading to higher ratings of sleepiness. The ratings generally reflect the drowsiness condition, with drivers in the late night condition tending to report higher levels of sleepiness; however, the distribution of reported sleepiness varies considerably with some drivers in the late night condition reporting lower levels of sleepiness compared to those in the daytime condition. Some drivers in the late night condition are quite alert and some in the daytime condition are quite drowsy. This pattern of impairment contrasts with that of alcohol, where BAC level is well-controlled across conditions—no drivers in the zero BAC condition were impaired by alcohol—and the BAC level was relatively constant across the drive. Assuming that BAC level reflects impairment due to alcohol, alcohol-impairment is controlled and constant across the drive. In contrast, Figure 6 shows that the drowsiness conditions induced substantial drowsiness, but that drowsiness varies considerably between drivers, within conditions, and across the drive.

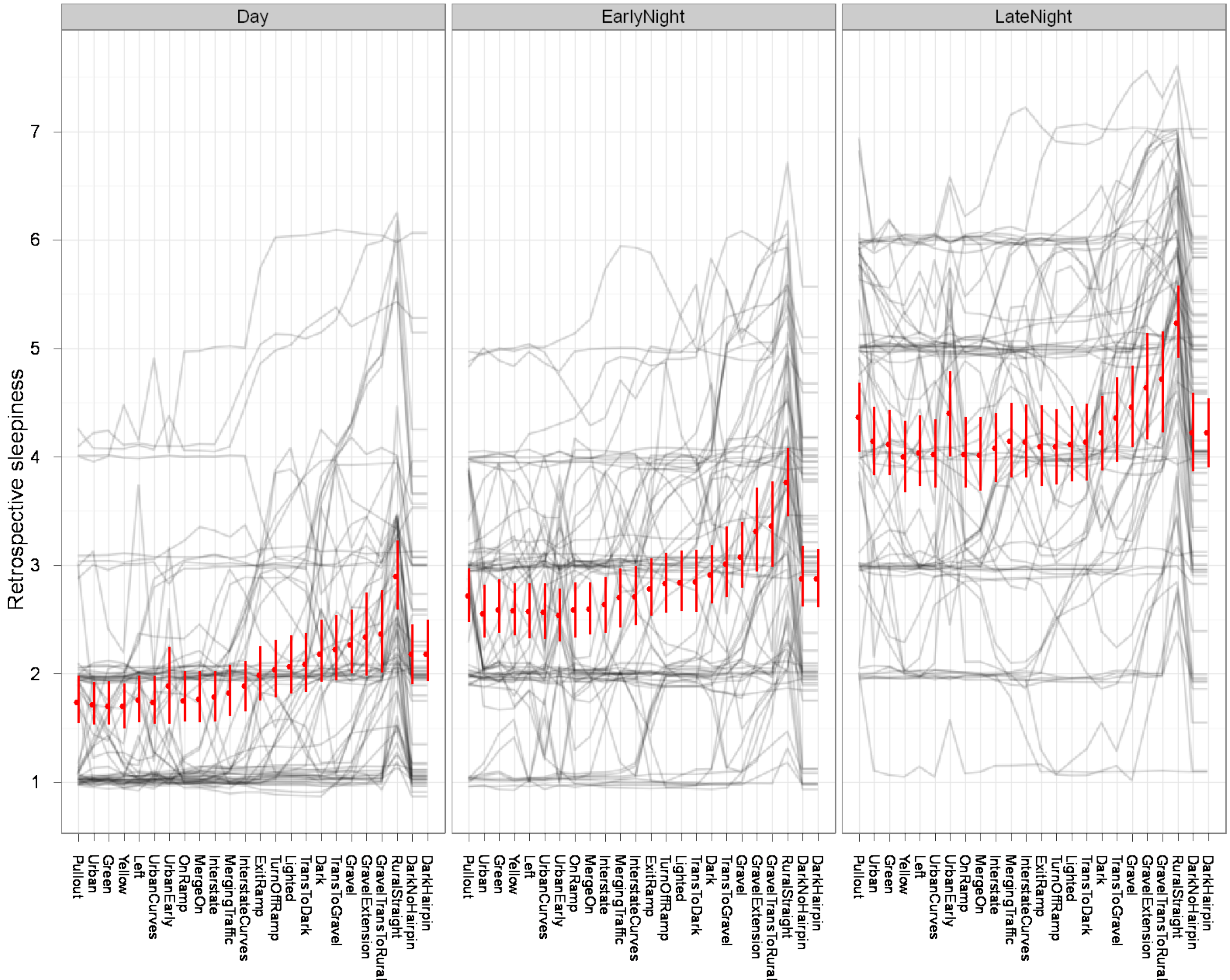

Figure 6. Retrospective sleepiness ratings across the drive. Each line represents a single driver and each point represents the mean with a 95-percent confidence interval

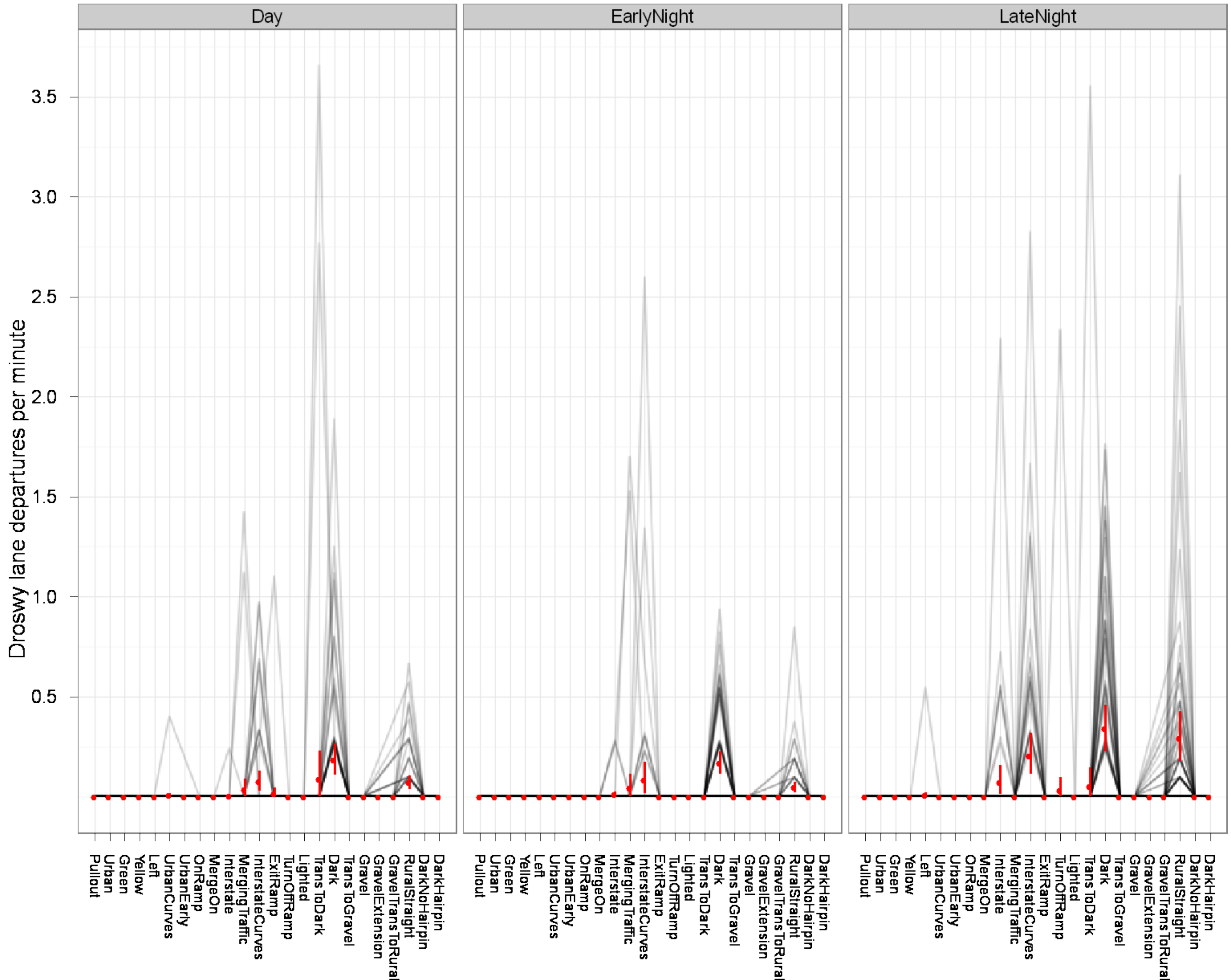

Figure 7. Frequency of drowsiness-related lane departures across the drive.

Overall, there were 623 verified lane departures during the drives with 202 being classified as drowsy lane departures. The drowsy departures represented 22 percent of the daytime departures, 14 percent of the early night departures, and 51 percent of the late night departures. Figure 7 shows the frequency of drowsiness-related lane departures, with each line representing data from a single driver. The distribution of these lane departures across the conditions, drive, and drivers shares important features with the ratings of sleepiness. Like the high ratings of sleepiness, more drowsy-related lane departures occurred later in the drive, during long, uneventful segments such as the straight rural and dark rural segments. These peaks likely represent the demands of the roadway (poorly lit and relatively narrow lanes) as well as the association with higher levels of drowsiness. The frequency of lane departures varied considerably across drivers and scenario events with some drivers frequently departing their lane and others departing their lane very infrequently if at all. Similarly, during some scenario events, such as those early in the drive, drivers never departed their lane.

The pattern of drowsiness-related impairment reflected in Figure 7 has several important implications for algorithm development and evaluation, as well as for drowsiness countermeasures. Extreme levels of drowsiness and associated lane departures occur even with seemingly well-rested drivers during the daytime. Unlike alcohol (as suggested by BAC), drowsiness and its effect on lane keeping varies considerably over a drive and across drivers, making the definition of impairment challenging: impairment might not exist for a given driver within a particular scenario event even though the drowsiness condition was designed to induce impairment. Likewise, an otherwise alert driver might experience a period of extreme drowsiness; but when averaged over a drive, the mean level of drowsiness might suggest the driver was safely alert. This makes it less likely that algorithms, such as those used to detect alcohol impairment, will be able to combine event-based (medium range) information to estimate impairment over the drive.

5.4 Detecting Drowsiness With Algorithms Designed for Alcohol Impairment and Distraction

The challenge of detecting drowsiness associated with differences between drivers across the three drowsiness conditions (daytime, early night, and late night) is reflected in the relatively poor detection performance summarized in Table 11. In this table, the algorithms were assessed according to how well they differentiated the day drive from the late night drive using the metrics of AUC, PPP, and accuracy described in Section 5.2. Each algorithm was applied on a long range timescale in which classification instances were accumulated throughout the entire drive.

Not surprisingly algorithms developed to detect distraction failed to detect drowsiness—the AUC of .50 indicates the algorithm performed no better than chance. Surprisingly, algorithms designed to detect drowsiness, such as PERCLOS and those based on EEG measures also performed no better than chance. Poor performance of the algorithms reflects, in part, the drivers in the late night condition who rated themselves as alert and drivers in the daytime condition as very sleepy.

Table 17 shows algorithm performance in detecting drowsiness, as defined by drivers' ratings of sleepiness using the SSS after they completed the drive. Drowsiness is indicated by post SSS of 5 or greater and alertness by post SSS of 3 or less. In this table, the algorithms were assessed according to how well they differentiated between drivers with a rated sleepiness score of 3 or less and those with a score of 5 or greater. Surprisingly, all algorithms performed poorly with only the PERCLOS algorithm having a confidence interval that did not include.50. The mean AUC for the PERCLOS algorithm was only.61, meaning that if the driver was drowsy the algorithm would only have a 61-percent chance of correctly detecting the drowsiness.

Table 16. Impairment detection algorithm performance based on drowsiness conditions with 95 percent confidence intervals

Label	Algorithm	AUC	PPP	Accuracy
MDD	Multi-Distraction Detection	.50 (.37-.57)	.52 (.50-.56)	.53 (.49-.53)
EEG	EEG	.54 (.43-.62)	.52 (.50-.53)	.53 (.51-.55)
PC	Perclos	.58 (.49-.67)	.65 (.57-.69)	.61 (.55-.61)
PC+	Perclos+	.51 (.41-.60)	.7 (.54-.80)	.55 (.51-.56)
SB	Steering-Based	.55 (.46-.63)	.55 (.54-.57)	.55 (.55-.56)
BN	Bayes network	.46 (.36-.57)	.50 (.38-.67)	.52 (.51-.53)

Table 17 Impairment detection algorithm performance based on post-drive sleepiness ratings with 95 percent confidence intervals

Label	Algorithm	AUC	PPP	Accuracy
MDD	Multi-Distraction Detection	.51 (.45-.61)	.59 (.55-.62)	.55 (.53-.55)
EEG	EEG	.58 (.48-.65)	.54 (.53-.55)	.59 (.56-.61)
PC	Perclos	.63 (.53-.70)	.60 (.59-.60)	.59 (.55-.61)
PC+	Perclos+	.53 (.43-.60)	.59 (.58-.60)	.54 (.53-.59)
SB	Steering-Based	.55 (.48-.62)	.59 (.58-.59)	.56 (.54-.59)
BN	Bayes network	.45 (.38-.57)	.48 (.45-.51)	.49 (.47-.51)

In both tables the algorithm developed to detect distraction (MDD) performed very poorly. Similarly, the Bayes network trained to detect alcohol impairment also performed very poorly, and algorithms developed to detect drowsiness performed almost as poorly. Overall, these results show that algorithms developed to detect other impairments will not necessarily detect overall drowsiness as determined by SSS rating.

To assess whether algorithms developed to detect alcohol impairment perform better when they are trained to detect drowsiness, the most sensitive algorithm from the IMPACT study—a boosted decision tree using data summarized for each event— was applied to detect drowsiness. Not all measures from IMPACT that were used to train the alcohol algorithm were used in this study, so the original DT algorithm was not used. However, a direct comparison was done with a similar Bayes network algorithm; and the alcohol-trained version did not perform well on drowsiness data (see Table 16 and Table 17). A best-case analysis would consider a DT trained on drowsiness data; and this analysis is presented and showed relatively poor performance. To further tune the DT to detect drowsiness PERCLOS was added to enhance performance.

Once again, post-SSS Ratings were used to classify true drowsiness, and a long-range timescale was used. Figure 8 shows receiver operator curves (ROC) that describe the performance of the algorithms. Comparing the upper panels shows that adding driving performance variables to PERCLOS increases its sensitivity substantially. The graphs in the lower panel show that the driving performance variables and variables that describe the driving context can also be used to detect drowsiness, but less well than PERCLOS. Figure 9 shows the driving performance variables that are most indicative of drowsiness, with lateral and longitudinal acceleration (Ax_max and Ay_max), as well as normalized speed (spn_avg) and lane position (lp_avg) exerting a particularly strong influence. These results show that when trained on data from drowsy drivers the boosted decision tree algorithm can successfully detect drowsiness.

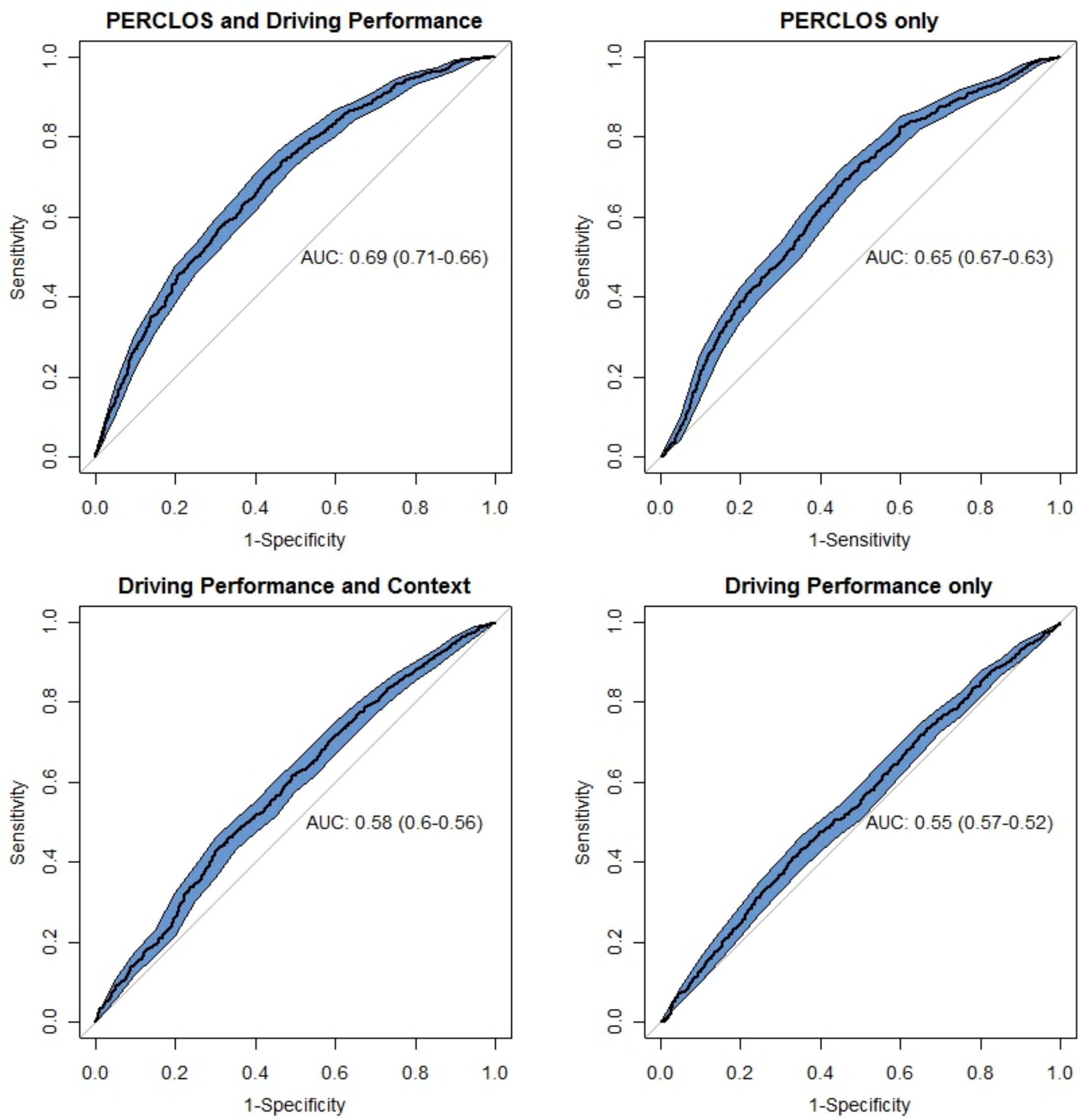

Figure 8. ROC plots for boosted trees to detect drowsiness as defined by Post Drive Stanford Sleepiness Score (5 or greater for drowsy, 3 or less for alert). The upper right ROC uses only PERCLOS, the upper left uses PERCLOS and driving performance and driving context variables. The lower left ROC uses only driving performance and driving context, and the lower right ROC uses only driving performance variables.

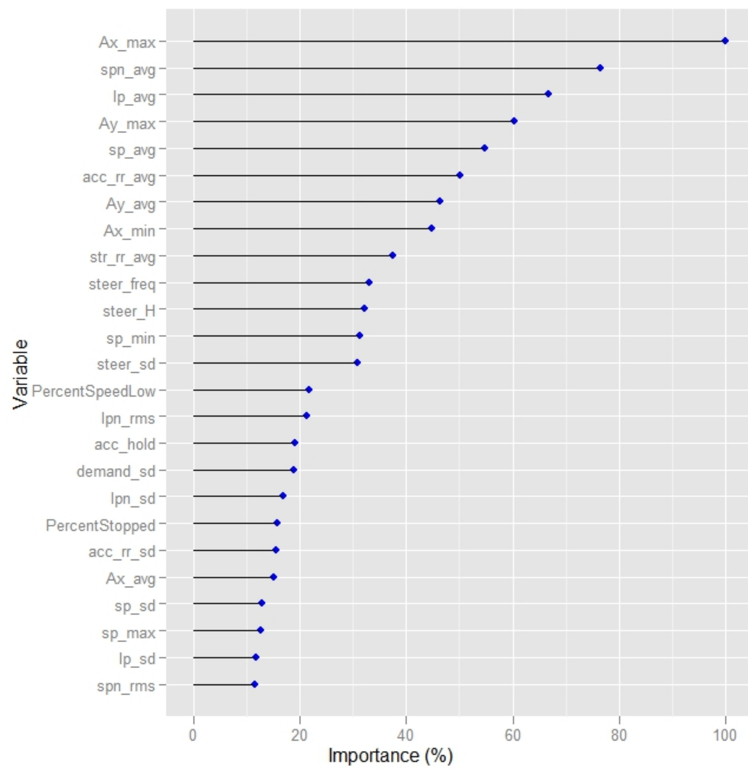

Figure 9. Relative importance of variables predicting drowsiness defined by the post-drive Stanford Sleepiness Score

If drowsiness is defined by retrospective sleepiness (RSS) ratings rather than post-drive SSS ratings a slightly different picture emerges. Figure 10 shows that boosted trees, detecting event-level measures of sleepiness, perform better than algorithms predicting drowsiness based on the post-drive Stanford Sleepiness Score. Importantly, the algorithms using the driving performance measures perform comparably to PERCLOS. Because sleepiness varied considerably over the drive, it is not surprising that algorithms predicting rated drowsiness for each scenario event performed better than those predicting drowsiness at the end of the drive.

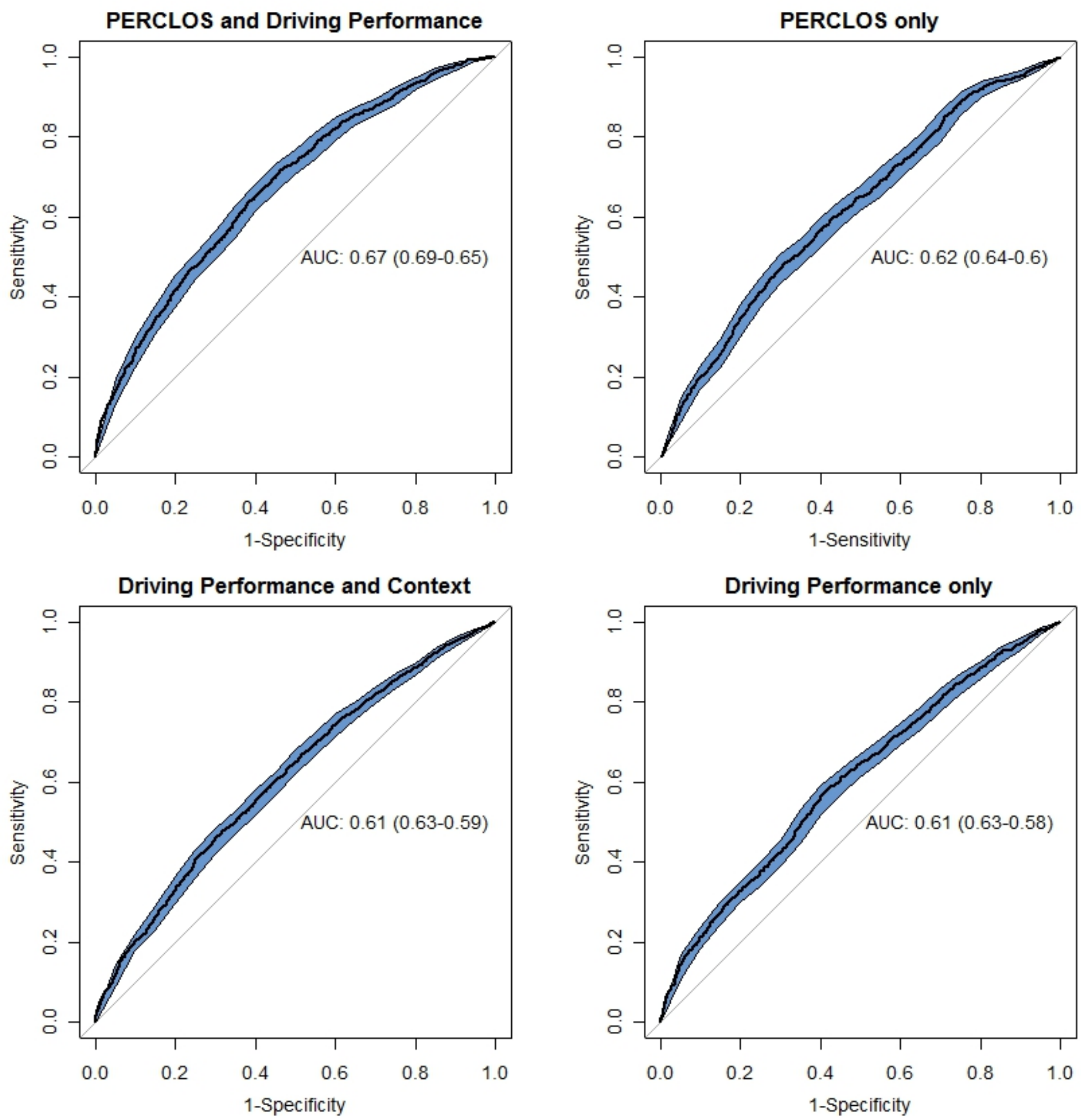

Figure 10. ROC plots for boosted trees to detect drowsiness defined by Retrospective Stanford Sleepiness Score (5 or greater for drowsy, 3 or less for alert).

The upper right ROC uses only PERCLOS, the upper left uses PERCLOS and driving performance and driving context variables. The lower left ROC uses only driving performance and driving context, and the lower right ROC uses only driving performance variables.

5.5 Discriminating between Drowsiness and Alcohol Impairment

To more directly assess why algorithms designed to detect alcohol impairment perform poorly in detecting drowsiness, algorithms using long timescales were created using the alcohol data and the drowsiness data. This approach can also evaluate the ability of an algorithm to differentiate between two types of impairment. For this analysis, a Bayes network was selected for investigation. Bayes nets and decision trees are comparable types of machine learning approaches and there is presently no motivation to prefer one over the other. A set of algorithms that range in type is instead provided. Many measures were considered for inclusion in a Bayes network (BN) algorithm. Table 18 summarizes the variables considered; however the classifications were not sensitive to the majority of them.

Table 18. Measures considered for inclusion in the Bayes network

AvgLP > 2	SRR small > 2.2	PERCLOS > 20	Ampd2theta < 50
AvgLP > 1.1	AECS > 1.75	PERCLOS > 5	Ampd2theta < 80
SDLP > 1.3	AECS > 1.2	PERCLOS+ = 3	PRC 17s > 90
SDLP > 1	TLC < 6.5	PERCLOS+ = 2	PRC 60s > 90
SRR > 0.1	TLC < 7.5	Outside% > 50	EEG DCAT = 1
SRR large > 0.03	TLC < 8	Wtflat0 > 300	SpdNorm > 5
SRR small > 2.8	PERCLOS > 40	Wtflat0 > 200	Ax > 0.005

The Bayes network algorithms were developed by computing each measure over a one-minute moving window (except for PERCLOS which is traditionally computed over a three-minute moving window). Threshold values were selected for each measure and each exceedance of the threshold was marked for the entire drive. The rate of exceedance events in a moving six minute window was computed for each measure, and metrics were applied to the rate variable including: average, median, inter-quartile range, 90th percentile, maximum. Additionally, the percentage of time during the drive that the threshold was exceeded was included as a metric. This analysis used the long range timescale that spanned the entire drive.

Estimates of the threshold values were obtained by examining ROC plots for each metric when applied to the data set composed of lane departures associated with drowsiness that were generated through a video review. Those metrics with the highest AUCs were selected for inclusion in the Bayes network.

When this method was applied to the alcohol data, only two measures emerged as indicative of alcohol impairment: small steering reversal rate (SRR small > 2.2) and percent road center gaze (PRC 17s > 90). A binary classification of BAC levels was used that included both .05 and .1 BACs as indicating alcohol-impaired drivers. The average and percent metrics for the first, along with the percent metric for the second measure were used to train the model. Although various depths of graph were tried, a one-level network, also known as a naïve Bayes model, performed the best. ROC performance with 95 percent confidence intervals created with the bootstrap method (Efron & Gong, 1983) is graphed in Figure 11. Point wise confidence intervals are shown by the light colored lines; and the range of AUC values is included in the figure.

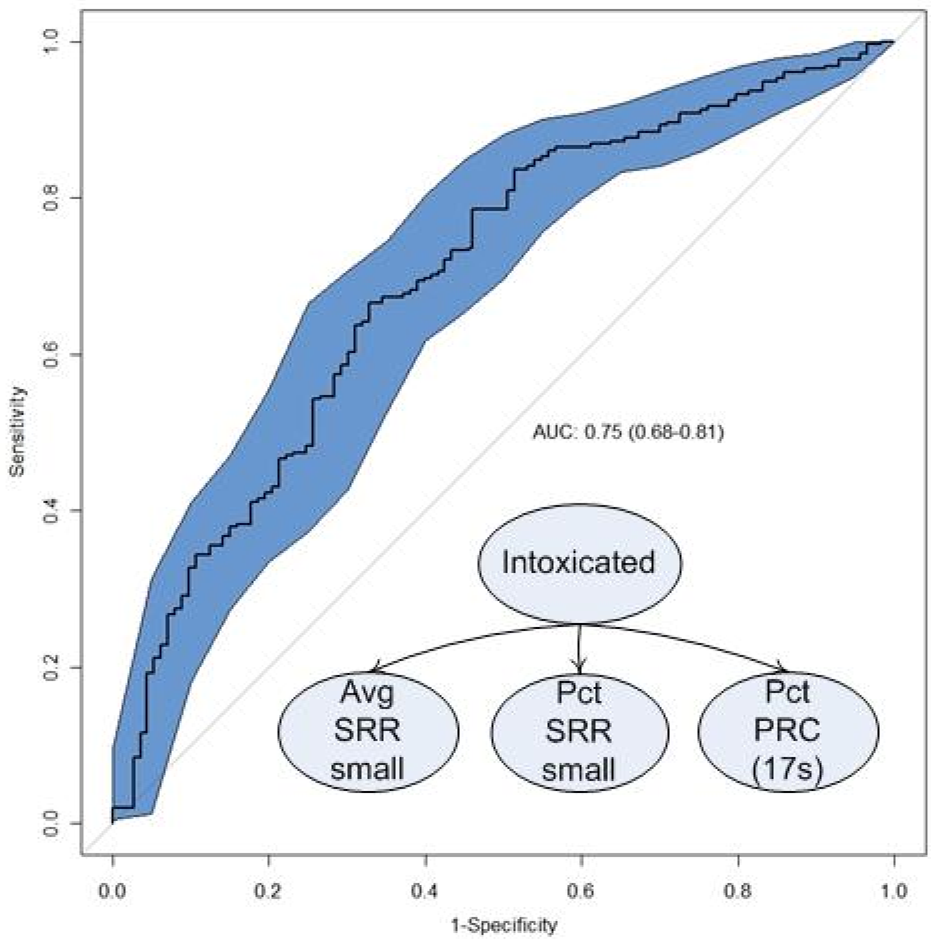

Figure 11. Performance of the Bayes network for detecting alcohol impairment

The drowsiness dataset was also amenable to this approach. The entire pool of drivers was considered rather than being restricted to verifiably awake subjects, as in the lane departure dataset. Drowsiness was selected as a binary classification, where drowsiness was defined as drives with pre and post SSS scores greater than three; and the alertness was defined as drives with pre and post SSS scores of 3 or less. Drives in which the pre and post SSS scores straddled the threshold were eliminated from the training and test set.

After examining ROC plots for all the measures using the lane departure dataset and the above classification of drowsiness, four measures were included in the drowsiness Bayes network: standard deviation of lane position (SDLP > 1), average eye closure speed (AECS > 1.2), and time to lane crossing (TLC < 6.5, TLC < 7.5), where the average, maximum, maximum, and percentage metrics were applied respectively. The model and ROC performance curve are shown in Figure 12.

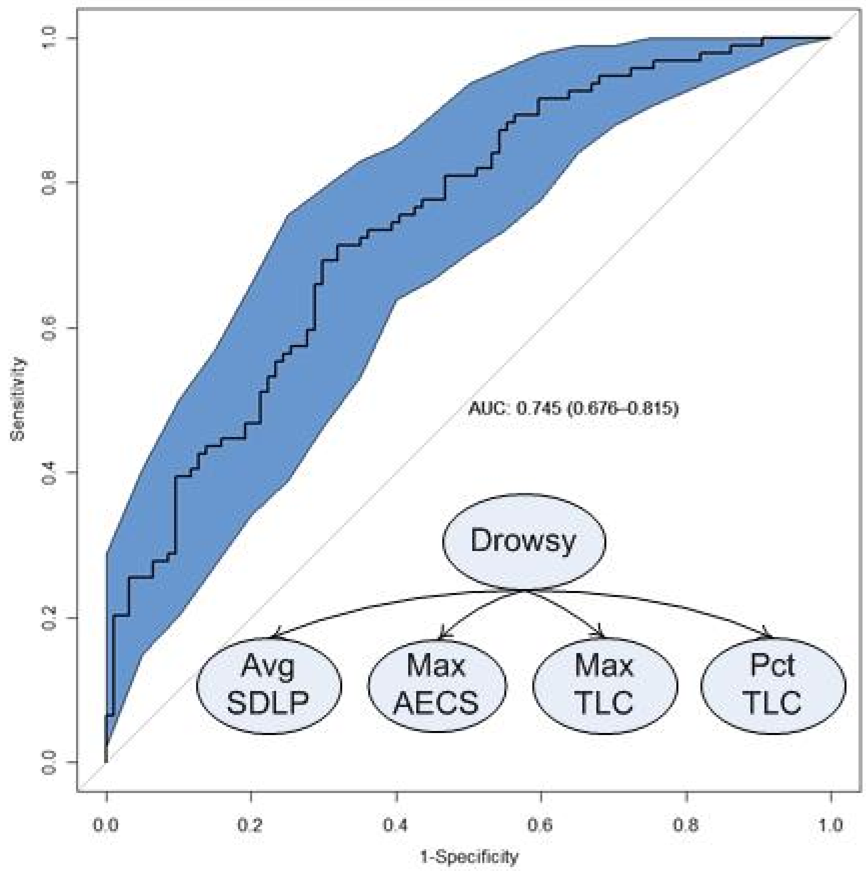

Figure 12. Performance of the Bayes network for detecting drowsiness

On the surface, it would seem that drowsiness and intoxication could be differentiated because a distinct set of measures was used to detect the two impairments. If a measure was used in both models, it would have been because both impairments influenced it. Because alcohol and drowsiness influence driver performance differently, the distinct set of measures suggests some degree of differentiation is possible.

Selecting data for an algorithm to distinguish alcohol impairment and drowsiness presented a challenge. The data for alcohol and drowsiness could not be combined because the thresholding operation was sensitive to minor bias differences in the measures between the two studies. These differences may have been due to small changes in the simulator hardware, software, or protocol between studies. Focusing on the alcohol data exclusively, there were only four drives where the driver was drowsy (post SSS > 3) but not intoxicated, so it was not possible to compare pure drowsiness with intoxication. Instead, a binary class was defined with intoxication and drowsiness as one level, and intoxication but no drowsiness as the other.

The measures that this algorithm used to discriminate between alcohol impairment and drowsiness were a combination of measures used in the previous two models: SRR small > 2.2, SDLP > 1.3, and TLC < 6.5, with average and percentage metrics applied to the first, percentage to the second, and both maximum and percentage applied to the last measure. The model and ROC curve are shown in Figure 13 demonstrate that the effects of alcohol impairment and drowsiness can be distinguished.

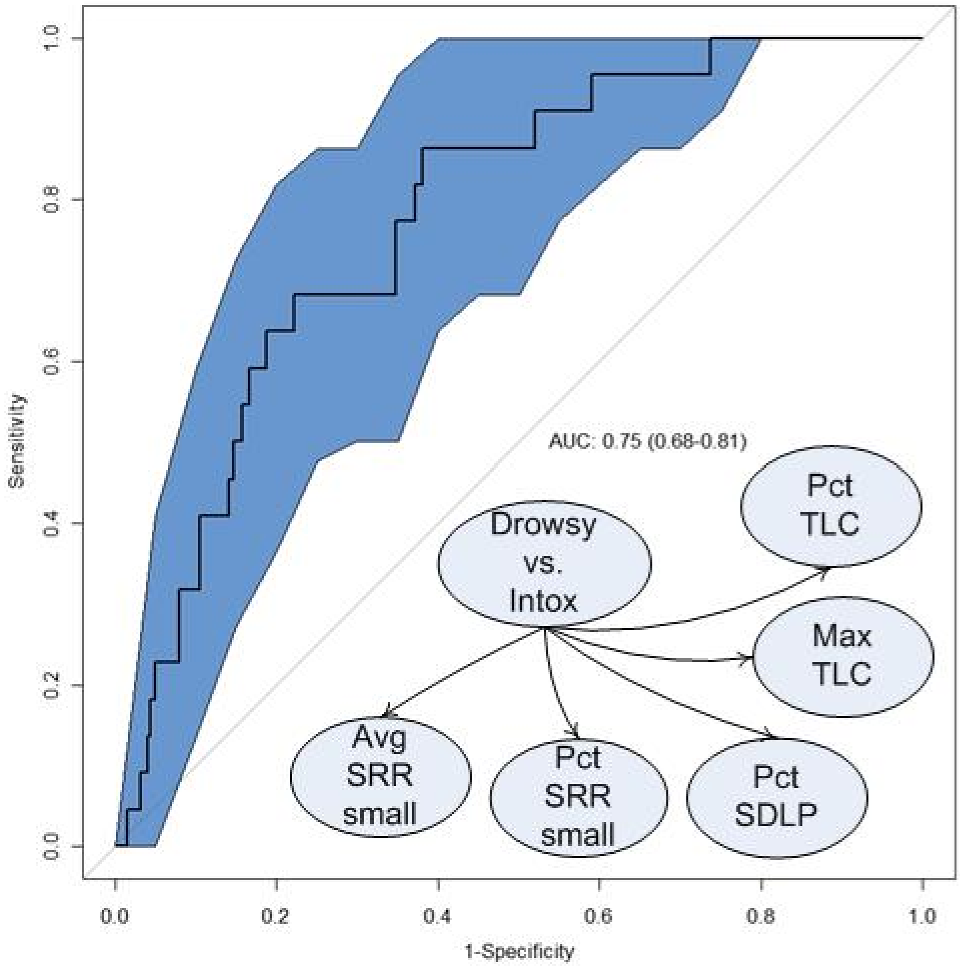

Figure 13. Performance of a Bayes network to differentiate drowsiness combined with alcohol impairment from just alcohol impairment

5.6 Detecting Drowsiness Associated with Lane Departures

Given the variability of drowsiness across conditions, drivers, and scenario events across the drive it is not surprising that algorithms detecting impairment defined by the drowsiness condition performed poorly. The transient nature of drowsiness suggests that algorithms that detect impairment associated with driving mishaps, such as lane departures, might be substantially more sensitive.

To assess this possibility, real-time algorithms were developed using short-range timescale continuous data, with a focus on data surrounding lane departures. The continuous data consists of driver and vehicle data recorded at 60 Hz for the entire drive. Each record of these datasets was coded as alert or drowsy according to three definitions: the drowsiness condition (day, early night, late night), a linear combination of PVT, pre-post and retrospective SSS, and the presence or absence of a lane departure. The details of defining truly drowsy lane departures and corresponding truly alert data points are described in Appendix W.

Ten-fold cross validation was used to assess each algorithm, producing a measure of accuracy, PPP, AUC, timeliness and corresponding confidence interval for each algorithm. Timeliness is defined by the AUC of the ROC curve measured at six seconds before the lane departure. ROC curves summarize the performance graphically.

Time-to-lane-crossing (TLC) is predictive of drowsy lane departures. Although the effectiveness of the classification at the point of departure is trivial and uninteresting because TLC is always equal to zero at this point, the ability of TLC to indicate drowsiness six seconds before a lane departure is very important. TLC is measured here as a moving average over a 60-second window. ROC performance of TLC is shown in Figure 14 below. An AUC of 0.79 of this algorithm shows that the TLC algorithm can identify almost 80 percent of drowsiness-related lane departures before they occur.

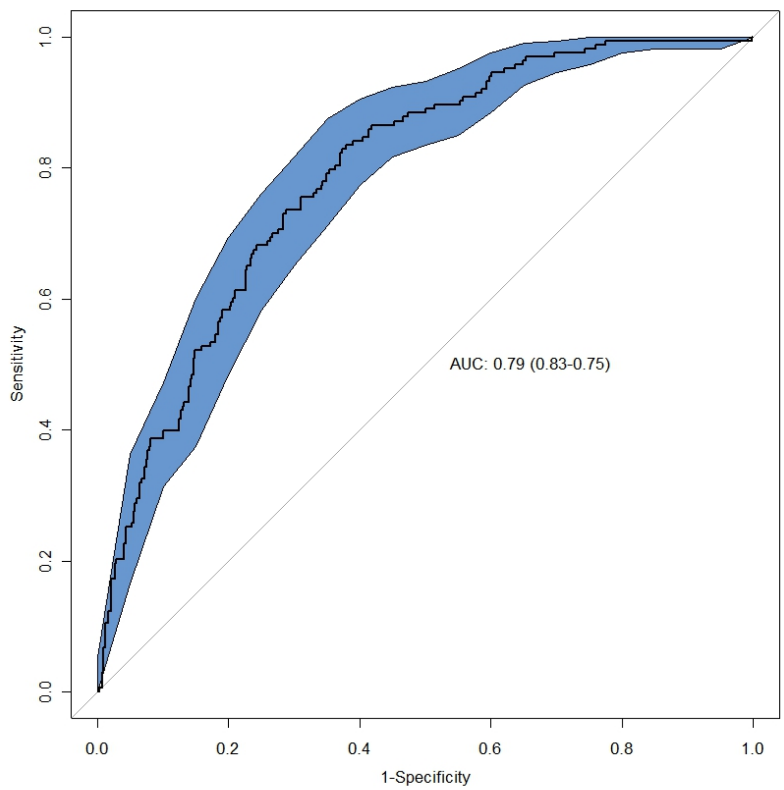

Figure 14. Timeliness using time-to-lane crossing (TLC)

Steering behavior can also detect drowsiness in advance of lane departures. Figure 15 shows that a relatively simple random forest algorithm (Breiman, 2001) that aggregates the steering wheel position over the previous 60 seconds detects drowsiness substantially better than chance, although not as well as the TLC algorithm. This detection performance is quite timely, detecting drowsiness even 15 seconds before the lane departure. Figure 16 shows the importance of steering wheel position information in detecting drowsiness. Interestingly, the position of the steering wheel at 60, 33, 51, and

56 seconds before the prediction are the most important in detecting drowsiness, showing that steering behavior from across the entire 60-second window preceding a lane departure is useful in predicting lane departures.

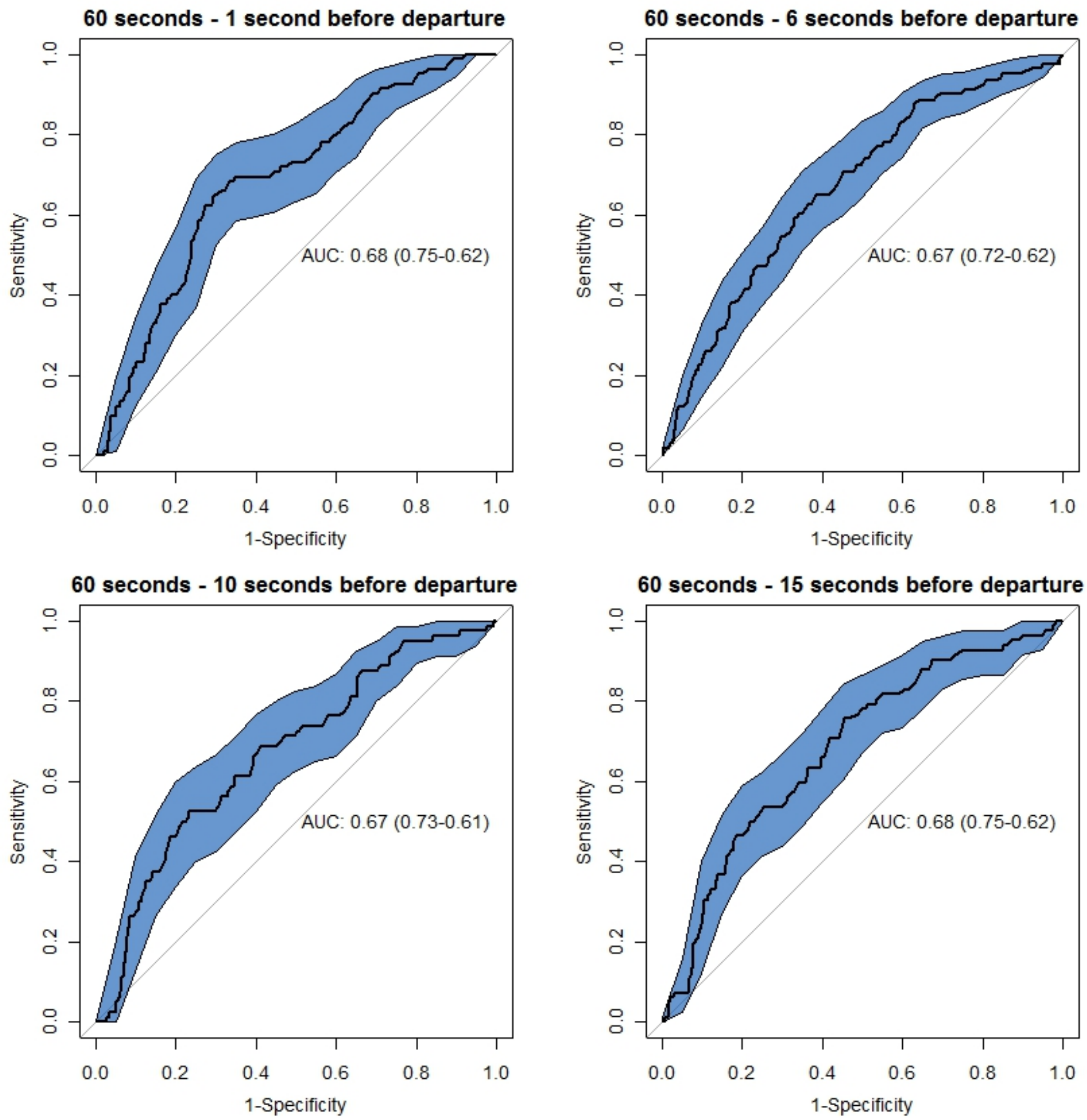

Figure 15. ROC curves for detecting drowsiness-related lane departure, using only continuous steering data with a moving window of 60 seconds

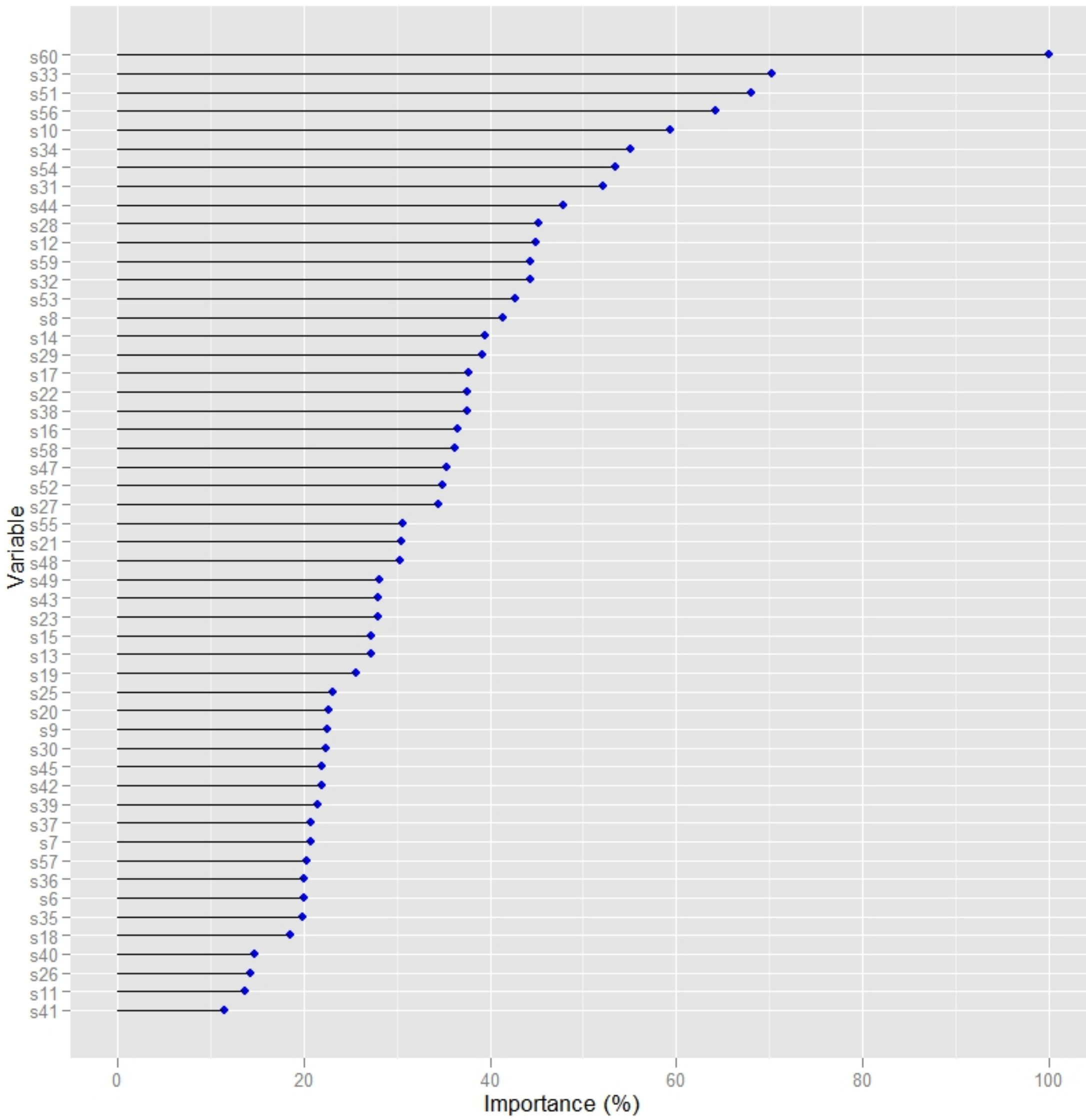

Figure 16. Variable Importance plot for 6 seconds prior classifier. Note that variables are labeled so that "s8" is the steering wheel angle 8 seconds prior to departure.

The promising performance of both the random forest applied to steering wheel position and the moving average of the TLC contrast with poor performance of PERCLOS. Figure 17 shows that PERCLOS performs only slightly above chance and markedly worse than either the TLC or steering wheel position algorithms. The accuracy of the steering models could likely be improved through data processing and filtering, as well as by combining TLC and steering wheel position information. PERCLOS might provide a useful complement to the steering and lane position algorithms because PERCLOS performs well in the ROC region associated with high specificity, where the algorithm using steering wheel movements performs relatively poorly.

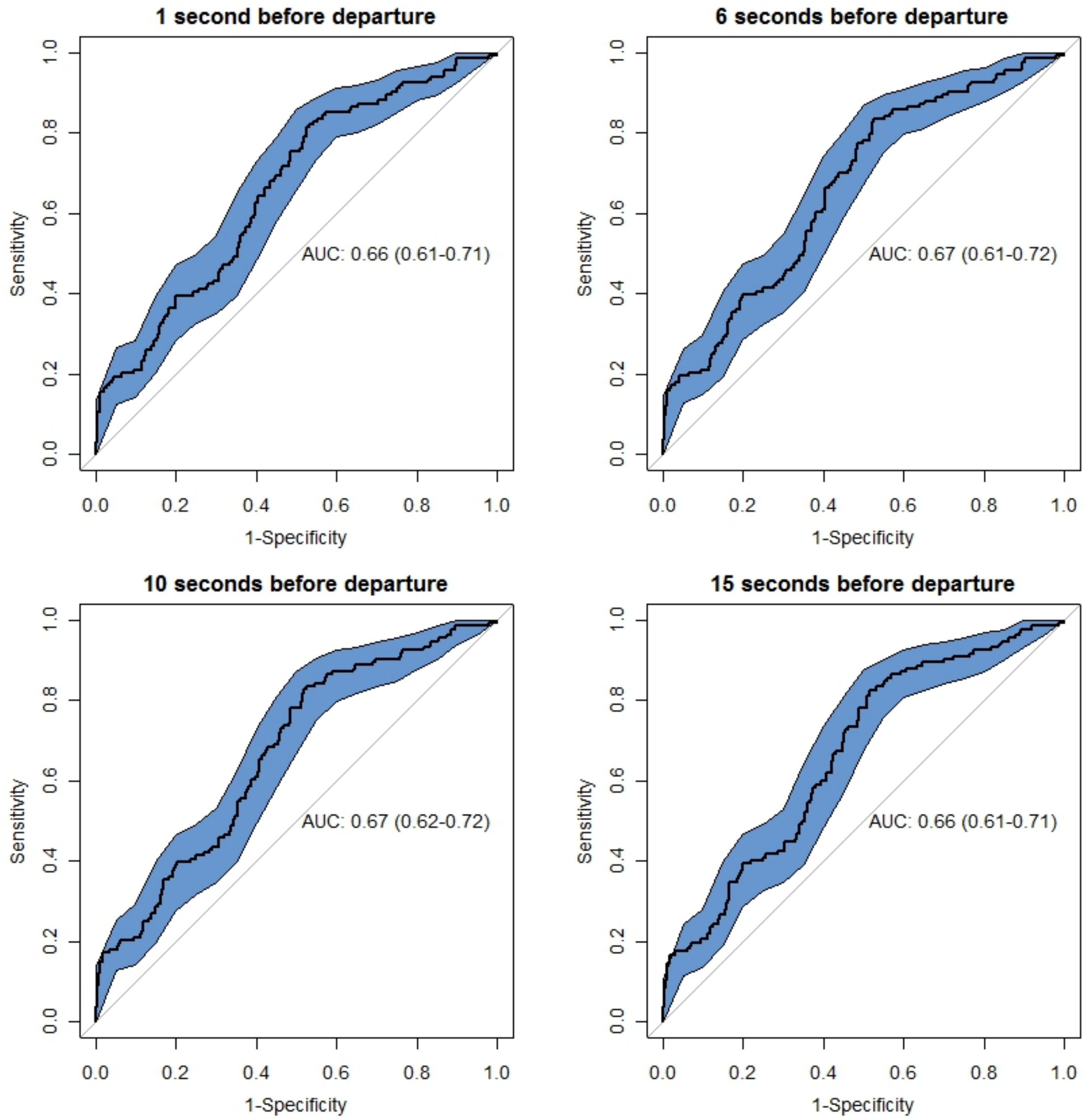

Figure 17. ROC curves for predictive models for drowsiness related lane departure, using only PERCLOS with a moving window of 60 seconds.

5.7 Conclusions and Implications

The development and evaluation of algorithms to detect drowsiness described in this chapter provide answers to the four questions that motivated the study.

Can algorithms designed to detect alcohol impairment and distraction also detect drowsiness? Algorithms developed to detect distraction and alcohol-impaired driving did not detect drowsiness reliably.

Can algorithms designed to detect alcohol impairment be generalized to work well for both alcohol and drowsiness? Algorithms, such as the boosted decision tree that successfully detected alcohol-impaired driving could be generalized to detect drowsiness when trained on drowsy-driver data.

Can algorithms distinguish between alcohol and drowsiness-related impairment? A Bayes network algorithm successfully differentiated alcohol-impaired drivers from drivers who were both drowsy and alcohol-impaired.

Do real-time algorithms perform better in detecting drowsiness in advance of a drowsiness-related mishap? Real-time algorithms, based on lane-keeping and steering behavior, successfully detected drowsiness six seconds before the lane departure. This contrasts with particularly poor performance of PERCLOS in detecting impending lane departures.

Beyond these specific questions, the results of developing and evaluating algorithms to detect drowsiness support important conclusion relative to impairment detection and countermeasure development. The results reinforce earlier findings regarding the qualitative differences between impairments, such as alcohol and distraction. Impairment due to drowsiness and alcohol affects drivers differently, with drowsiness being somewhat transient and alcohol being more persistent, assuming that alcohol impairment is associated with BAC level. The transient nature of drowsiness makes accurate detection of drowsiness at the level of a drive somewhat more difficult than with alcohol impairment.

Beyond the relatively transient nature of drowsiness, the variables most sensitive to detecting each impairment are different. This difference demonstrates the need for separate algorithms to detect the two impairments. Moreover, it was possible to discriminate drowsy intoxicated drivers from non-drowsy intoxicated drivers, showing that the symptoms of intoxication do not necessarily mask those of drowsiness. Ultimately, the results are favorable in regards to the possibility of detecting both drowsiness and intoxication using two independent Bayes network algorithms and discriminating between the two.

Algorithms based on easily accessible measures of steering and lane position performed as well or better than algorithms, such as PERCLOS, that use expensive eye tracking or brain activity sensors. Combining other driving performance measures with PERCLOS leads to substantially better drowsiness detection compared to PERCLOS alone.

Algorithms to detect drowsiness-related lane departures performed very well, providing accurate indications of impending lane departures 6 to 15 seconds before the departure. These algorithms used simple measures of lane keeping and steering behavior. In contrast, PERCLOS performed particularly poorly as a real-time algorithm and depends on a complex sensor to track eye closure. One reason for the poor performance of PERCLOS might be attributed to poor quality eye tracking data and not to the algorithm itself. Such sensitivity to sensor quality represents an important consideration in algorithm design. Accurate measures of lane position are likely to become accessible as lane departure warning systems become more common, and steering behavior can be measured accurately with inexpensive sensors. Naturalistic driving data would better characterize sensor performance because impairment detection depends not only on the algorithm performance, but also on the sensor performance. Alternatively, more accurate sensor models for lane tracking cameras can be added to the simulation. Then the signal-to-noise level can be adjusted and the sensitivity of TLC to sensor accuracy evaluated.

Generally, these results demonstrate the utility in considering indicators of drowsiness beyond PERCLOS in creating real-time algorithms to detect drowsiness.

Although drowsiness produces acute impairment associated lane departures, drowsiness is also revealed with data over a timescale of several minutes. Such long-term drowsiness is revealed by standard deviation of lane position (SDLP), eye closure rate (AECS), and time to lane crossing (TLC). The last measure reinforces the selection of lane departures as an appropriate event to study in relation to impairment. Interestingly, different measures indicate alcohol impairment: small steering reversal rate (SRR) and percent road center (PRC) measure of gaze concentration within a 17-second window. These results suggest that the algorithms to detect long-term drowsiness might be paired with real-time algorithms to improve their performance. Even more broadly, the strong effect of time of day, time spent driving, and even diagnosis of sleep apnea, could further augment the long-term indicator of drowsiness. If such a long-term algorithm indicates the driver is drowsy then the criteria used by the real-time algorithm could be adjusted so that more of the imminent drowsiness-related lane departures are detected before the driver departs the lane.

The success of drowsiness detection algorithms that use low-cost measurements, such as steering inputs, suggests substantial value in further exploration of how such simple sensors can identify impairment. A plan for this exploration would consist of three primary approaches:

1. Investigate the features of the random forest algorithm to understand the features that underlie its success.
2. Apply techniques for impairment detection from time series data including: distribution parameters (mean, standard deviation, kurtosis, etc.), system identification techniques, time-frequency analysis (e.g., Fourier and wavelet analysis), and symbolic aggregate approximation (SAX) time series analysis.
3. Develop hierarchical, variable-time-window algorithms. Such algorithms integrate information from a long time scale, such as the time of day, with information from a short time scale, such as the previous minute of steering behavior.

These approaches support a deeper understanding of the data that can detect and discriminate impairments using simple sensors, such as steering wheel instrumentation. The hierarchal algorithm will indicate how best to combine such data to improve detection and discrimination performance.

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7 APPENDICES

APPENDIX A: ALGORITHM APPROACHES

Table 1. Summary of algorithm approaches.

Approach	Type	Description	Inputs	Individualization Procedures	Output	Effectiveness
PERCLOS (Dinges et.al., 1998) (Grace et. al, 1998)	Eye Closure	An implementation of Wierwille et al. (1994) approach that utilized video of the driver's face to determine when the driver's eyes were more than 80% closed over a one minute time window.	Eye closure	Based on model of driver eyes	Continuous Classification relative to a single threshold	Good coherences[1] with performance lapses on 20 minute time interval (0.87), but less useful on minute-by-minute predictions (0.63)
EEG algorithm (Dinges et.al., 1998)	EEG	This algorithm by Consolidated Research uses EEG waveform data from either O1 or O2 to estimate drowsiness over a 2.4 second time window with updates every 1.2 seconds.	EEG sensor	None	Discrete output of continuous signal	Low coherence with performance lapses (ranged from 0.12 to 0.38) for subjects tested
EEG algorithm (Dinges et.al.,	EEG	This EEG algorithm from the Naval Health Research Center utilizes multiple EEG reference points and	EEG sensor	None	Discrete output of continuous	Authors observed that performance

[1] Coherence can be defined as the extent to which two signals vary in a constant relationship. Perfect coherence would be achieved when two signals are identical in terms of magnitude and timing.

1998)		electrooculographic (EOG) data in conjunction with a continuous tracking task			signal	varied significantly by participant with some on par with PERCLOS while others perform poorly.
Proximity Array Sensing System (Dinges et.al., 1998)	Head	Advanced Safety Concepts developed this algorithm to detect changes in the x, y, z position of the drivers head to detect onset of drowsiness through different head movement patterns	head	None	Discrete output of continuous signal	Performance varied significantly by participant with some on par with PERCLOS while others perform poorly.
Alertness Monitor (Dinges et.al., 1998)	Eye Blink	Through the use of specialized glasses changes in eye closure were monitored through measurement of movement of the eyelashes with an infrared emitter/detector. Specifically the system predicts drowsiness based on the ratio of eyelid closure versus eyelid open.		Adjustment of system based upon normal eyelid position	Discrete output based upon ratio	Performance varied significantly by participant with some on par with PERCLOS while others perform poorly.

Blinkometer (Dinges et.al., 1998)	Eye Blink	Has two modes for measuring drowsiness: blinks per minute and blink to blink ratio. This study evaluated blinks per minute.		None	Discrete output based upon frequency.	Authors noted that performance varied significantly by participant with some on par with PERCLOS while others perform poorly.
In Vehicle Predictor (Mattsson, 2007)	Vehicle Based Measures	Uses a variety of in-vehicle measures including steering wheel, lane position, and reaction time. It was developed based upon self-reports of sleepiness. Six part equation to account for missing data. Only two would be needed for actual implementation.		None	Scaled to 10 point scale	Showed specificity of 0.985 and sensitivity of 0.774.
Amplitude Duration Squared Theta (King, et al, 1998)	Vehicle Based Measures	Uses steering wheel angle and velocity in the time domain to detect steering that is outside the normal control region specified by an ellipse with parameters that do not vary by driver.	Steering wheel	None	Three continuous measures that combine to provide a binary indication of drowsiness	Detected 12/17 before first lane departure and all 17 during their night drive.
PERCLOS + (Hanowski et.	Eye Closure	This combined algorithm incorporates both PERCLOS and the frequency of		Individualization of eye models	Pseudo-continuous	System performed

al., 2008)	and Lane Position	out of lane occurrences.				successfully for 15/17 system tests, but sensor limitations were present that limited accuracy in real-world environment.
ePerclos	Lane Keeping/ Steering	A vehicle control based approximation of PERCLOS proposed in Wierwille et al. (1996). Relies on steering, lane keeping and lateral velocity measures over a 3 minute window.		None	Continuous Classification relative to a single threshold	Promising simulator results which translated to on-road data
BEST ePERC	Lane Position	Vehicle control algorithm based on lane exceedences and variance in lane position proposed by Tijerina et al. (1999).		None	Continuous Classification relative to a single threshold	Less effective than using mean square lane position alone.
Facial Expression	Eye Closure/ Facial	This algorithm combines information extracted from video of the drivers face (Ji et al., 2004). Uses information about eyelid position (PERCLOS), head and gaze movement, and general facial expression. They report that		Individual models of the face require models of drivers face.	No	Showed success across a range of subjects.

		certain facial expressions are predictive of fatigue.				
Hypovigilance Diagnosis Module (HDM)	Eye Closure/ Grip / Lane Keeping	This algorithm from the AWAKE project fuse data on eye closure with grip data from the steering wheel and lane. Data is individualized to the driver and reports three states: drowsy, may be drowsy, and awake. (AWAKE, 2010)		Yes	No	Results are not yet available.

Appendix A References

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APPENDIX B: RECRUITMENT MATERIAL

Advertisement Wording

Main Study

Adults ages 21-34, 38-51, and 55-68 are invited to participate in a driving simulation study evaluating the impact of drowsiness on driver performance. Must have normal sleep patterns, live within 30 minute drive of University of Iowa Oakdale Campus/UI Iowa Research Park, and have not participated in any driving simulation studies regarding distraction or alcohol and driving conducted at the National Advanced Driving Simulator. 3 visits total (One visit between 7pm and 6am). Drug and pregnancy screen completed at some visits. You will be paid for your time and effort. For more information, call 319-335-4719 or www.drivingstudies.com

Adults 55-68 are invited to participate in a driving simulation study evaluating the impact of drowsiness on driver performance. Must have normal sleep patterns, live within 30 minute drive of University of Iowa Oakdale Campus/UI Iowa Research Park, and have not participated in any driving simulation studies regarding distraction or alcohol and driving conducted at the National Advanced Driving Simulator. 3 visits total (One visit between 7pm and 6am). Drug and pregnancy screen completed at some visits. You will be paid for your time and effort. For more information, call 319-335-4719 or www.drivingstudies.com

Adults 38-51 are invited to participate in a driving simulation study evaluating the impact of drowsiness on driver performance. Must have normal sleep patterns, live within 30 minute drive of University of Iowa Oakdale Campus/UI Iowa Research Park, and have not participated in any driving simulation studies regarding distraction or alcohol and driving conducted at the National Advanced Driving Simulator. 3 visits total (One visit between 7pm and 6am). Drug and pregnancy screen completed at some visits. You will be paid for your time and effort. For more information, call 319-335-4719 or www.drivingstudies.com

Women 55-68 are invited to participate in a driving simulation study evaluating the impact of drowsiness on driver performance. Must have normal sleep patterns, live within 30 minute drive of University of Iowa Oakdale Campus/UI Iowa Research Park, and have not participated in any driving simulation studies regarding distraction or alcohol and driving conducted at the National Advanced Driving Simulator. 3 visits total (One visit between 7pm and 6am). Drug and pregnancy screen completed at some visits. You will be paid for your time and effort. For more information, call 319-335-4719 or www.drivingstudies.com

Women 38-51 are invited to participate in a driving simulation study evaluating the impact of drowsiness on driver performance. Must have normal sleep patterns, live within 30 minute drive of University of Iowa Oakdale Campus/UI Iowa Research Park, and have not participated in any driving simulation studies regarding distraction or alcohol and driving conducted at the National Advanced Driving Simulator. 3 visits total (One visit between 7pm and 6am). Drug and pregnancy screen completed at some visits. You will be paid for your time and effort. For more information, call 319-335-4719 or www.drivingstudies.com

Email Script

Subject: Participants invited for driving study

THE
NATIONAL ADVANCED
DRIVING SIMULATOR

The National Advanced Driving Simulator at The University of Iowa Oakdale Campus is inviting adults to participate in a driving simulation evaluating the impact of drowsiness on driver performance.

Who can be part of this study?

- Adults ages 21-34, 38-51 and 55-68
- Live within 30 minute drive of University of Iowa Oakdale Campus / Research Park
- Have normal sleep patterns
- Have not participated in any driving simulation studies regarding distraction or alcohol and driving conducted at the National Advanced Driving Simulator
- Able to attend 3 study visits (One visit between 7pm and 6am)
- Drug and pregnancy screen completed at some visits

If you meet the above criteria and are interested in participating, please visit:

www.drivingstudies.com
Email: recruit@nads-sc.uiowa.edu
Call: 319-335-4719

If you do participate in the study, you will be paid for your time and effort. Even if you don't qualify to participate in this study, please forward this message to anyone you know who does!

APPENDIX C: SCREENING PROCEDURES

For a participant to be eligible for a study they must meet **ALL** of the following criteria:

- Be able to participate when the study is scheduled
- Meet all inclusion criteria
- Pass the phone health screening questions

Overview

The purpose of this research study is to evaluate algorithms designed to detect drowsy driving.

- **Study Information, Time Commitment and Compensation**:
  This study involves 3 study visits, the first visit will be a screening appointment which will last approximately 1 ½ hours in length and will determine if you are eligible to be in the study. If you are eligible, the next 2 visits will be conducted over a 2 week period of time. One visit will take place between 9am-12pm and will last approximately 1½-2 hours in length and the other visit will take place overnight beginning around 7 pm and lasting for approximately 11 hours. You may complete the daytime visit at your second or third visit.

  Each of the three visits requires you to come to the University Research Park (formerly the Oakdale Campus) to participate. If you do enroll into the study, arrangements will be made for your transportation to and from your residence to the National Advanced Driving Simulator for the overnight visit, as you will not be allowed to drive or be driven to this study visit.

  We ask that you not drink alcoholic beverages within 24 hours of these study visits, not drink caffeine 12 hours prior to your visit, and to refrain from using recreational drugs 30 days of your scheduled visits. Additionally, we will be conducting urine drug screens at some visits and for females; a urine pregnancy test will be completed for some study visits. Your eligibility to complete each visit will be determined at each visit.

  Participation involves signing a consent form, wearing an activity monitoring device which is similar to wearing a watch, completion of an activity log, and wearing of EEG monitoring device. This device is a wireless non-intrusive device that fits comfortably on your head. You will also complete several questionnaires before and after your study drives. You will receive instructions regarding driving the simulator and the study drives at your visits. A short interview will take place on your third visit.

  Compensation
  If you complete all study visits and procedures you will be paid $250 for your time and effort.
  If you withdraw from the study or your participation ends your compensation will be pro-rated:
  Visit 1 $10
  Visit 2 $90
  Visit 3 $150
  If you fail to meet study criteria you will be paid only $15 for the visit.

- **Willing to participate?**
  Are you still interested in participating?

  - If YES, continue with Inclusion Criteria
  - IF NO, ask if he/she would like us to keep him/her in our recruitment database for consideration of future participation.
    - IF NOT interested in future studies and wish to be removed from database
      - Make note regarding deletion
      - Reason if given

Inclusion Criteria ~ General Questions

Overview

Before this list of questions is administered, please communicate the following:

There are several criteria that must be met for participation in this study. I will need to ask you several questions to determine your eligibility.

If a subject fails to meet one of the following criteria, **(answers must be YES unless otherwise specified)** proceed to Closing.

1) **Do you possess a valid U.S. Drivers' License and have been a licensed driver for two years?**
2) **Are the ONLY restrictions on your driver's license limited to vision correction?**
   -vision restriction acceptable if vision is corrected to 20/20 with lenses
3) **Do you drive at least 10,000 miles per year?**
4) **You do not need to use any special equipment to help you drive such as pedal extensions, hand brake or throttle, spinner wheel knobs or other non-standard equipment? (no mechanical aid or use of prosthetic aid)**
5) **Are you between the ages: 21-34, 38-51, or 55-68**
6) **Do you live within a 30 minute drive time to The National Advanced Driving Simulator, located at Oakdale Campus?**
7) **Are you able to come to at least one study visit after 7 pm and stay overnight without sleeping?**
8) **Are you able to refrain from caffeine after 12pm on the day of the overnight visit?**
9) **Are you able to abstain from driving for the day following your overnight drive?**
10) **Do you go to sleep and wake at approximately the same time every day? (i.e., you don't work the night shift)?**
11) **Have you no reason to believe that you have might have obstructive sleep apnea?**
    (Inclusion criteria: no daytime fatigue, no excessive daytime sleepiness, no loud snoring or snorting while sleeping)
12) **Would this be the first time you have you participated in a driving simulator study?**
    (If NO to above)

    Was the study about alcohol and driving?

    (Must answer NO)

    Was the study about distraction and driving?

    (Must answer NO)

General Inclusion Criteria is met – proceed to General Health Exclusion Criteria

Because we are conducting a study to determine how sleep impacts driving performance, the following questions ask you about your sleep patterns. Your answer will determine if you continue to meet the study qualifications.

Administer Morning_Evening Phone Screening

- If all Inclusion Criteria are met, proceed to General Health Exclusion
- If subject doesn't meet criteria, proceed to Closing

General Health Exclusion Criteria

1.1.1 Overview

1.1.2 Before administering this list of questions, please communicate the following:

- Because of pre-existing health conditions, some people are not eligible for participation in this study.
- I need to ask you several health-related questions before you can be scheduled for a study session.
- **Your responses are voluntary and all answers are confidential.**
- You can refuse to answer any questions and only a record of your motion sickness susceptibility will be kept as part of this study.
- No other responses will be kept.

- If a participant fails to meet one of the following criteria, proceed to the Closing (If unsure about exclusion criteria, consult Principal Investigator)

1) If the subject is female:

- **Are you, or is there any possibility that you are pregnant? Or, are you currently breast feeding?**

Exclusion criteria:

- If there is ANY possibility of pregnancy
- If breast feeding.

2) Have you been diagnosed with a serious illness?

- If YES, is the condition still active?
- Are there any lingering effects?
  - If YES, do you care to describe?

Exclusion criteria:

- Cancer (receiving any radiation and/or chemotherapy treatment within last 6 months)
- Crohn's disease
- Hodgkin's disease
- Parkinson's disease
- Currently receiving any radiation and/or chemotherapy treatment

3) Do you have Diabetes?

- Have you been diagnosed with hypoglycemia?
- If yes, do you take insulin or any other medication for blood sugar?

NOTE: Type II Diabetes accepted if controlled (medicated and under the supervision of physician)

Exclusion criteria:

- Type I Diabetes - insulin dependent
- Type II – **Uncontrolled** (see above)

4) Do you suffer from a heart condition such as disturbance of the heart rhythm or have you had a heart attack or a pacemaker implanted within the last 6 months? ➢ If YES, please describe?
Exclusion criteria: • History of ventricular flutter or fibrillation • Systole requiring cardio version (atrial fibrillation may be acceptable if heart rhythm is stable following medical treatment or pacemaker implants)
5) Have you ever suffered brain damage from a stroke, tumor, head injury, or infection? ➢ If YES, what are the resulting effects? ➢ Do you have an active tumor? ➢ Any visual loss, blurring or double vision? ➢ Any weakness, numbness, or funny feelings in the arms, legs or face? ➢ Any trouble swallowing or slurred speech? ➢ Any uncoordination or loss of control? ➢ Any trouble walking, thinking, remembering, talking, or understanding?
Exclusion criteria: • A stroke within the past 6 months • An active tumor • Any symptoms still exist

6) Have you ever been diagnosed with seizures or epilepsy? ➢ If YES, how frequently and what type?
Exclusion criteria: • A seizure within the past 12 months

7) Do you have Ménière's Disease or any inner ear, dizziness, vertigo, hearing, or balance problems? ➢ Wear hearing aides - full correction with hearing aides acceptable ➢ If YES, please describe. ➢ **Ménière's Disease** is a problem in the inner ear that affects hearing and balance. Symptoms can be low- pitched roaring in the ear (tinnitus), hearing loss, which may be permanent or temporary, and vertigo. ➢ **Vertigo** is a feeling that you or your surroundings are moving when there is no actual movement, described as a feeling of spinning or whirling and can be sensations of falling or tilting. It may be difficult to walk or stand and you may lose your balance and fall.
Exclusion criteria: • Meniere's Disease • Any recent history of inner ear, dizziness, vertigo, or balance problems

8) Do you currently have a sleep disorder such as sleep apnea, narcolepsy or Chronic Fatigue Syndrome? ➢ If YES, please describe. ➢ Sleep apnea: how long under treatment and was treatment successful
Exclusion criteria: • Untreated sleep apnea • Narcolepsy • Chronic Fatigue Syndrome

9) **Do you have migraine or tension headaches that require you to take medication daily?** ➢ If YES, please describe.
Exclusion criteria: • Any narcotic medications
10) **Do you currently have untreated depression, drug dependency, anxiety disorder, ADHD or claustrophobia?** ➢ If YES, please describe.
Exclusion criteria: • Untreated depression • Agoraphobia, hyperventilation, or anxiety attacks • ADHD (treated and untreated) • Dependency or abuse of psychoactive drugs, illicit drugs, or alcohol

11) **Are you currently taking any prescription or over the counter medications?** ➢ If YES, what is the medication? ➢ Are there any warning labels on your medications, such as potential for stimulation or drowsiness?
Exclusion criteria: • Sedating medications or drowsiness label on medication UNLESS potential participant indicates they have been on the medication consistency for the last 6 months AND states they have NO drowsiness effects from this medication • Stimulant medication UNLESS potential participant indicates they have been on the medication consistency for the last 6 months AND states they have NO drowsiness effects from this medication

12) **Do you experience any kind of motion sickness?** ➢ If YES, what were the conditions you experienced: when occurred (age), what mode of transportation, (boat, plane, train, car), and what was the intensity of your motion sickness? ➢ On a scale of 0 to 10, **how often** do you experience motion sickness with **0 = Never and 10 = Always** ➢ On a scale of 0 to 10, **how severe** are the symptoms when you experience motion sickness with **0 = Minimal and 10 = Incapacitated**
Exclusion criteria: • One single mode of transportation where intensity is high and present • More than 2 to 3 episodes for mode of transportation where intensity is moderate or above • Severity and susceptibility scores rank high

13) **Have you experienced any pain from neck or back injuries within the last year?** ➢ If YES, is it current or chronic neck or back injury?
Exclusion criteria: • Any current skeletal, muscular or neurological problems in neck or back regions • Chronic neck and back pain • Pinched nerves in neck or back • Back surgery within last year

Proceed to Closing

Closing

<u>MEETS ALL CRITERIA</u>

Instructions:

- Refrain from drinking alcohol and taking any **NEW** prescription or over the counter drugs for the 24 hours preceding your driving session. If you do need to take a new medication 24 hours preceding your driving session, please call us. Ibuprofen, Tylenol, aspirin, and vitamins are acceptable to take prior to driving session.

- Bring Driver's License with you to appointment.

- We ask that cell phones and pagers be turned off or left home or in your car outside as they are not allowed while participating in the driving study.

- Request the following of all participants:
    - Wear flat shoes to drive in
    - No hats worn or gum chewing allowed while driving
    - Refrain from wearing artificial scents (perfume or cologne) as some staff allergic to scents

- You will be required to wear a seat belt while driving.

- If your appointment is before 8am or after 5pm, the front door will be locked, therefore, please use the After Hours Call Box located at the right side on the front door. Press the call button and someone will let you in.

- Provide directions, explain where to park and ask them to check in at the front desk inside the main entrance.

- Inform participants to call **(319) 335-4775** they are unable to make this appointment and need to reschedule as soon as possible (prefer 24 hour notice). Please leave a message if they receive voicemail and a staff member will return their call.

<u>DOES NOT MEET CRITERIA</u>:

- Inform participant that they may qualify for a future study and ask if they wish to remain in our database to be called for future studies.

- If participant is not in our database, ask if they would like to be considered for future driving research studies, if yes, fill out NADS database form.

APPENDIX D: MORNING/EVENING PHONE SCREENING

Morning/Evening Phone Screening

Because we are conducting a study to determine how sleep impacts driving performance, the following questions ask you about your sleep patterns. Your answer will determine if you continue to meet the study qualifications. We need participants with a variety of levels and patterns of sleep, so there are no right or wrong answers. Please respond as honestly and accurately as you can.

1. Considering your own "feeling beat" rhythm, at what time would you get up if you were entirely free to plan your day?
   - 5 a.m.-6:30 a.m.—5 points
   - 6:30 a.m.-7:45 a.m.—4 points
   - 7:45 a.m.-9:45 a.m.—3 points
   - 9:45 a.m.-11 a.m.—2 points
   - 11 a.m.-12 p.m.—1 point

2. During the first half hour after woken in the morning, how tired do you feel?
   - Very tired—1 point
   - Fairly Tired—2 points
   - Fairly refreshed—3 points
   - Very refreshed—4 Points

3. At what time in the evening do you feel tired and as a result in need of sleep?
   - 8 p.m. - 9 p.m.—5 points
   - 9 p.m. - 10:15 p.m.—4 points
   - 10:15PM - 12:45 a.m.—3 points
   - 12:45 a.m.- 2a.m. —2 points
   - 2 a.m.- 3 a.m.—1 point

4. At what time of the day do you think you reach your "feeling best" peak?
   - 5 a.m. – 8 a.m. – 5 points
   - 8 a.m. – 10 a.m. – 4 points
   - 10 a.m. – 5 p.m. – 3 points
   - 5 p.m. – 10 p.m. – 2 points
   - 10 p.m. – 5 a.m. – 1 point

5. One hears about "morning" and "evening" types of people. Which ONE of these types do you consider yourself to be?
   - Definitely a "morning" type—6 points
   - Rather more a "morning" than an evening type—4 points
   - Rather more a "evening" than a "morning" type —2 points
   - Definitely a "evening" type"—0 Points

Scores 12 and above include in study and proceed to General Health Exclusion Criteria (page 3 Phone screening procedures)

Scores 11 and below will not be included in study, proceed to Closing (page 6 Phone Screening procedures)

APPENDIX E: PARTICIPANT ENROLLMENT AND CHARACTERISTICS

A total of 103 participants were enrolled to achieve the final sample of 72 completed data sets. Table E1 provides details of enrollment by visit. Four were screened but not randomized into the study. Six were lost to screen failures. 10 withdrew due to simulator discomfort. Four withdrew for other reasons. Seven were dropped by the investigators.

Table E1. Number of participants reporting to visits for main study.

Group	**Enrolled Visit 1 (Screening)**	**Passed Screening**	**Visit 2**	**Visit 3**	**Completed**
Young Male	14	14	13	12	12
Young Female	20	18	15	13	12
Middle Male	17	17	14	13	12
Middle Female	18	17	17	12	12
Older Male	16	15	15	13	12
Older Female	18	16	14	13	12
Total	103	97	88	76	72

APPENDIX F: SCENARIO SPECIFICATION

F.1 Scenario/Experiment Overview

F.2 Introduction

The ACMI main scenarios are built based on the IMPACT scenarios and ACMI pilot scenarios. For the Pilot, towards the end of the rural segment, half of the participants veered left at the Y intersection continuing on a paved road and half of the participants veered right onto gravel road. For the main study, all participants will veer to the right at the Y intersection and continue onto the gravel road. Additional roadway has been added after the gravel section to accommodate transitions to a rural straight paved segment of road at the end of the drive. There will be 10 minutes of driving after reaching the straight segment of road.

The ACMI study consists of three equivalent scenarios. Each scenario consists of a total of 22 events. It has an estimated time of driving of about 35-40 minutes. Each scenario has urban, interstate and rural driving environments.

F.3 Common Performance Measures

Each scenario is analyzed by computing common as well as scenario-specific performance measures. Scenario-specific measures are described within the individual scenario event descriptions, and the common measures are listed below.

The rest of this document contains the following:

- A description of the measures
- A description of differences between the scenarios
- A description of the scenario events

Table F1. Definitions of dependent measures

Category	Dependent Measure	Source	Description
Lateral control			
Input	Standard deviation of steering wheel position		Standard deviation of mean steering wheel position
	Velocity of steering wheel		Mean absolute velocity in degrees per minute
	Jerk of steering wheel		Mean absolute derivative of acceleration
	Steering error		Deviation from Taylor series approximation
	Steering wheel reversals	Mark Savino's thesis	Change from the negative (clockwise movement) to a positive (counterclockwise) rotational velocity OR the change from a positive rotational velocity to a negative rotational velocity. Absolute value of rotational velocity exceeds 3.0 degrees per second
	Intersection turn signal use	(Crancer, Dille, Delay, Wallace, & Haykin, 1969)	Number of times participant used turn signal for left turn at light and right turn at stop sign
	Highway turn signal use	(Crancer et al., 1969)	Ratio of lane changes while using turn signal in comparison to all lane changes
	Transition turn signal use	(Crancer et al., 1969)	Number of times participant used turn signals in transitions
Output	Mean lane position	Triggs & Redman, 1999)	Mean position in the lane relative to the center (positive to the right of center, negative to the left)
	Standard deviation of lane position	(Gawron & Ranney, 1988; Ramaekers, Robbe, & O'Hanlon, 2000)	Standard deviation of mean lane position
	Standard deviation of lane position from center	(Harrison, 2005)	Standard deviation of lane position from center of the lane
	Time to line crossing	(Van Winsum, Brookhuis, & de Waard (2000))	TLC = y/y' where y = lateral distance between the front

Category	Dependent Measure	Source	Description
			wheel and the lane boundary y' = lateral velocity
	Proportion of time TLC < 2 sec		Percentage of time TLC is less than 2 seconds for each lane boundary
	95% TLC		[5th] Percentile TLC
	Exponentially weighted moving average of lane position		Mean lane position and previous few graphed over entire drive
	Lateral acceleration		Change in velocity in lateral direction
	Number of center line crossings		Number of times any part of the vehicle crossed the center line
	Number of right line crossings		Number of times any part of the vehicle crossed the right line
	Frequency of lane changes		Frequency per minute of when entire car switches from one lane to the other
Longitudinal control			
Input	Accelerator holds		Percentage of time accelerator position is constant
	Velocity of accelerator position		Velocity of changing accelerator position
	Jerk of accelerator position		Derivative of acceleration
	Standard deviation of accelerator position		Standard deviation of mean accelerator position
	Mean brake force		Mean brake force applied
	Standard deviation of brake force		Standard deviation of mean brake force
Output	Mean speed		Mean speed
	Standard deviation of speed	(Arnedt, Wilde, Munt, & MacLean, 2001; Gawron & Ranney, 1988)	Standard deviation of mean speed
	Deviation from Posted Speed Limit	(Arnedt, 2001)	Standard deviation of speed relative to posted speed limit
	Exponentially weighted moving average of speed		Mean speed and previous few, graphed over entire drive

Category	Dependent Measure	Source	Description
	Time to collision		Distance between front bumper of participant's vehicle and the rear bumper of the vehicle in front divided by the difference in the two vehicles' velocities
	Time headway		Distance between front bumper of participant's vehicle and the rear bumper of the vehicle in front divided by the velocity of the participant's vehicle
	Variation in time headway		SD of time headway
	Did participant stop? (left turn, yellow light)		Minimum velocity
	Stopping location		Location of front bumper when vehicle reached zero velocity
Event contingent			
	Time gap accepted	(Leung & Starmer, 2005)	Distance between the two vehicles divided by the speed of the second vehicle
	Time between brake release and gap		The amount of time between when participant releases the brake and the front car's rear bumper (car in front in gap chosen) is in line with participant's car's front bumper. Positive relates to releasing brake before gap is available, negative equates to after.
	Time headway when centers of vehicles are in line		Time headway of second car in gap when center of participant's vehicle is in line with the center of the second car in gap
	Amount of time between initial stop to midpoint though intersection		Amount of time between first full stop and when midpoint of participant's vehicle is in line with midpoint of second car in gap
	Decision time	(Leung & Starmer, 2005)	Amount of time it took for participant to react to stimulus (i.e., yellow light)
	Number of traffic control violations	(Macdonald, Mann, Chipman, & Anglin-Bodrug, 2004)	Number of times participant violated traffic laws (speed limit, driving through red light, etc.)

Category	Dependent Measure	Source	Description
	Number of collisions	(Flanagan, Strike, Rigby, & Lochridge, 1983)	Number of times participant's vehicle collided with another object
	Near misses		Number of times participant's vehicle came within 2 feet of another object
	Near misses	(Neale, 2002) 100-car study	Number of times a conflict situation requiring a rapid, severe evasive maneuver to avoid a crash occurred during the event
	Degree of conflict	(Neale, 2002) 100-car study	Minimum time to contact
Smoothness: applicable to acceleration, lane change	Delay time	(Ogata, 1997)	Time at which half settling (speed, lane position, etc.) is reached; see Figure 1
	Rise time	(Ogata, 1997)	Time at which first reaches settling lane position, etc.); see Figure 1
	Peak time	(Ogata, 1997)	Time the maximum (speed, lane position, etc.) occurs at; see Figure 1
	Max overshoot	(Ogata, 1997)	The difference between the maximum and the settling lane position, etc); see Figure 1
	Settling time	(Ogata, 1997)	The amount of time required for the lane position, to stay within a bounded allowable tolerance; see Figure 1
	How well it fits the model (Robertson, 1996)		Correlation between model and performance of participant
Eye movement			
Micro-movements	Smooth pursuit velocity	(Katoh, 1988)	Velocity of smooth pursuit eye movements
	Smooth pursuit duration	(Moskowitz, Ziedman, & Sharma, 1976)	Time taken to smooth pursuit from one location to another
	Smooth pursuit frequency	(Moskowitz et al., 1976)	Number of smooth pursuit movements per second
	Smooth pursuit maximum velocity	(Stapleton, Guthrie, & Linnoila, 1986)	Maximum velocity of smooth pursuit eye movements
	Smooth pursuit gain	(Fetter & Buettner, 1990)	Cumulative amplitude of smooth pursuit (subtracts away saccades) divided by the amplitude of the

Category	Dependent Measure	Source	Description
			stimulus (%)
Statistical distribution	Standard deviation of gaze	(Victor, 2005)	Combine horizontal and vertical gaze position components using Pythagorean theorem
	Another standard deviation of gaze	(Recarte, Nunes, 2000)	SD of horizontal gaze distribution * SD of vertical gaze distribution
	Gaze kurtosis		The extent to which a frequency distribution is concentrated about its mean: “peakedness”
	Dwell duration	(Moskowitz et al., 1976)	Total time the participant focused on a particular object
	Frequency of rear view mirror glances	(Recarte & Nunes, 2000)	Frequency of participant’s glances at rear view mirror
	Frequency of side mirror glances		Frequency of participant’s glances at side mirrors
	Frequency of speedometer glances	(Recarte & Nunes, 2000)	Frequency of participant’s glances at speedometer
Event contingent	Glance direction (glance to hazards)		Number of times participant did not look at critical features or focused on unnecessary features
	Head movement		Number of times participant did not look at critical features or focused on unnecessary features
	Timing of participant looking at side mirror?		Amount of time between looking at mirror and taking action
	Timing of participant looking at rear view mirror?		Amount of time between looking at mirror and taking action
	Glance frequency at particular object		Number of times per minute participant glanced at particular object
Driver physical state			
Postural stability	Pressure output (global and local)		Sum of pressures across all pressure points
	Pressure and force over time		Distance between peak pressure points over time
	Pressure point mapping		Location of peak pressure points
Eye blink	PERCLOS	(Hayami, 2002)	Percent eye closure

Category	Dependent Measure	Source	Description
	Eye blink frequency	(Beideman & Stern, 1977)	Number of blinks per minute
	Eye blink duration	(Beideman & Stern, 1977)	Duration of eye blinks
Combined measures			
	Correlation between road curvature and eye movements	(Chattington, Wilson, Ashford, & Marple-Horvat, 2007)	Correlation between road curvature and eye movements
	Correlation between eye movements and steering		Correlation between eye movements and steering
	Correlation between steering and road curvature		Correlation between steering and road curvature
	Correlation between eye movements and SDLP		Correlation between eye movements and SDLP
	Correlation between head turn and steering wheel movement		Correlation between head turn and steering wheel movement

Table F2. Dependent measures by event

		Events																				
		Urban (1)						Highway (2)						Rural (3)								
	Dependent measure	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	7	8	9
Lateral control																						
Input	SD of steering wheel position																					
	Velocity of steering wheel																					
	Jerk of steering wheel																					
	Steering error																					
	Steering wheel reversals																					
	Intersection turn signal use																					
	Highway turn signal use																					
	Transition turn signal use																					
Output	Mean lane position																					
	SD of lane position																					
	SD from center																					
	Time to line crossing (TLC)																					
	Proportion of time TLC<2s																					
	95% TLC																					
	Exponentially																					

		Events																				
		Urban (1)						Highway (2)						Rural (3)								
	Dependent measure	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	7	8	9
	weighted moving average of lane position																					
	Lateral Acceleration																					
	Number of center line crossings																					
	Number of right line crossings																					
	Frequency of lane changes																					
Longitudinal																						
Input	Accelerator holds																					
	Velocity of accelerator position																					
	Jerk of accelerator position																					
	SD of accelerator position																					
	Mean brake force																					
	SD of brake force																					
Output	Mean speed																					
	SD of speed																					
	Exponentially weighted moving average of speed																					
	Time to collision																					

		Events																				
		Urban (1)						Highway (2)						Rural (3)								
	Dependent measure	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	7	8	9
	(TTC)																					
	Time headway																					
	Variation in time headway																					
	Did participant stop?																					
Event Contingent																						
Traffic related	Time gap accepted																					
	Decision time																					
	Number of traffic control violations																					
	Number of collisions																					
	Near misses																					
	Degree of conflict																					
Smoothness	Delay time																					
	Rise time																					
	Peak time																					
	Max overshoot																					
	Settling time																					
	How well it fits the model																					
Eye movement																						
Statistical distribution	SD of gaze																					
	Gaze kurtosis																					
	Dwell duration																					
	Frequency of rear view																					

		Events																				
		Urban (1)						Highway (2)						Rural (3)								
	Dependent measure	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	7	8	9
	mirror glances																					
	Frequency of side mirror glances																					
	Frequency of speedometer glances																					
Event Contingent	Glance direction																					
	Had movement																					
	Timing of participant looking at side mirror																					
	Timing of participant looking at rear view mirror																					
	Glance frequency at particular object																					
Driver physical state																						
Postural stability	Pressure output (global and local)																					
	Pressure and force over time																					
	Pressure point mapping																					
Eye blink	PERCLOS																					
	Eye blink frequency																					

		Events																				
		Urban (1)						Highway (2)						Rural (3)								
	Dependent measure	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6	7	8	9
	Eye blink duration																					
Combined measures																						
	Correlation between road curvature and eye movements																					
	Correlation between eye movements and steering																					
	Correlation between Steering and Road Curvature																					
	Correlation between eye movements and SDLP																					
	Correlation between head turn and steering wheel movement																					

F.4 Logstream Descriptions

A logstream is a data variable that can be set by the scenario. This is usually used to express in the data stream that the subject has reached a specific location or that a specific event has occurred.

F.4.1 Logstream 1: Event Count

Logstream 1 indicates a sequential count of scenario events from beginning to end. Since the order of events is different for the three equivalent scenarios, this number does not always correspond to the same scenario event.

F.4.2 **Logstream 2: Event ID**

Logstream 2 indicates the current active scenario event; each event has a unique ID that remains the same for each event across all three equivalent drives. The ID is 3 digits in length. The digit in the hundreds place is 1 for urban events, 2 for interstate events, and 3 for rural events. For example, for the second urban event, Logstream 2 is set to 102.

F.4.3 **Logstream 3: Temporal Event Data**

Logstream 3 indicates the occurrence of sub-events that have a temporal reference to the position of the subject vehicle or other objects or events in the scenario event. For example, information relating to the timing of stoplights is recorded in this logstream. The specific sub-events is described in the specification of each scenario event.

F.4.4 **Logstream 4: Spatial Event Data**

Logstream 4 indicates the occurrence of sub-events that have a spatial reference to the position of the subject vehicle or other objects or events in the scenario event. For example, this logstream will change when the subject vehicle is 500 feet from an intersection. The specific sub-events are described in the specification of each scenario event.

F.4.5 **Logstream 5: Road Sub-Section**

Logstream 5 indicates the current road section type. A value of

- 11 indicates the participant is on an urban commercial segment
- 12 indicates the participant is on an urban residential segment
- 13 indicates the participant is on an urban section without parking
- 14 indicates the participant is leaving the residential section
- 21 indicates the participant is on an interstate entrance ramp
- 22 indicates the participant is on the interstate
- 23 indicates the participant is on the exit ramp
- 31 indicates the participant is on the rural lit segment
- 32 indicates the participant is on the rural unlit segment
- 33 indicates the participant is on the rural gravel segment
- 34 indicates the participant is on the driveway segment
- 35 indicates the participant is leaving the Impact rural section
- 36 indicates the participant is on the rural straight segment

F.5 Embedded Audio

During the drive the participant will have prerecorded audio instructions played to them. The audio instructions will provide the participant with landmark-based navigational instructions. The restart instructions are played at the start of a “restart” drive. A restart drive is required if the participant misses a turn or makes an incorrect turn. The drive is restarted, and the participant is placed a short distance before the turn they missed. The instruction number is the audio instruction that matches the value in the SCC_Audio_Trigger cell in the DAQ file. Table F3 provides a full list of embedded audio messages used in the study.

Table F3. Embedded audio messages

Instruction Number	Title	Audio Message	Location Played
301	Start Drive	Drive until you see the Shell gas station and then turn left at the intersection.	125 ft. after the participant pulls out.
302	Urban Portion	Continue driving and take Interstate 30 south.	Shortly after beginning of Urban Event 106: Urban Curves
313	Distraction 1	At this time, please turn on the CD player, select track 17, then track 9, then press off.	As soon participant gets within 5 seconds headway to the first heavy truck; no later than approximately 6,500 ft. from the end of the on-ramp
314	Distraction 2	At this time, please turn on the CD player, select track 2, then track 15, then press off.	approximately 10,000 ft. from the end of the on-ramp
315	Distraction 3	At this time, please turn on the CD player, select track 6, then track 11, then press off.	approximately 15,000 ft. from the end of the on-ramp
303	Interstate 37	Drive to the Highway 94 exit and continue towards Carbondale.	Start of Interstate Event 205: Interstate Curves
326	Rural Right	Continue on Highway 94 and bear to the right after passing Earl’s service station.	375 ft. after start of Rural Event 302: Lighted Rural
305	Destination	Your destination is the first residence on the right.	Start of Rural Event 306: Gravel Rural

306	Stop	You have reached your destination.	75 ft. after entrance to driveway in Rural Event 307: Driveway
321	Restart 1	On the green light, drive until you see the Shell gas station and then turn left at the intersection.	The first intersection before Urban Event 105: Left Turn
322	Restart 2	Continue driving and take Interstate 30 South.	500 ft. before Interstate Event 201: Turn On Ramp
323	Restart 3	Drive to the Highway 94 exit and continue towards Carbondale.	Interstate Event 206: Exit Ramp
326	Restart 4 Right	Continue on Highway 94 and bear to the right after passing Earl's service station	Immediately after hairpin curve in Rural Event 304: Dark Rural
326	Restart 5 Right	Continue on Highway 94 and bear to the right after passing Earl's service station	Immediately after hairpin curve in Rural Event 304: Dark Rural
351	Stop	This is the end of your drive. Please come to a complete stop and shift into park.	10 minutes after starting event 311

F.6 In-cab Instructions

The following instructions are given to the participant after they have been seated in the simulator cab and before they begin to drive.

F.6.1 **Simulator motion**

This file is recorded message that is played by the control room experimenter as the simulator is moving to the starting position. "The simulator is moving towards its start position. During this time you may hear rumbling and feel vibrations. This is perfectly normal. There are microphones in the cab so the simulator operator can hear you at all times. If for any reason you wish to stop driving, please let us know. The operator can bring you to a stop in just a few seconds."

F.6.2 **Practice drive**

The ride-along experimenter reads these instructions before the start of the drive. "Your first drive will be a practice drive. It is designed to help you get used to the simulator. During this drive you should become familiar with driving at the various posted speed limits and recognizing traffic control devices. When it is time to begin, instructions will tell you to merge into traffic. Onboard navigational instructions will provide directions to the interstate. A recording will tell you when it is time to stop. Do you have any questions?"

F.6.3 **Data Collection Drive**

The ride-along experimenter reads these instructions before the start of the drive. "The main drive will start shortly. Remember to listen to the on-board instructions carefully. If you have any uncertainty about navigating during the drive, please ask. When the scenery comes on, please press on the brake, shift into drive and merge into traffic when it is safe to do so. Do you have any questions at this time?" (In-cab researcher responds to questions).

F.7 Scenarios

This section describes the layout of the scenarios for this study. A scenario consists of several driving segments that combine to form an experimental drive. All scenarios in this study have three distinct driving segments in the following order: urban, interstate, and rural. The order of these segments remains the same in all scenarios. Only the order of the events within the segments changes between scenarios. Although the order of events changes between scenarios, the scenario is designed to remain similar in duration and comprised of the same tiles. The urban section is comprised of 3 different versions of buildings, gas stations and different rotations. The differences in the interstate and rural sections are related to curve direction and radii of curve. Table F4 provides details about the differences across the scenarios. Figure 18 illustrates the three different road networks.

Table F4. Scenario Differences

	Scenario 1	Scenario 2	Scenario 3
1st Urban Intersection	1 (rotation:0)	2 (rotation: 90)	3 (rotation: 180)
2nd Urban Intersection	2 (rotation: 90)	3 (rotation: 0)	1 (rotation: 180)
3rd Urban Intersection	3 (rotation: 0)	2 (rotation: 90)	1 (rotation: 180)
1st Freeway Curve	Left (4500)	Left (4500)	Right (3100)
2nd Freeway Curve	Right (3100)	Right (3100)	Left (4010)
3rd Freeway Curve	Right (4010)	Left (4010)	Left (4500)
1st Rural Curve	Left (2100)	Right (2100)	Left (2100)
2nd Rural Curve	Right (456)	Left (456)	Right (456)
3rd Rural Curve	Left, Right (hill) (2446 total)	Left, Right (hill) (2446 total)	Left (3850)
4th Rural Curve	Left (3850)	Right (3850)	Left, Right (hill) (2446 total)
Additional segments for ACMI			
5th Rural Curve (Gravel after driveway)	Right (2741)	Right (2741)	Right (hill) (2741 total)

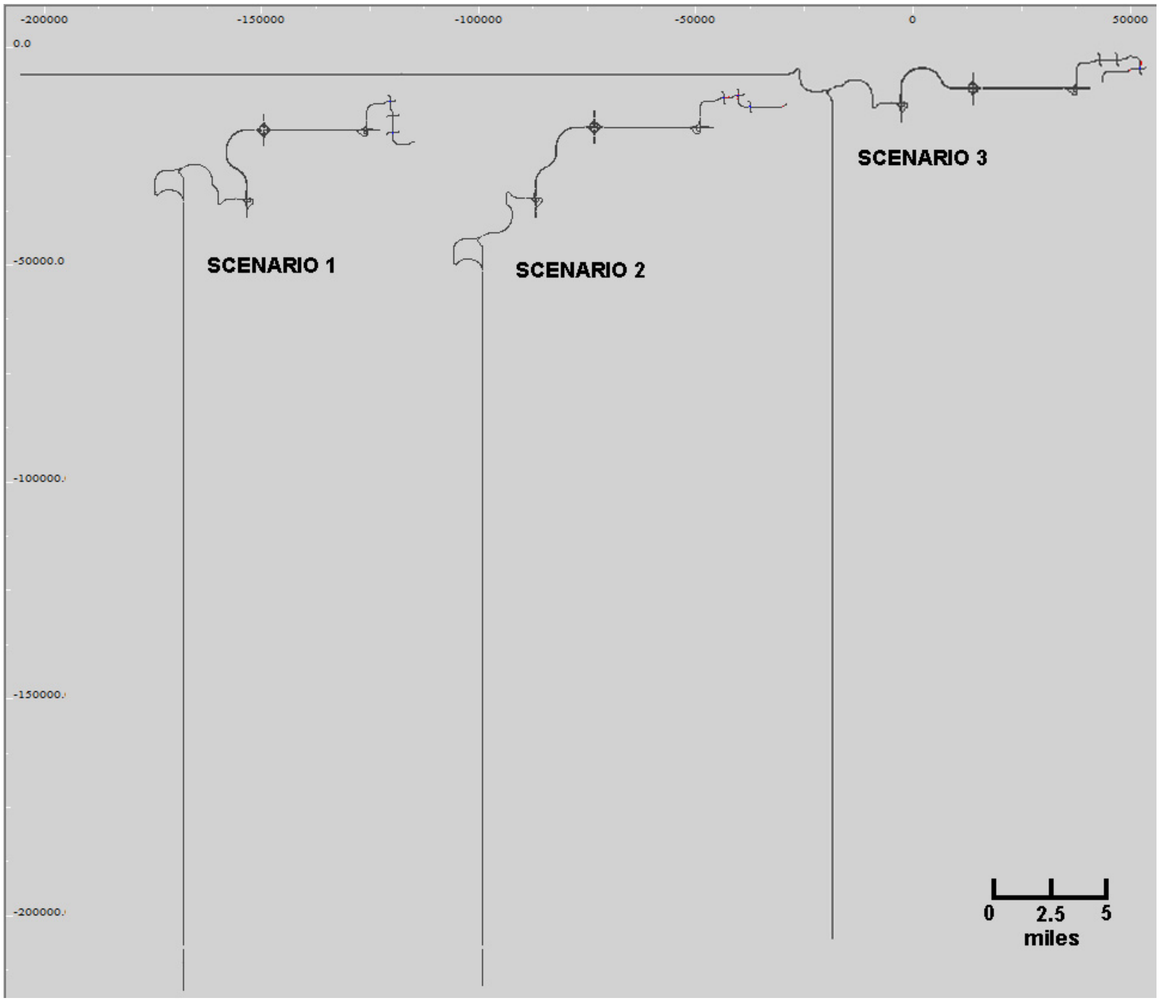

Figure F1. Road networks for this study

The spatial and logical constraints require that the order of most events remains the same between scenarios. Those events that are different have been marked in gray in Table F5.

Table F5. Scenario event orders

Event	Scenario 1	Scenario 2	Scenario 3
1	Urban Event 101: Pull Out	Urban Event 101: Pull Out	Urban Event 101: Pull Out
		Urban Event 111: Urban Drive	Urban Event 111: Urban Drive
2	Urban Event 102: Urban Drive	Urban Event 103: Green Light	Urban Event 105: Left Turn
3	Urban Event 103: Green Light	Urban Event 102: Urban Drive	Urban Event 102: Urban Drive
4	Urban Event 104: Yellow Light Dilemma	Urban Event 105: Left Turn	Urban Event 103: Green Light
5	Urban Event 105: Left Turn	Urban Event 104: Yellow Light Dilemma	Urban Event 104: Yellow Light Dilemma
6	Urban Event 106: Urban Curves	Urban Event 106: Urban Curves	Urban Event 106: Urban Curves
7	Interstate Event 201: Turn On Ramp	Interstate Event 201: Turn On Ramp	Interstate Event 201: Turn On Ramp
8	Interstate Event 202: Merge On	Interstate Event 202: Merge On	Interstate Event 202: Merge On
9	Interstate Event 203:	Interstate Event 203:	Interstate Event 203:
10	Interstate Event 204: Merging Traffic	Interstate Event 204: Merging Traffic	Interstate Event 204: Merging Traffic
11	Interstate Event 205: Interstate Curves	Interstate Event 205: Interstate Curves	Interstate Event 205: Interstate Curves
12	Interstate Event 206: Exit Ramp	Interstate Event 206: Exit Ramp	Interstate Event 206: Exit Ramp
13	Rural Event 301: Turn Off Ramp (Transitional)	Rural Event 301: Turn Off Ramp (Transitional)	Rural Event 301: Turn Off Ramp (Transitional)

14	Rural Event 302: Lighted Rural	Rural Event 302: Lighted Rural	Rural Event 302: Lighted Rural
15	Rural Event 303: Transition to Dark Rural	Rural Event 303: Transition to Dark Rural	Rural Event 303: Transition to Dark Rural
16	Rural Event 304: Dark Rural	Rural Event 304: Dark Rural	Rural Event 304: Dark Rural
17	Rural Event 305: Gravel Transition (Y-intersection)	Rural Event 305: Gravel Transition (Y-intersection)	Rural Event 305: Gravel Transition (Y-intersection)
18 (Right)	Rural Event 306: Gravel Rural	Rural Event 306: Gravel Rural	Rural Event 306: Gravel Rural
19 (Right)	Rural Event 307: Driveway	Rural Event 307: Driveway	Rural Event 307: Driveway
20 (Right)	Rural Event 308: Gravel Extension	Rural Event 308: Gravel Extension	Rural Event 308: Gravel Extension
21(Right)	Rural Event 309: Gravel Transition to Straight Segment	Rural Event 309: Gravel Transition to Straight Segment	Rural Event 309: Gravel Transition to Straight Segment
22 (Right)	Rural Event 311: Straight Segment	Rural Event 311: Straight Segment	Rural Event 311: Straight Segment

F.7.1 **Practice Drive**

This scenario allows participants the opportunity to get familiar with the simulator and the study drive route. It is comprised of an urban section, an interstate ramp and interstate driving. The drive begins in the urban area where participants are instructed to turn left at the first intersection and then listen to the navigational instructions provided. The practice route using the same database as Scenario 1, with the exception they take a different exit ramp.

F.7.2 **Scenario 1**

This scenario has three segments as shown in Figure F2. Each segment is shown in more detail in Figure F3, Figure F4, and Figure F5. Each figure is accompanied with a table that provides more detailed information about the duration and length of each event within the segment. It should be noted that the elevation throughout the scenario is the same with two exceptions. Those two are the exit ramp the participant takes and during a curve in the rural segment. More detail is provided later.

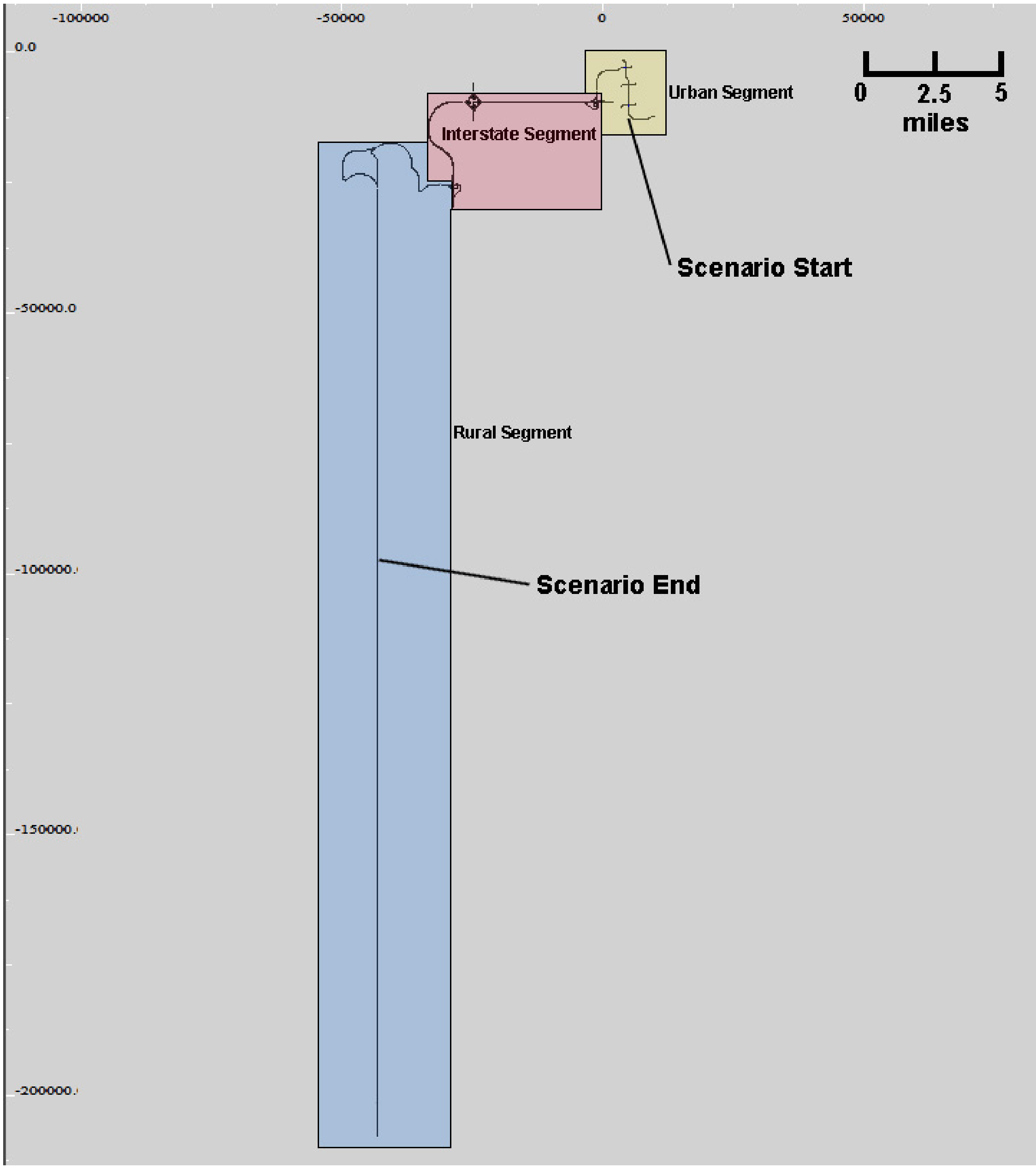

Figure F2. Scenario 1 road network

F.7.2.1 **Urban Segment**

The participant begins the urban portion of the scenario at the pullout event (location 101). The participant then continues through the events through the urban section (marked in yellow) toward the interstate segment.

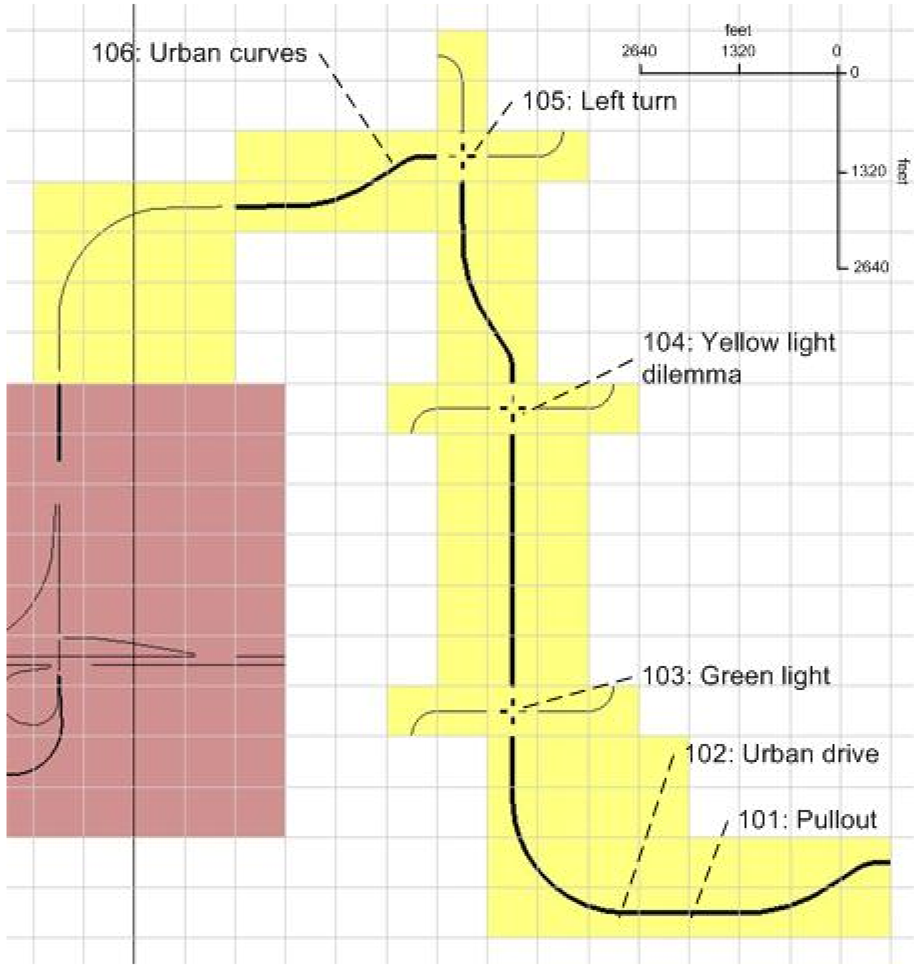

Figure F3. Segment 1, urban events

Table F6 indicates the distance required for each event and the approximate length of time that it takes a participant to traverse this segment at the posted speed limits. The urban events are designed to work at speeds from 15 to 45 mph.

Table F6. Scenario 1, urban segment times and distances

Event	Assumed Speed (mph)	Actual Distance (feet)	Cumulative Distance (feet)	Actual Time (minutes)	Cumulative Time (minutes)
101: Pull Out	15	270	270	0.20	0.20
102: Urban Drive	25	3,670	3,940	1.67	1.79
103: Green Light	25	3,970	7,910	1.80	3.60
104: Yellow Dilemma	25	3,450	11,360	1.57	5.16
105: Left Turn	25	890	12,250	0.40	5.57
106: Urban Curves	30, 45 for last 400’	73,10	19,560		
Total		**19,300**		**8.31**	

F.7.2.2 **Interstate Segment**

Following the urban segment, the participant takes the on-ramp to get on the interstate.

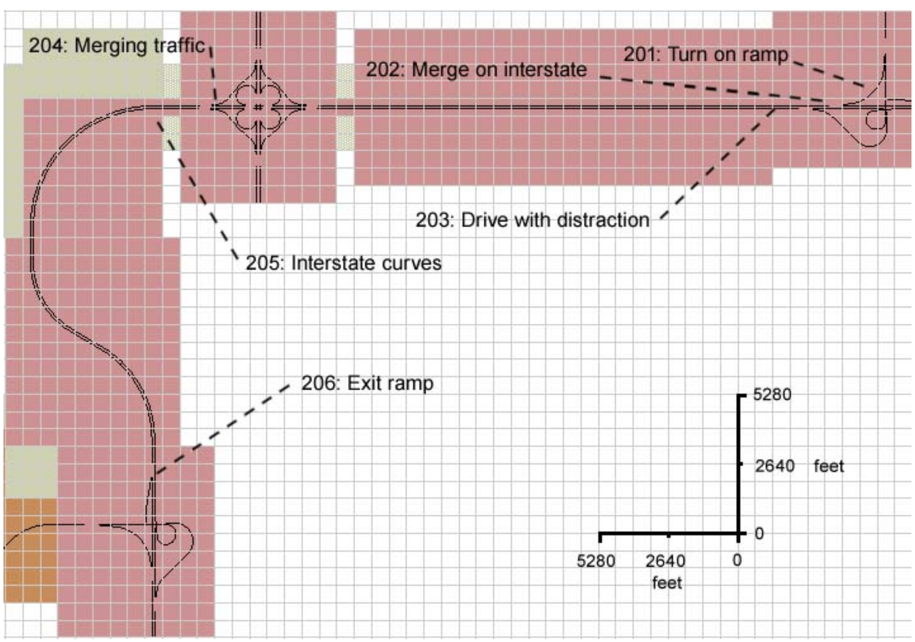

Figure F4. Segment 2, interstate events

Table F7 indicates the distance required and the approximate length of time that it takes a participant to traverse this segment at posted speed limits.

Table F7. Scenario 1, interstate segment times, and distances

Event	Assumed Speed (mph)	Actual Distance (feet)	Cumulative Distance (feet)	Actual Time (minutes)	Cumulative Time (minutes)
201: Turn On Ramp	25	1,000	1,000	0.45	0.45
202: Merge On	45	3,500	4,500	0.88	1.34
203: Drive with Distraction	70	18,000	22,500	2.96	4.30
204: Merging Traffic	70	6,100	28,600	0.99	5.29
205: Interstate Curves	70	19,300	47,900	3.13	8.43
206: Exit Ramp	35	1,500	49,400	0.49	8.91
Total		**49,400**		**8.91**	

F.7.2.3 **Rural Segment**

Following the interstate segment, the participant takes the off-ramp to exit the interstate and takes a right turn at the intersection to turn toward the rural portion of the scenario.

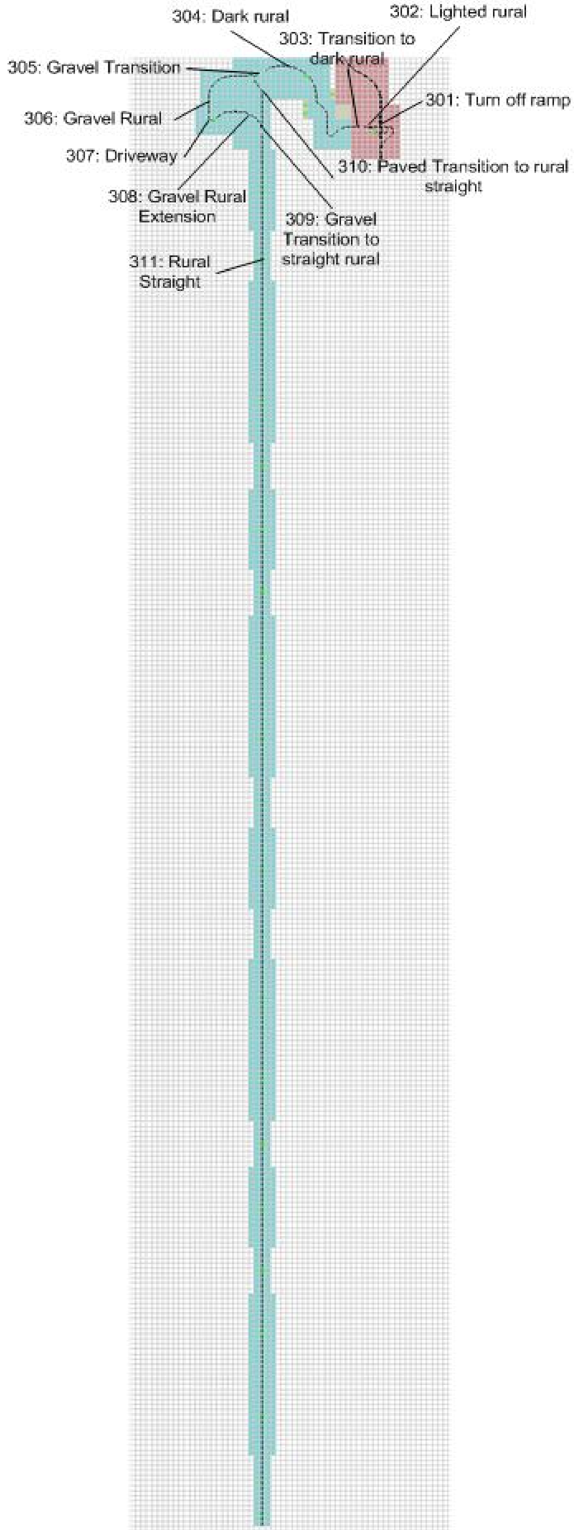

Figure F5. Segment 3, rural events

Table F8 indicates the distance required and the approximate length of time that it takes a participant to traverse this segment at posted speed limits.

Table F8. Scenario 1, rural segment times, and distances

Event	Assumed Speed (mph)	Actual Distance (feet)	Cumulative Distance (feet)	Actual Time (minutes)	Cumulative Time (minutes)
301: Turn Off Ramp	30	1,500	1,500	0.5	0.5
302: Lighted Rural	55	750	2,250	0.15	0.65
303: Transition to Dark	55	1,500	3,750	0.30	0.95
304: Dark Rural	55	14,510	18,260	3	4
305: Gravel Transition	55	2,420	20,680	0.5	4.5
306: Gravel Rural	45	5,940	26,620	1.5	6
307:Driveway	15	660	27,280	0.5	6.5
Total		**27,280**		**6.5**	
ACMI ADDITIONS					
Bear Right at Y					
308: Gravel Extension	45	6,600	27,940	2.36	8.86
309: Gravel/straight transition	45	1,000	28,940	0.25	9.11
311: Rural Straight	55	48,400	77,340	10	19.11
Total		**83,280**		**19.11**	

F.7.3 Scenario 2

The segments for this scenario are shown in Figure F6.

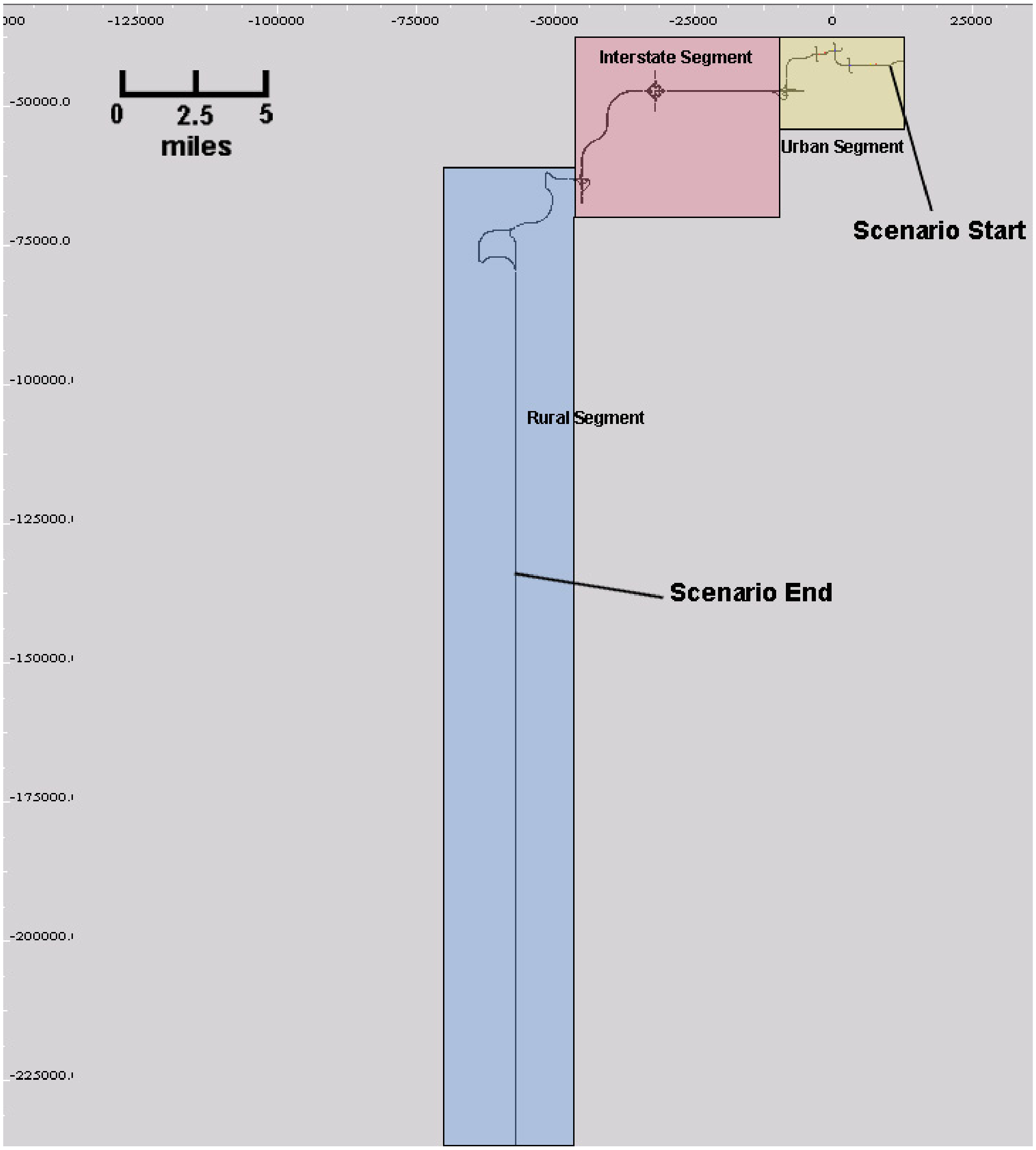

Figure F6. Scenario 2 road network

F.7.4 Scenario 3

The segments for this scenario are shown in Figure F7.

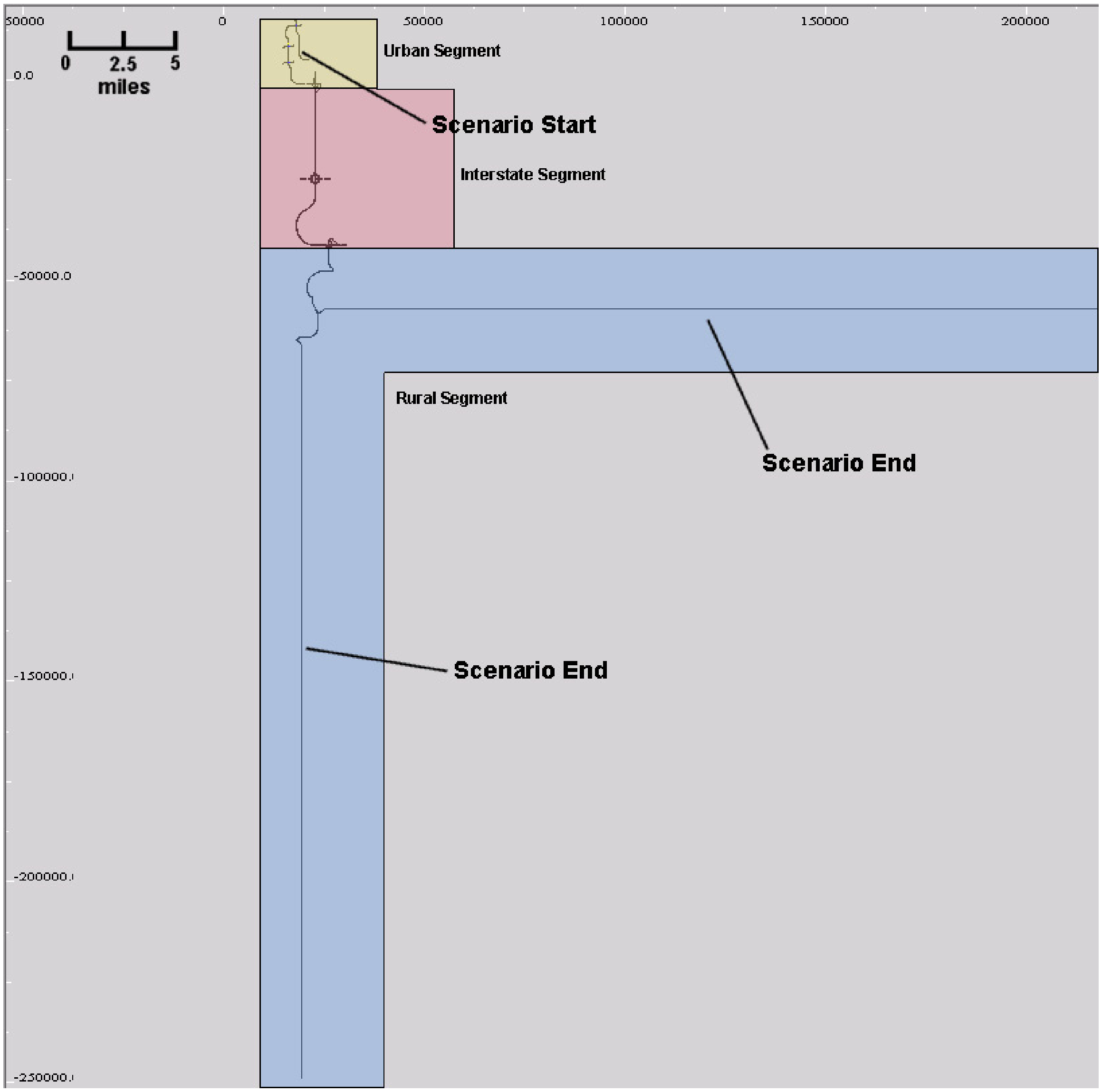

Figure F7. Scenario 3 road network

F.8 ACMI changes to event specification

The rationale for ACMI scenarios was to make as few changes to the IMPACT scenarios as possible. Table 28 represents the changes made to IMPACT scenarios to create ACMI events. Additional database and events were added to the end of the original IMPACT scenario.

Table F9. ACMI CHANGES

Event	Change
Event 101: Pull out	No change
Event 111: Urban Drive	No change
Event 102: Urban Drive	No change
Event 103: Green Light	No change
Event 104: Yellow Light Dilemma	No change
Event 105: Left Turn	No change
Event 106: Urban Curves	No change
Event 201: Turn on Ramp	No change
Event 202: Merge On	No change
Event 203: Drive with Distraction	No change
Event 204: Merging Traffic	No change
Event 205: Interstate Curves	No change
Event 206: Exit Ramp	No change
Event 301: Turn off Ramp	No change
Event 302: Lighted Rural	No change
Event 303: Transition to Dark Rural	No change
Event 304: Dark Rural	No change
Event 305: Gravel Transition	Gravel transition title changed to gravel/paved transition at y-intersection.
Event 306: Gravel Rural	<u>Actual Event</u> **F.3 Logstream 1 is incremented; logstream 2 is set to 306. Instruction #305 is not played for ACMI.** The participant continues along the gravel road section.

	The participant navigates a series of curves. (The participant adjusts their speed appropriately for the gravel road surface and curves.) <u>End Condition:</u> The participant is 550 feet before driveway
Event 307: Driveway	<u>End Condition:</u> **200 ET AFTER THE PARTICIPANT PASSES THE DRIVEWAY**

F.9.1 **Rural Event 308: Gravel Rural Extension**

At distance of 250 feet after the driveway the gravel road continues, the participant will experience a series of curves and straight-a ways. Figure F8 Gravel rural extension provides illustration of gravel rural extension.

RURAL EVENT 306: GRAVEL RURAL			
RATIONALE	In this segment, the driver will continue to navigate on an unlighted gravel rural road that contains a series of curves and has no posted speed limit to provide a transition to straight paved section		
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 6600 Road type (lanes, surface): 2-lane gravel with little or no shoulder Speed limit (in mph): Not posted (assumed 45 mph) Curvature: Varying straight and curved sections (approximate radius 2741) Intersection type: None Time of Day/Date: Night, dark		
PREPARATION	The participant passes driveway to IMPACT end. The participant navigates an unlighted two-lane rural gravel road that contains a series of curves straight a ways and has no posted speed limit. (The participant is assumed to travel at approximately 45 mph.)		
START CONDITIONS	The participant has traveled 250 feet past the driveway for IMPACT.		
ACTUAL EVENT	Logstream 1 is incremented; logstream 2 is set to 308. The participant continues along the gravel road section. The participant navigates a series of curves and straight roads. (The participant adjusts their speed appropriately for the gravel road surface and curves.)		
END CONDITIONS	The participant is 500 feet before transition from gravel to pavement.		
CLEANUP	None		
EVENT	DESCRIPTION	IDENTIFIER	UNITS

Rural Event 306: Gravel Rural			
Contingency (Variables that define dependence of the current event on the interpretation of the previous event)			
Scenario Performance (Measures that indicate if the event is operating as expected)	Description	Identifier	Units
	No cars in either direction		
	Dark gravel road		
	No oncoming traffic	E308_oncoming_freq	avg. sec between cars
Assumed Driver Behavior (Measures that indicate whether the participant behaves according to the assumptions)	Description	Identifier	Units
	Initial speed (speed at beginning of event)	E308_sp_init	mph
	End speed (speed at end of event)	E308_sp_mavgnd	mph
Impairment Indicators (Measures that assess whether the event is sensitive to alcohol impairment)	Description	Identifier	Units
	SD of lane position relative to mean lane position	E308_lp_sd	ft
	SD of lane position relative to center of lane	E308_lpn_sd	ft
	Lane position	E308_lp_avg	ft
	SD of speed (relative to mean speed)	E308_sp_sd	mph
	SD of speed (relative to assumed or posted speed limit)	E308_spn_sd	mph
	Speed	E308_sp_avg	mph
	Speed relative to assumed speed	E308_spn_avg	mph
	Frequency of glances to rear view mirror	E308_glance_freq_rear	glances/sec

RURAL EVENT 306: GRAVEL RURAL			
	Steering wheel reversals	E308_steer_rev	
	SD of steering wheel position	E308_steer_sd	
	Velocity of steering wheel	E308_steer_vel	
	Jerk of steering wheel	E308_steer_jerk	
	Steering error	E308_steer_error	
	Time to line crossing (TLC)	E308_tlc	
	Proportion of time TLC>2s	E308_tlc_2	proportion
	95% TLC	E308_tlc_95	
	Accelerator holds	E308_accel_holds	
	Number of left line crossings	E308_left_cross	count
	Number of right linet crossings	E308_right_cross	count
	Velocity of accelerator position	E308_accel_vel	
	Jerk of accelerator position	E308_accel_jerk	
	SD of accelerator position	E308_accel_sd	
	Glance frequency at particular object	E308_freq_glance	
	Pressure output(global and local)	E308_out_pres	
	Pressure and force over time	E308_force_pres	
	Pressure point mapping	E308_map_pres	
	PERCLOS	E308_perclos	
	Eye blink frequency	E308_blink_freq	
	Eye blink duration	E308_blink_dur	
	Percent in center based on median location of gaze	E308_gaze_center	
	Correlation between road curvature and eye movements	E308_eye_curve	
	Correlation between steering and road curvature	E308_steer_curve	
	Correlation between eye movements and SDLP	E308_eye_sdlp	
	Correlation between eye movements and steering	E308_eye_steer	
	Number of collisions	E308_num_col	
	Near misses	E308_num_miss	
	SD of gaze	E308_gaze_sd	

Rural Event 306: Gravel Rural			
	Gaze kurtosis	E308_gaze_kurt	
	Dwell duration	E308_dwell_time	
	Frequency of side mirror glances	E308_glance_freq_side	
	Frequency of speedometer glances	E308_glance_freq_speed	
	Glance direction	E308_glance_dir	
Algorithm Input (Measures that is input to the algorithm)	Description	Identifier	Units
	Mean lane position		
	Mean speed		
	SD of lane position relative to mean		
	SD of speed relative to mean		
	Steering wheel reversals		

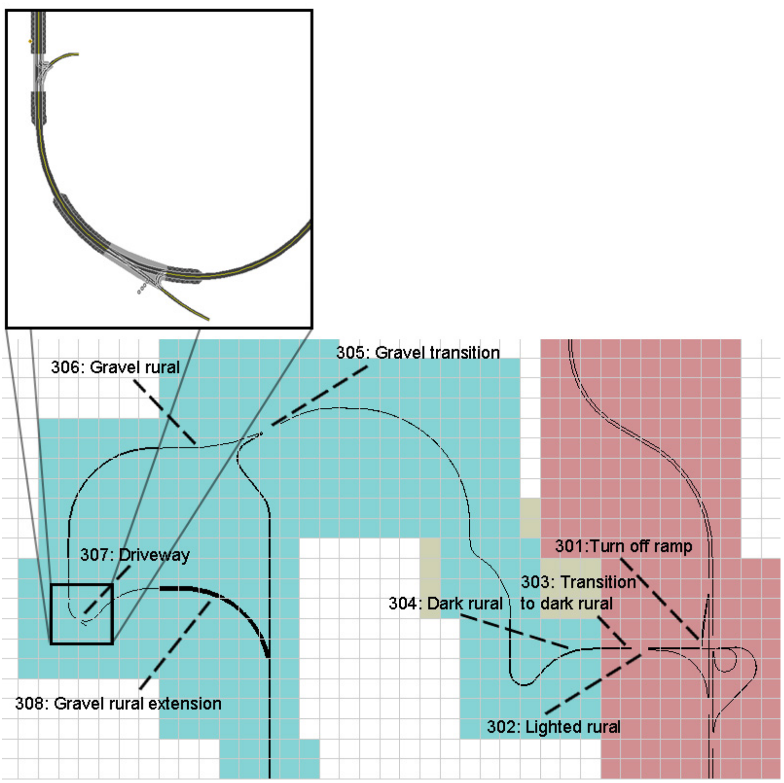

Figure F8. Gravel rural extension

F.9.2 Rural Event 309: Gravel Transition to Straight Rural

After driving on gravel extension the participant will merge onto a paved straight segment. This event only occurs when subject bears right at y-intersection. Figure F9 represents that transition from gravel to straight rural segment.

RURAL EVENT 306: GRAVEL RURAL			
RATIONALE	In this segment, the driver will continue to navigate from an unlighted gravel rural road and merge onto a paved straight segment of road.		
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 1000 Road type (lanes, surface): 2-lane gravel with little or no shoulder Speed limit (in mph): Not posted (assumed 45 mph) Curvature: None Intersection type: Merge Time of Day/Date: Night, dark		
PREPARATION	The participant approaches merge to pavement. The participant navigates an unlighted two-lane rural gravel road that contains a series of curves and has no posted speed limit. (The participant is assumed to travel at approximately 45 mph.)		
START CONDITIONS	The participant is 500 feet from paved straight.		
ACTUAL EVENT	Logstream 1 is incremented; logstream 2 is set to 309. The participant continues along the gravel road section and merges onto paved straight. The participant navigates merge transition.		
END CONDITIONS	The participant is 500 feet past merge onto straight segment.		
CLEANUP	None		
EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS
SCENARIO PERFORMANCE (MEASURES THAT	DESCRIPTION	IDENTIFIER	UNITS
	No cars in either direction		
	Dark gravel road		

Rural Event 306: Gravel Rural			
indicate if the event is operating as expected)	No oncoming traffic	E309_oncoming_freq	avg. sec between cars
Assumed Driver Behavior (Measures that indicate whether the participant behaves according to the assumptions)	Description	Identifier	Units
	Initial speed (speed at beginning of event)	E309_sp_init	mph
	End speed (speed at end of event)	E309_sp_mavgnd	mph
Impairment Indicators (Measures that assess whether the event is sensitive to alcohol impairment)	Description	Identifier	Units
	SD of lane position relative to mean lane position	E309_lp_sd	ft
	SD of lane position relative to center of lane	E309_lpn_sd	ft
	Lane position	E309_lp_avg	ft
	SD of speed (relative to mean speed)	E309_sp_sd	mph
	SD of speed (relative to assumed or posted speed limit)	E309_spn_sd	mph
	Speed	E309_sp_avg	mph
	Speed relative to assumed speed	E309_spn_avg	mph
	Frequency of glances to rear view mirror	E309_glance_freq_rear	glances/sec
	Steering wheel reversals	E309_steer_rev	
	SD of steering wheel position	E309_steer_sd	
	Velocity of steering wheel	E309_steer_vel	
	Jerk of steering wheel	E309_steer_jerk	
	Steering error	E309_steer_error	
	Time to line crossing (TLC)	E309_tlc	
	Proportion of time TLC>2s	E309_tlc_2	proportion
	95% TLC	E309_tlc_95	
	Accelerator holds	E309_accel_holds	

RURAL EVENT 306: GRAVEL RURAL			
	Number of left line crossings	E309_left_cross	count
	Number of right line crossings	E309_right_cross	count
	Velocity of accelerator position	E309_accel_vel	
	Jerk of accelerator position	E309_accel_jerk	
	SD of accelerator position	E309_accel_sd	
	Glance frequency at particular object	E309_freq_glance	
	Pressure output(global and local)	E309_out_pres	
	Pressure and force over time	E309_force_pres	
	Pressure point mapping	E309_map_pres	
	PERCLOS	E309_perclos	
	Eye blink frequency	E309_blink_freq	
	Eye blink duration	E309_blink_dur	
	Percent in center based on median location of gaze	E309_gaze_center	
	Correlation between road curvature and eye movements	E309_eye_curve	
	Correlation between steering and road curvature	E309_steer_curve	
	Correlation between eye movements and SDLP	E309_eye_sdlp	
	Correlation between eye movements and steering	E309_eye_steer	
	Number of collisions	E309_num_col	
	Near misses	E309_num_miss	
	Frequency of side mirror glances	E309_glance_freq_side	
	Frequency of speedometer glances	E309_glance_freq_speed	
	Glance direction	E309_glance_dir	
ALGORITHM INPUT (MEASURES THAT IS INPUT TO THE ALGORITHM)	DESCRIPTION	IDENTIFIER	UNITS
	Mean lane position		
	Mean speed		
	SD of lane position relative to mean		
	SD of speed relative to mean		
	Steering wheel reversals		

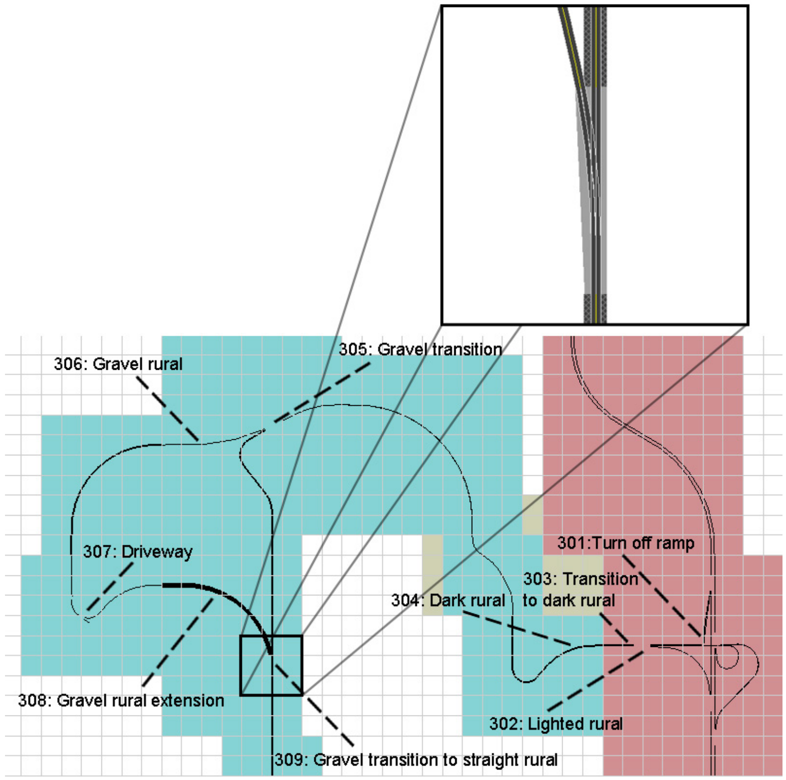

Figure F9. Gravel transition to straight rural

F.9.3 **Rural Event 311: Rural Straight**

The starting locations for this event are different depending on which direction is taken at y-intersection. If left is taken, the event follows the paved transition (begins 500 feet after transition to straight), if right is taken, the event follows the gravel transition (begins 500 feet after transition to straight). Figure F10 represents the rural straight road.

RURAL EVENT 306: GRAVEL RURAL	
RATIONALE	In this segment, the driver will continue to navigate on an unlighted paved rural road for 10 minutes. Previous drowsy driving research indicates that long straight roadways provide a monotonous route that leads to increased drowsiness measures.
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 48400 Road type (lanes, surface): 2-lane asphalt Speed limit (in mph): 55 mph Curvature: Straight, no curves Intersection type: None Time of Day/Date: Night, dark

RURAL EVENT 306: GRAVEL RURAL

PREPARATION	The participant passes driveway to IMPACT end. The participant navigates an unlighted two-lane rural gravel road that contains a series of curves and straight a ways and has no posted speed limit and merges onto straight away. (The participant is assumed to travel at approximately 45 mph.)		
START CONDITIONS	The participant has traveled 500 feet past paved transition onto rural straight The participant has traveled 500 ft. past the gravel transition onto rural straight		
ACTUAL EVENT	Logstream 1 is incremented; logstream 2 is set to 311. The participant continues along straight paved road for 10 minutes. Audio file # 351 is triggered to fire after 10 minutes of driving. The participant navigates a straight roadway.		
END CONDITIONS	The participant drives for 10 minutes and end of drive file #351 plays.		
CLEANUP	None		
EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS
SCENARIO PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	DESCRIPTION	IDENTIFIER	UNITS
	No cars in either direction		
	No oncoming traffic	E311_oncoming_freq	avg. sec between cars
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES	DESCRIPTION	IDENTIFIER	UNITS
	Initial speed (speed at beginning of event)	E311_sp_init	mph
	End speed (speed at end of event)	E311_sp_mavgnd	mph

Rural Event 306: Gravel Rural			
according to the assumptions)			
Impairment Indicators (Measures that assess whether the event is sensitive to alcohol impairment)	Description	Identifier	Units
	SD of lane position relative to mean lane position	E311_lp_sd	ft
	SD of lane position relative to center of lane	E31_lpn_sd	ft
	Lane position	E311_lp_avg	ft
	SD of speed (relative to mean speed)	E311_sp_sd	mph
	SD of speed (relative to assumed or posted speed limit)	E311_spn_sd	mph
	Speed	E311_sp_avg	mph
	Speed relative to assumed speed	E311_spn_avg	mph
	Frequency of glances to rear view mirror	E311_glance_freq_rear	glances/sec
	Steering wheel reversals	E311_steer_rev	
	SD of steering wheel position	E311_steer_sd	
	Velocity of steering wheel	E311_steer_vel	
	Jerk of steering wheel	E311_steer_jerk	
	Steering error	E311_steer_error	
	Time to line crossing (TLC)	E311_tlc	
	Proportion of time TLC>2s	E311_tlc_2	proportion
	95% TLC	E311_tlc_95	
	Accelerator holds	E311_accel_holds	
	Number of left line crossings	E311_left_cross	count
	Number of right line t crossings	E311_right_cross	count
	Velocity of accelerator position	E31_accel_vel	
	Jerk of accelerator position	E311_accel_jerk	
	SD of accelerator position	E311_accel_sd	
	Glance frequency at particular object	E311_freq_glance	
	Pressure output(global and local)	E311_out_pres	
	Pressure and force over time	E311_force_pres	
	Pressure point mapping	E311_map_pres	

RURAL EVENT 306: GRAVEL RURAL			
	PERCLOS	E311_perclos	
	Eye blink frequency	E311_blink_freq	
	Eye blink duration	E311_blink_dur	
	Percent in center based on median location of gaze	E311_gaze_center	
	Correlation between road curvature and eye movements	E311_eye_curve	
	Correlation between steering and road curvature	E311_steer_curve	
	Correlation between eye movements and SDLP	E311_eye_sdlp	
	Correlation between eye movements and steering	E311_eye_steer	
	Number of collisions	E311_num_col	
	Near misses	E311_num_miss	
	Frequency of side mirror glances	E311_glance_freq_side	
	Frequency of speedometer glances	E311_glance_freq_speed	
	Glance direction	E311_glance_dir	
ALGORITHM INPUT (MEASURES THAT IS INPUT TO THE ALGORITHM)	DESCRIPTION	IDENTIFIER	UNITS
	Mean lane position		
	Mean speed		
	SD of lane position relative to mean		
	SD of speed relative to mean		
	Steering wheel reversals		

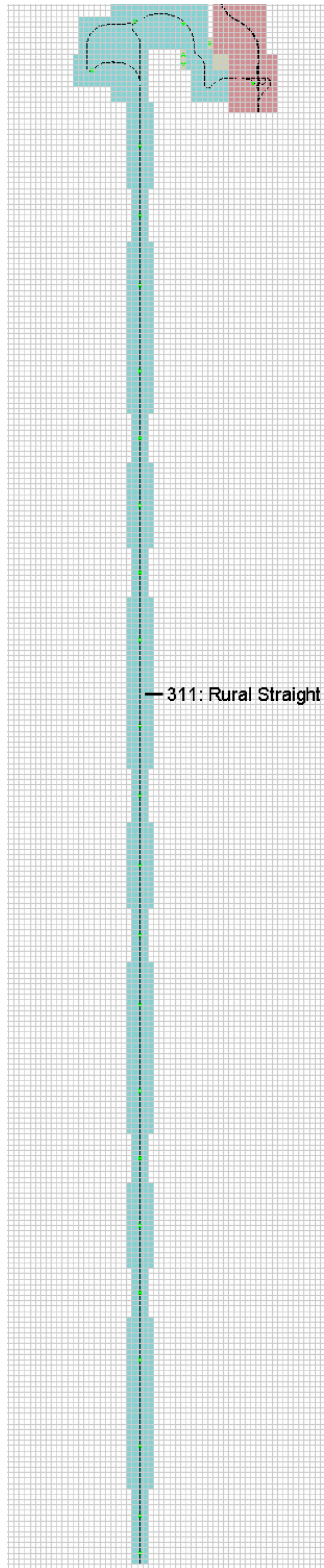

Figure F10. Rural Straight

F.10 IMPACT Event Specification

This section describes each event in detail. The order of the events will change across the three scenarios.

F.10.1 Urban Event 101: Pull Out

The vehicle is parallel parked along the side of the road. The participant will start the drive by pulling out onto a main road and driving in the same direction. The participant is pulling out into traffic with intermittent gaps. The gaps will vary in distance, and the participant will have to decide when to pull out. Figure F11 represents the vehicle pull out. The driver is represented by the red car.

URBAN EVENT 101: PULL OUT	
RATIONALE	The assumption is that the participant is driving home at night after being at a bar. The drive starts from parking spot parallel to the driving lane on an urban street. There is a car in front and behind the driver's vehicle. He must look for traffic in the rear and pull out when it is clear. There is no FARS rationale for this, but it represents a typical situation for a drinking driver and presents some challenges for an impaired driver---judging the distance from the car in front and in the rear and pulling out onto the street when traffic is clear from behind. Police blotters are filled with complaints by citizens of damage to their cars while they were parked. Many impaired drivers strike these cars and then leave the scene. This is a judgment situation for the driver and comes in the first scenario event. Drivers can easily leave this parking spot when sober. When impaired at .08 BAC, it may present a challenge.
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 660 Road type (lanes, surface): 2 driving lanes with on-road parking Speed limit (in mph): 25 Curvature: none Intersection type: none Time of Day/Date: night
PREPARATION	The simulation starts; the participant is parked in parking lane 21.5 ft behind one vehicle and 137 ft in front of a second vehicle. A series of cars pass the participant in the driving lane at varying gaps; the first gap that is presented is short (The participant waits for a reasonable gap between cars to pull out)
START CONDITIONS	Start of Simulation
ACTUAL EVENT	The simulation starts; logstream 1 is incremented, logstream 2 is set to 101, logstream 3 is set to 0, logstream 4 is set to 1, logstream 5 is set to 11. A series of cars is created behind the participant at the start of the drive. The cars are located approximately 60, 200, 465, and 1000 ft (CG to CG) behind the participant in the driving lane. The participant pulls out once a reasonable gap has presented itself. (The participant waits for a reasonable gap.) (The participant pulls out into the driving lane.) After participant has pulled out, a vehicle parked behind the driver pulls out into the driving lane. After the participant crosses the back of the first parked car, logstream 4 is set to 100 Approximately 125 feet after the driver pulls out of the parking lane, instruction #301 is played.

URBAN EVENT 101: PULL OUT			
END CONDITIONS	The participant has pulled out into traffic and is 250 feet from the initial start location.		
CLEANUP	None		
SCENARIO PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	DESCRIPTION	IDENTIFIER	UNITS
	Length of gaps	E101_gap_d_X (where X is the gap number, 1-6)	ft
	Length of gaps	E101_gap_t_X (where X is the gap number, 1-6)	Sec
	Vehicle creation distance from subject	E101_vehX_create_d (where X is passing vehicle 1-6)	ft
	Distance to vehicle parked in front of subject	E101_front_veh_d	ft
	Distance to vehicle parked behind subject	E101_rear_veh_d	ft
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES ACCORDING TO THE ASSUMPTIONS)	DESCRIPTION	IDENTIFIER	UNITS
	Pull-out time (time from start of simulation until participant passes rear of forward parked car)	E101_pullout_t	sec
	Time to finish accelerating (time from pull out until absolute value of acceleration averaged over 1 sec is less than a TBD threshold)	E101_acc_done_t	sec
	Distance to finish accelerating (time from pull out until absolute value of acceleration averaged over 1 sec is less than a TBD threshold)	E101_acc_done_d	ft
	Steering angle (min and max)	E101_steer_min E101_steer_max	deg
	Pulls forward (check to make sure participant does not put vehicle into reverse and back up before pulling out)	E101_pull_forward	binary 1=yes, 0 = no
ALCOHOL IMPAIRMENT INDICATORS (MEASURES THAT ASSESS WHETHER THE EVENT IS SENSITIVE TO ALCOHOL IMPAIRMENT)	DESCRIPTION	IDENTIFIER	UNITS
	Number of head turns to left before pulling out (threshold angle that defines a turn needs TBD)	E101_head_turn	count
	Number of glances at side mirror before pulling out (definition TBD once we have eye data)	E101_side_mirror	count
	Number of glances at rear mirror before pulling out (definition TBD once we have eye data)	E101_rear_mirror	binary 1=yes, 0 = no
	Time from last glance (head turn, side mirror, or rear mirror) until pullout	E101_last_glance	sec
	Gap participant takes	E101_gap_taken E101_gap_taken_d	number ft

URBAN EVENT 101: PULL OUT			
		E101_gap_taken_t	sec
	Collision	E101_collision	binary 1=yes, 0 = no
	Collision object	E101_collision_obj	Text descriptor of object
	Turn signal use	E101_turn_signal	Binary 1=yes, 0 = no
	Number of collisions	E101_num_col	
	Smoothness of lane change	E101_smooth_lat	
	Smoothness of acceleration	E101_smooth_long	
	Velocity of steering wheel	E101_steer_vel	
	Jerk of steering wheel	E101_steer_jerk	
	Velocity of accelerator position	E101_accel_vel	
	Jerk of accelerator position	E101_accel_jerk	
	SD of accelerator position	E101_accel_sd	
	PERCLOS	E101_perclos	
	Eye blink frequency	E101_blink_freq	
	Eye blink duration	E101_blink_dur	
	Percent in center based on median location of gaze	E101_gaze_center	
	Correlation between head turn and steering wheel movement	E101_headturn_wheel	
	Near misses	E101_num_miss	
	Degree of conflict	E101_deg_conflict	
	SD of gaze	E101_gaze_sd	
	Gaze kurtosis	E101_gaze_kurt	
	Dwell duration	E101_dwell_time	
ALGORITHM INPUT (MEASURES THAT IS INPUT TO THE ALGORITHM)	DESCRIPTION	IDENTIFIER	UNITS
	Time from last glance (head turn, side mirror, or rear mirror) until pullout	E101_last_glance	sec
	Gap participant takes	E101_gap_taken	number

URBAN EVENT 101: PULL OUT			
		E101_gap_taken_d E101_gap_taken_t	ft sec
	Mean accelerator position		
	Time from last glance (head turn, side mirror, or rear mirror) until pullout		
	Smoothness of lane change		
	Smoothness of acceleration		

- Jerk of accelerator position
- Jerk of steering wheel position
- Velocity of accelerator position
- Smoothness of lane change
- Over- or undershoot in lane position relative to nominal pullout maneuver
- Time from last glance (head turn, side mirror, or rear mirror) until pullout
- Max overshoot
- Minimum TTC to following vehicle during pullout
- Minimum TTC to parked vehicle ahead
- Relationship to passing vehicle as pullout

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when pulling out of a parking space are: time from last glance until pulling out, how close the vehicle came to another moving vehicle, the smoothness of pulling out, max overshoot, and jerk and velocity of accelerator position. As a person pulls out of the parking space, looking for other traffic is essential to safe driving and is something that alcohol impaired drivers tend to ignore**. The smoothness of lane change and max overshoot go hand in hand in the way a person pulls out of the parking space as unimpaired drivers will get into the lane fairly quickly and impaired drivers will have to adjust their position before settling on an adequate location (Struster, 1997). Jerk and velocity of accelerator position look at how smoothly the participant pulled out of the parking space in a longitudinal perspective. Alcohol impaired drivers have trouble slowing and speeding up in a smooth manner (Struster, 1997).

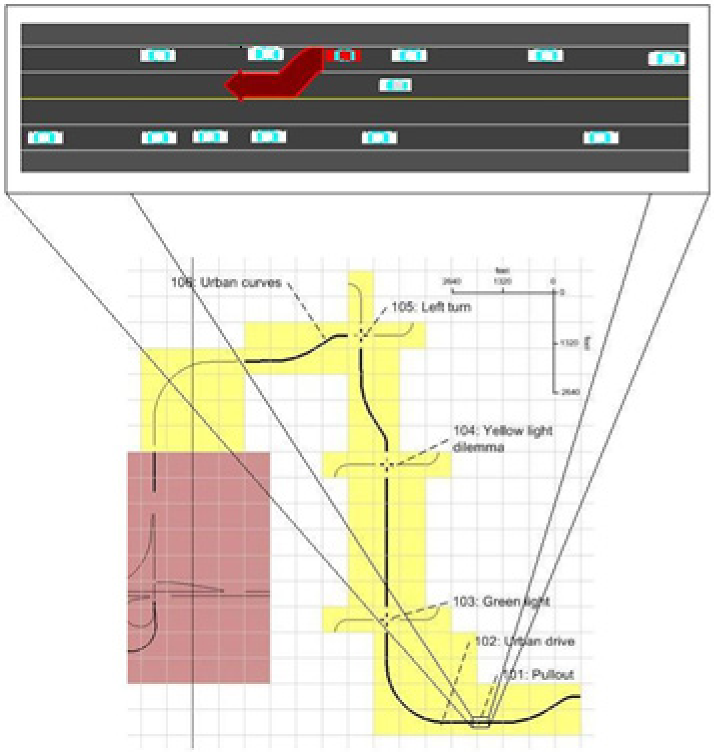

Figure F11. Participant pull out

F.10.2 Urban Event 111: Urban Drive

The main street onto which the participant will have pulled out is relatively narrow, with cars parked on both sides of the road. This event only exist in drives 2 and 3. This section was added to give the participant space get up to speed before the 2nd event in the drive. There is oncoming traffic and traffic behind and in front of the participant.

Urban Event 111: Urban Drive	
Rationale	This involves driving on a narrow urban road with parked cars on both sides and, oncoming traffic about once every 10 seconds. FARS rationale include over-representations in nighttime conditions on a dark but lighted road which is two lanes and undivided with oncoming traffic (over-representation of driving over center line). Impaired drivers also tend to drive too fast for these conditions.
Road Network Requirements	Overall length/distance needed to support event (in feet): 4620 Road type (lanes, surface): 2 driving lanes with on-road parking Speed limit (in mph): 25 Curvature: 90 deg turn, radius of 1100 ft Intersection type: none Time of Day/Date: night

URBAN EVENT 111: URBAN DRIVE			
PREPARATION	The participant drives on a narrow urban road with parking on both sides of the street and oncoming traffic approximately once per 10 seconds (The participant is traveling 25 miles per hour)		
START CONDITIONS	End of previous event		
ACTUAL EVENT	Logstream 1 is be incremented, logstream 2 is set to 111, logstream 5 is set to 100 (The participant is traveling 25 miles per hour) A lead vehicle is approximately 6 seconds ahead of the participant with a minimum speed of 15 and a maximum speed of 50, and maximum acceleration rate of 4.9 meters per second squared, and maximum deceleration of -0.68 meters per second squared. A series of oncoming cars is created ahead of the participant at around one per 10 seconds; a few cars are behind the participant. (The participant does not cross the center line.)		
END CONDITIONS	The participant is 500 ft from the next intersection.		
CLEANUP	None		
EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS
	Participant has finished accelerating from parking space before start of this event.	E101_acc_done	binary 1=yes, 0 = no
SCENARIO PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	DESCRIPTION	IDENTIFIER	UNITS
	Minimum time headway to lead vehicle	E102_ttc_t_min	sec
	Maximum time headway to lead vehicle	E102_ttc_t_max	sec
	Oncoming traffic every 10 seconds	E102_oncoming_freq	avg. sec between cars
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES	DESCRIPTION	IDENTIFIER	UNITS
	Speed (average, min, and max)	E102_sp_avg E102_sp_min E102_sp_max	Mph

URBAN EVENT 111: URBAN DRIVE			
ACCORDING TO THE ASSUMPTIONS)	Speed entering and leaving curve	E102_sp_init E102_sp_end	Mph
ALCOHOL IMPAIRMENT INDICATORS (MEASURES THAT ASSESS WHETHER THE EVENT IS SENSITIVE TO ALCOHOL IMPAIRMENT)	DESCRIPTION	IDENTIFIER	UNITS
	Lane Position	E102_lp_avg	Ft
	SD of lane position (relative to mean lane position)	E102_lp_sd	Ft
	SD of lane position (relative to center of lane)	E102_lpn_sd	Ft
	Speed	E102_sp_avg	Mph
	Speed (relative to posted or assumed speed limit)	E102_spn_avg	Mph
	SD of speed (during "steady state") relative to mean speed	E102_sp_sd	Mph
	SD of speed (during "steady state") relative to posted speed limit	E102_spn_sd	Mph
	Number of center line crossings (any part of the car leaves the lane)	E102_center_cross	Count
	Number of right line crossings (any part of the car leaves the lane)	E102_right_cross	Count
	Did participant glance toward hazard X (hazards are described and numbered in 14.11)?	E102_haz_glance_X	binary 1 = yes, 0 = no
	Steering wheel reversals	E102_steer_rev	
	SD of steering wheel position	E102_steer_sd	
	Velocity of steering wheel	E102_steer_vel	
	Jerk of steering wheel	E102_steer_jerk	
	Steering error	E102_steer_error	
	Time to line crossing (TLC)	E102_tlc	
	Proportion of time TLC>2s	E102_tlc_2	proportion
	95% TLC	E102_tlc_95	
	Accelerator holds	E102_accel_holds	
	Velocity of accelerator position	E102_accel_vel	
	Jerk of accelerator position	E102_accel_jerk	

URBAN EVENT 111: URBAN DRIVE			
	SD of accelerator position	E102_accel_sd	
	Glance frequency at particular object	E102_freq_glance	
	Pressure output(global and local)	E102_out_pres	
	Pressure and force over time	E102_force_pres	
	Pressure point mapping	E102_map_pres	
	PERCLOS	E102_perclos	
	Eye blink frequency	E102_blink_freq	
	Eye blink duration	E102_blink_dur	
	Percent in center based on median location of gaze	E102_gaze_center	
	Correlation between road curvature and eye movements	E102_eye_curve	
	Correlation between steering and road curvature	E102_steer_curve	
	Correlation between eye movements and SDLP	E102_eye_sdlp	
	Number of collisions	E102_num_col	
	Near misses	E102_num_miss	
	Smooth pursuit velocity	E102_smpur_vel	
	Smooth pursuit duration	E102_smpur_dur	
	Smooth pursuit frequency	E102_smpur_freq	
	Smooth pursuit maximum velocity	E102_smpur_maxvel	
	Smooth pursuit gain	E102_smpur_gain	
	SD of gaze	E102_gaze_sd	
	Gaze kurtosis	E102_gaze_kurt	
	Dwell duration	E102_dwell_time	
	Frequency of side mirror glances	E102_glance_freq_side	
	Frequency of speedometer glances	E102_glance_freq_speed	
	Glance direction	E102_glance_dir	
ALGORITHM INPUT (MEASURES THAT IS INPUT TO THE ALGORITHM)	DESCRIPTION	IDENTIFIER	UNITS
	SD of lane position		
	SD of speed		
	Steering wheel reversals		

URBAN EVENT 111: URBAN DRIVE			
	Number of center line crossings		
	Number of right line crossings		

F.10.3 Urban Event 102: Urban Drive

The main street onto which the participant will have pulled out is relatively narrow, with cars parked on both sides of the road. There is oncoming traffic and traffic behind and in front of the participant.

URBAN EVENT 102: URBAN DRIVE			
RATIONALE	This involves driving on a narrow urban road with parked cars on both sides and, oncoming traffic about once every 10 seconds. FARS rationale include over-representations in nighttime conditions on a dark but lighted road which is two lanes and undivided with oncoming traffic (over-representation of driving over center line). Impaired drivers also tend to drive too fast for these conditions.		
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 4620 Road type (lanes, surface): 2 driving lanes with on-road parking Speed limit (in mph): 25 Curvature: 90 deg turn, radius of 1100 ft Intersection type: none Time of Day/Date: night		
PREPARATION	The participant drives on a narrow urban road with parking on both sides of the street and oncoming traffic approximately once per 10 seconds (The participant is traveling 25 miles per hour)		
START CONDITIONS	End of previous event		
ACTUAL EVENT	Logstream 1 is be incremented, logstream 2 is set to 102, logstream 5 is set to 100 (The participant is traveling 25 miles per hour) A lead vehicle is approximately 6 seconds ahead of the participant with a minimum speed of 15 and a maximum speed of 50 and a maximum acceleration rate of 4.9 meters per second squared, and maximum deceleration of -0.68 meters per second squared. A series of oncoming cars is created ahead of the participant at around one per 10 seconds; a few cars are behind the participant. (The participant does not cross the center line.)		
END CONDITIONS	The participant is 500 ft from the next intersection.		
CLEANUP	None		
EVENT	DESCRIPTION	IDENTIFIER	UNITS

URBAN EVENT 102: URBAN DRIVE			
CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	Participant has finished accelerating from parking space before start of this event.	E101_acc_done	binary 1=yes, 0 = no
SCENARIO PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	DESCRIPTION	IDENTIFIER	UNITS
	Minimum time headway to lead vehicle	E102_ttc_t_min	sec
	Maximum time headway to lead vehicle	E102_ttc_t_max	sec
	Oncoming traffic every 10 seconds	E102_oncoming_freq	avg. sec between cars
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES ACCORDING TO THE ASSUMPTIONS)	DESCRIPTION	IDENTIFIER	UNITS
	Speed (average, min, and max)	E102_sp_avg E102_sp_min E102_sp_max	Mph
	Speed entering and leaving curve	E102_sp_init E102_sp_end	Mph
ALCOHOL IMPAIRMENT INDICATORS (MEASURES THAT ASSESS WHETHER THE EVENT IS SENSITIVE TO ALCOHOL IMPAIRMENT)	DESCRIPTION	IDENTIFIER	UNITS
	Lane Position	E102_lp_avg	Ft
	SD of lane position (relative to mean lane position)	E102_lp_sd	Ft
	SD of lane position (relative to center of lane)	E102_lpn_sd	Ft
	Speed	E102_sp_avg	Mph
	Speed (relative to posted or assumed speed limit)	E102_spn_avg	Mph
	SD of speed (during "steady state") relative to mean speed	E102_sp_sd	Mph

URBAN EVENT 102: URBAN DRIVE			
	SD of speed (during "steady state") relative to posted speed limit	E102_spn_sd	Mph
	Number of center line crossings (any part of the car leaves the lane)	E102_center_cross	Count
	Number of right line crossings (any part of the car leaves the lane)	E102_right_cross	Count
	Did participant glance toward hazard X (hazards described and numbered in 14.11)?	E102_haz_glance_X	binary 1 = yes, 0 = no
	Steering wheel reversals	E102_steer_rev	
	SD of steering wheel position	E102_steer_sd	
	Velocity of steering wheel	E102_steer_vel	
	Jerk of steering wheel	E102_steer_jerk	
	Steering error	E102_steer_error	
	Time to line crossing (TLC)	E102_tlc	
	Proportion of time TLC>2s	E102_tlc_2	proportion
	95% TLC	E102_tlc_95	
	Accelerator holds	E102_accel_holds	
	Velocity of accelerator position	E102_accel_vel	
	Jerk of accelerator position	E102_accel_jerk	
	SD of accelerator position	E102_accel_sd	
	Glance frequency at particular object	E102_freq_glance	
	Pressure output(global and local)	E102_out_pres	
	Pressure and force over time	E102_force_pres	
	Pressure point mapping	E102_map_pres	
	PERCLOS	E102_perclos	
	Eye blink frequency	E102_blink_freq	
	Eye blink duration	E102_blink_dur	
	Percent in center based on median location of gaze	E102_gaze_center	
	Correlation between road curvature and eye movements	E102_eye_curve	
	Correlation between steering and road curvature	E102_steer_curve	
	Correlation between eye movements and SDLP	E102_eye_sdlp	

Urban Event 102: Urban Drive			
	Number of collisions	E102_num_col	
	Near misses	E102_num_miss	
	Smooth pursuit velocity	E102_smpur_vel	
	Smooth pursuit duration	E102_smpur_dur	
	Smooth pursuit frequency	E102_smpur_freq	
	Smooth pursuit maximum velocity	E102_smpur_maxvel	
	Smooth pursuit gain	E102_smpur_gain	
	SD of gaze	E102_gaze_sd	
	Gaze kurtosis	E102_gaze_kurt	
	Dwell duration	E102_dwell_time	
	Frequency of side mirror glances	E102_glance_freq_side	
	Frequency of speedometer glances	E102_glance_freq_speed	
	Glance direction	E102_glance_dir	
Algorithm Input (Measures that is input to the algorithm)	Description	Identifier	Units
	SD of lane position		
	SD of speed		
	Steering wheel reversals		
	Number of center line crossings		
	Number of right line crossings		

- SD of lane position (relative to mean lane position)
- SD Speed (relative to mean)

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when going through a green lighted intersection are: SDLP and SD Speed relative to mean speed. One of the most widely thought of behaviors of alcohol impaired drivers is weaving around the lane. This can be represented by the variable SDLP, which has been shown to be sensitive to alcohol (Calhoun et al., 2005; Gawron & Ranney, 1988; Reed & Green, 1999). The same has been shown for variation in speed which can be measured by SD Speed (Arnedt et al., 2001; Gawron & Ranney, 1988).

F.10.4 **Urban Event 103: Green Light**

The participant continues to drive down the narrow street with cars parked on both sides of the road with oncoming traffic, and traffic behind the participant. The participant encounters an intersection with a green traffic light.

URBAN EVENT 103: GREEN LIGHT			
RATIONALE	This scenario involves approaching an intersection where the light is green. The driver must drive through the intersection (no turns) with oncoming traffic. There is no specific FARS rationale for this, but it could involve some lane maintenance problems and some judgment problems that are described in the DWI Detection Guide.		
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 3080 Road type (lanes, surface): 2 driving lanes with on-road parking Speed limit (in mph): 25 Curvature: none Intersection type: 4 way Time of Day/Date: night		
PREPARATION	The participant approaches an intersection; the light is green (The participant is traveling 25 miles per hour)		
START CONDITIONS	The participant is 500 feet from the intersection		
ACTUAL EVENT	When the participant is 500 feet from the intersection, logstream 1 is incremented, logstream 2 is set to 103, logstream 4 is set to 1 When the participant is 250 feet from the intersection, logstream 4 is set to 2 As the participant crosses the stop line, logstream 4 is set to 3 The participant drives through the intersection, the light is green, and the participant experiences oncoming traffic (The participant does not turn at the intersection) (The participant is traveling 25 miles per hour) Once the participant passes the stop line on the far side of the intersection, logstream 4 is set to 100		
END CONDITIONS	The participant is 500 feet from the next intersection		
CLEANUP	None		
EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS

URBAN EVENT 103: GREEN LIGHT			
SCENARIO PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	DESCRIPTION	IDENTIFIER	UNITS
	Distance from start of event to intersection	E103_start_d	ft
	Distance from 250 ft logstream change to intersection	E103_250_d	ft
	Scenario cars from left/right don't enter intersection		
	Any oncoming cars go through light		
	Oncoming traffic (on average once every 6 sec)	E103_oncoming_freq	avg. sec between cars
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES ACCORDING TO THE ASSUMPTIONS)	DESCRIPTION	IDENTIFIER	UNITS
	SV goes through light	E103_go_thru	binary 1=yes, 0 = no
	Speed (average, min, and max) as participant approaches intersection	E103_sp_avg E103_sp_min E103_sp_max	mph
	Brake press	E103_brake_press	binary 1=yes, 0 = no
ALCOHOL IMPAIRMENT INDICATORS (MEASURES THAT ASSESS WHETHER THE EVENT IS SENSITIVE TO ALCOHOL IMPAIRMENT)	DESCRIPTION	IDENTIFIER	UNITS
	Frequency of glances to own traffic light	E103_glance_freq_light	glances/sec
	Frequency of glances to cross traffic light	E103_glance_freq_cross_light	glances/sec
	Frequency of glances to traffic on left	E103_glance_freq_left	glances/sec
	Frequency of glances to traffic on right	E103_glance_freq_right	glances/sec
	Did participant glance toward hazard X (hazards TBD)?	E103_haz_glance_X	binary 1 = yes, 0 = no
	Lane Position	E103_lp_avg	ft
	SD of lane position relative to mean lane position	E103_lp_sd	ft
	SD of lane position relative to center of lane	E103_lpn_sd	ft
	Speed	E103_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E103_spn_avg	mph
	SD of speed relative to mean speed	E103_sp_sd	mph

URBAN EVENT 103: GREEN LIGHT			
	SD of speed relative to posted speed limit	E103_spn_sd	mph
	Number of center line crossings	E103_center_cross	count
	Number of right light crossings	E103_right_cross	count
	Head Turn		Binary 1=yes 0=no
	SD of steering wheel position	E103_steer_sd	
	Velocity of steering wheel	E103_steer_vel	
	Jerk of steering wheel	E103_steer_jerk	
	Steering error	E103_steer_error	
	Steering wheel reversals	E103_steer_rev	
	Time to line crossing (TLC)	E103_tlc	
	Proportion of time TLC>2s	E103_tlc_2	proportion
	95% TLC	E103_tlc_95	
	Accelerator holds	E103_accel_holds	
	Velocity of accelerator position	E103_accel_vel	
	Jerk of accelerator position	E103_accel_jerk	
	SD of accelerator position	E103_accel_sd	
	Glance frequency at particular object	E103_freq_glance	
	Pressure output(global and local)	E103_out_pres	
	Pressure and force over time	E103_force_pres	
	Pressure point mapping	E103_map_pres	
	PERCLOS	E103_perclos	
	Eye blink frequency	E103_blink_freq	
	Eye blink duration	E103_blink_dur	
	Percent in center based on median location of gaze	E103_gaze_center	
	Correlation between road curvature and eye movements	E103_eye_curve	
	Correlation between steering and road curvature	E103_steer_curve	
	Correlation between eye movements and SDLP	E103_eye_sdlp	
	Number of collisions	E103_num_col	

URBAN EVENT 103: GREEN LIGHT			
	Near misses	E103_num_miss	
	Smooth pursuit velocity	E103_smpur_vel	
	Smooth pursuit duration	E103_smpur_dur	
	Smooth pursuit frequency	E103_smpur_freq	
	Smooth pursuit maximum velocity	E103_smpur_maxvel	
	Smooth pursuit gain	E103_smpur_gain	
	SD of gaze	E103_gaze_sd	
	Gaze kurtosis	E103_gaze_kurt	
	Dwell duration	E103_dwell_time	
	Frequency of side mirror glances	E103_glance_freq_side	
	Frequency of speedometer glances	E103_glance_freq_speed	
	Glance direction	E103_glance_dir	
	Head movement	E103_head_mov	
ALGORITHM INPUT (MEASURES THAT IS INPUT TO THE ALGORITHM)	DESCRIPTION	IDENTIFIER	UNITS
	SD of lane position relative to mean		
	SD of speed relative to mean		
	SD of speed relative to posted		
	Steering wheel reversals		

- SD of lane position (relative to mean lane position)
- SD Speed (relative to mean)

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when going through a green lighted intersection are: SDLP and SD Speed relative to mean speed. One of the most widely thought of behaviors of alcohol impaired drivers is weaving around the lane. This can be represented by the variable SDLP, which has been shown to be sensitive to alcohol (Calhoun et al., 2005; Gawron & Ranney, 1988; Reed & Green, 1999). The same has been shown for variation in speed which can be measured by SD Speed (Arnedt et al., 2001; Gawron & Ranney, 1988).

F.10.5 **Urban Event 104: Yellow Light Dilemma**

The participant approaches an intersection; the light is green. The light turns yellow at a time when the participant must decide if they should stop or drive through the intersection.

URBAN EVENT 104: YELLOW LIGHT DILEMMA	
RATIONALE	In this segment, the driver approaches a 4-way intersection with oncoming traffic. When the driver is 4.00 seconds from the stop line at the intersection, the signal turns yellow. The light turns red after 3.0 seconds. The driver either stops or drives through the intersection risking going through a red light. This is the yellow light dilemma. There is no particular FARS rationale for this (except clearly running the red light), however, several DWI detection cues could arise: e.g., stopping problems, slow response to traffic signal, lane maintenance, etc.
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 4620 Road type (lanes, surface): 2 driving lanes with on-road parking Speed limit (in mph): 25 Curvature: S-curve after intersection, radius of 365 ft entry, 1460 exit Intersection type: 4-way Time of Day/Date: night
PREPARATION	The participant approaches a 4-way intersection with oncoming traffic (The participant is traveling 25 miles per hour) When the participant is 4.00seconds from the stop line, the light turns yellow (The participant either stops at the stop line or drives through the intersection) The light turns red after 3.0 seconds (The participant has either stopped or cleared the intersection) If participant stops, the vehicle from the right turns right (Scenario 1). Vehicle from left (Scenarios 2 and 3) passes through the intersection (The participant remains in stopped position.) The light turns green. (If the participant stopped at the intersection, they then accelerate forward)
START CONDITIONS	The participant is 500 feet from the intersection

URBAN EVENT 104: YELLOW LIGHT DILEMMA	
ACTUAL EVENT	When the participant is 500 feet from the traffic light, logstream 1 is incremented, logstream 2 is set to 104, logstream 4 is set to 1 (The participant is traveling 25 miles per hour.) When the participant is within 250 feet of the intersection, logstream 4 is set to 2 When the participant's time to arrival is 4.00 seconds from the stop line, the light turns yellow, and logstream 3 is set to 1 (Some participants go through the intersection without stopping and some stop.) As the participant crosses the stop line, logstream 4 is set to 3 (The participant does not turn at the intersection) The light is set to red after 3.0 seconds, based on: (www.ct.gov/dot/lib/dot/Documents/dpublications/Capacity_Analysis_&_Signal_Timing.pdf) **Y = t + V/(2a+2Ag)** Where: **Y =** yellow clearance interval in seconds **t =** reaction time (no reaction time assumed in pilot) **V** = 85 percent percentile approach speed in ft/sec or m/sec (40 mph used) **a** = deceleration rate of a vehicle (use 10 ft/sec/sec) **A** = acceleration due to gravity (32.2 ft/sec/sec) **g** = percent grade in decimal form (+ for upgrade, - for downgrade) (0 used) - Calculate the yellow clearance interval to the nearest 0.1 second. -Do not use a yellow clearance interval of less than 3 seconds. When the light turns red, logstream 3 is set to 2. After a delay of .5 seconds from the light turning red, the light turns green for the cross traffic. A vehicle in the cross street on the participant's travels across the intersection (go straight). Another vehicle in the cross street on the participant's right makes a right turn onto the same street and travels the same direction as the participant. Logstream 3 is set to 3 The light turns yellow for the cross traffic 15 seconds after turning green, and logstream 3 is set to 4 (The participant drives through the intersection) 3 seconds after the yellow light, all the lights is turned red. Logstream 3 is set to 5 0.5 seconds after the all red state, the light changes to green for the participant, logstream 5 is set to 6. When the participant has passed through the intersection, logstream 4 is set to 100. Logstream 3 is set to 0, and the sequence changing the logstreams based on the current light pattern is stopped.
END CONDITIONS	The participant is 500 feet from next intersection.
CLEANUP	None

EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS

Scenario Performance (Measures that indicate if the event is operating as expected)	Description	Identifier	Units
	Distance from start of event to intersection	E104_start_d	ft
	Distance from 250 ft marker to intersection	E104_250_d	ft
	Time to arrive at stop line when light changes to yellow (should be 3.16 seconds)	E104_change_to_yellow	sec
	Time after yellow until light changes to red (should be 3 sec after yellow light)	E104_change_to_red	sec
	Others lead scenario car to go through yellow Y/N		
	Scenario cars from left and right behave as specified		
	Any oncoming cars go through light		
	Oncoming traffic every 30 seconds	E104_oncoming_freq	avg. sec between cars
Assumed Driver Behavior (Measures that indicate whether the participant behaves according to the assumptions)	**Description**	**Identifier**	**Units**
	Speed (average, min, and max) as participant approaches intersection	E104_sp_avg E104_sp_min E104_sp_max	mph
	Go through light	E104_complete_stop	binary 1=yes, 0 = no
	Accelerator release	E104_accel_release	binary 1=yes, 0 = no
	Brake press	E104_brake_press	binary 1=yes, 0 = no
	Acceleration (greater than some threshold value TBD)	E104_accelerate	binary 1=yes, 0 = no
Alcohol Impairment Indicators (Measures that assess whether the event is sensitive to alcohol impairment)	**Description**	**Identifier**	**Units**
	Frequency of glances to traffic light	E104_glance_freq_light	glances/sec
	Frequency of glances to traffic on left	E104_glance_freq_left	glances/sec
	Frequency of glances to traffic on right	E104_glance_freq_right	glances/sec
	Did participant glance toward hazard X (hazards TBD)?	E104_haz_glance_X	binary 1 = yes, 0 = no
	Lane Position	E104_lp_avg	ft
	SD of lane position relative to mean lane position	E104_lp_sd	ft
	SD of lane position relative to center	E104_lpn_sd	ft
	Speed	E104_sp_avg	mph

	Speed (relative to posted or assumed speed limit)	E104_spn_avg	mph
	SD of speed	E104_sp_sd	mph
	SD of speed relative to posted speed limit	E104_spn_sd	mph
	Number of center line crossings	E104_center_cross	count
	Number of right light crossings	E104_right_cross	count
	Decision time (time from fixation on light until release or depression of accelerator)	E104_decison_t	sec
	Stopping location (relative to stop line, negative value means before line)	E104_stop_pos	ft
	Smoothness of deceleration	E104_smooth_decel	
	Smoothness of acceleration	E104_smooth_acc	
	Dwell time		
	SD of steering wheel position	E104_steer_sd	
	Velocity of steering wheel	E104_steer_vel	
	Jerk of steering wheel	E104_steer_jerk	
	Steering error	E104_steer_error	
	Steering wheel reversals	E104_steer_rev	
	Time to line crossing (TLC)	E104_tlc	
	Proportion of time TLC>2s	E104_tlc_2	proportion
	95% TLC	E104_tlc_95	
	Mean Brake Force		
	Accelerator holds	E104_accel_holds	
	Velocity of accelerator position	E104_accel_vel	
	Jerk of accelerator position	E104_accel_jerk	
	SD of accelerator position	E104_accel_sd	
	Mean brake force	E104_brake_avg	
	SD of brake force	E104_brake_sd	
	Decision time	E104_dec_time	
	Glance frequency at particular object	E104_freq_glance	
	Pressure output(global and local)	E104_out_pres	
	Pressure and force over time	E104_force_pres	
	Pressure point mapping	E104_map_pres	

	PERCLOS	E104_perclos	
	Eye blink frequency	E104_blink_freq	
	Eye blink duration	E104_blink_dur	
	Percent in center based on median location of gaze	E104_gaze_center	
	Correlation between road curvature and eye movements	E104_eye_curve	
	Correlation between steering and road curvature	E104_steer_curve	
	Correlation between eye movements and SDLP	E104_eye_sdlp	
	Number of collisions	E104_num_col	
	Near misses	E104_num_miss	
	Delay time	E104_delay_time	
	Rise time	E104_rise_time	
	Peak time	E104_peak_time	
	Max overshoot	E104_over_max	
	Settling time	E104_set_time	
	How well it fits the model	E104_model_fit	
	Smooth pursuit velocity	E104_smpur_vel	
	Smooth pursuit duration	E104_smpur_dur	
	Smooth pursuit frequency	E104_smpur_freq	
	Smooth pursuit maximum velocity	E104_smpur_maxvel	
	Smooth pursuit gain	E104_smpur_gain	
	SD of gaze	E104_gaze_sd	
	Gaze kurtosis	E104_gaze_kurt	
	Dwell duration	E104_dwell_time	
	Frequency of side mirror glances	E104_glance_freq_side	
	Frequency of speedometer glances	E104_glance_freq_speed	
	Glance direction	E104_glance_dir	
	Head movement	E104_head_mov	
ALGORITHM INPUT	DESCRIPTION	IDENTIFIER	UNITS
(MEASURES THAT IS INPUT TO THE	SD of lane position relative to mean		
	Mean brake force		

ALGORITHM)	Number of center line crossings		
	Number of right line crossings		

- RT to yellow light onset (after accelerator release or brake pedal depressed)
- SD of lane position (relative to mean lane position)
- Hover time (after accelerator release, time not depressing either pedal, sum across time to catch multiple)

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when encountering a yellow light dilemma are: reaction time and SDLP. One of the most widely thought of behaviors of alcohol impaired drivers is weaving around the lane. This can be represented by the variable SDLP, which has been shown to be sensitive to alcohol (Calhoun et al., 2005; Gawron & Ranney, 1988; Reed & Green, 1999). Reaction time has been known to be affected by alcohol long before research was being done on alcohol and driving (Liguori, D'Agostino, Dworkin, Edwards, & Robinson, 1999; Maylor, Rabbitt, James, & Kerr, 1990; Strayer, Drews, & Crouch, 2006). Provided the participant reacts to the yellow light, this variable should be sensitive to alcohol impairment.

F.10.6 **Urban Event 105: Left Turn**

The participant passes through an intersection with a green traffic light on an urban two-lane road with parked vehicles in the right lane, oncoming traffic, and traffic behind the participant. The participant turns left at this intersection and has to wait for a gap in oncoming traffic to make the turn. Figure F12 shows a close up view of the left turn.

Urban Event 105: Left Turn	
RATIONALE	This scenario involves the participant approaching a 4-way intersection with a green light (They will have received landmark based instruction telling them to turn at the light). The driver must wait until oncoming traffic clears to make the turn. There is no specific FARS rationale for this, but it does involve judgment and is a typical maneuver in a drive home from a bar. This could involve some driving cues that indicate impairment (from NHTSA's DWI Detection Guide): e.g., turning with a wide radius, misjudgment of the oncoming vehicle speed, turning too fast, too sharp or in a jerky manner.
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 3300 Road type (lanes, surface): 2 driving lanes with on-road parking Speed limit (in mph): 25 mph Curvature: none Intersection type: 4-way, no dedicated left turn lane Time of Day/Date: night

Urban Event 105: Left Turn

PREPARATION	The light is green at the intersection with oncoming traffic; the participant pulls into the intersection (The participant attempts to make a left turn) A series of gaps in oncoming traffic is presented to the participant (the participant waits for a gap of appropriate length) The participant makes a left turn at the intersection
START CONDITIONS	Distance 500 ft from the stop line of the intersection
ACTUAL EVENT	There are five oncoming vehicles at the intersection waiting for the red light to turn green. When the participant is 21 seconds from the intersection, an additional stream of cars at various gaps (gap times specified below) is created in the oncoming lane, approaching the red light. When the lead car of the oncoming traffic stream is 650 feet from the intersection, the light turns green and logstream 3 is set to 80. Also at the same time, a car is created in the inner lane of the cross street on the left (with respect to the driver); this car will restrict the participant's path as they execute left turn maneuver. The lead vehicle in front of the participant will continue on straight through the intersection without turning. When the participant is 500 feet from the intersection , logstream 1 is incremented, logstream 2 is set to 105, and logstream 4 is set to 1 When the participant is 250 feet from the intersection, logstream 4 is set to 2 When the participant crosses the stop line, logstream 4 is set to 3 At the intersection, 8 gaps of varying size is presented to the participant in this order (gap size is approximate): 4 seconds, 2 seconds, 3 seconds, 4.2 seconds, 6.7 seconds, 5.7 seconds, 8.2 seconds, and 10.2 seconds. After these gaps, no more cars appear. (The participant has stopped at the intersection and is attempting to make a left turn) Once the participant has made the left turn, logstream 3 is set to 0, logstream 4 is set to 100, logstream 5 is set to 12 (The participant has made a left turn at the intersection)
END CONDITIONS	Driver has completed left hand turn and is 266 ft beyond the intersection.
CLEANUP	None

EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS
	The light turns from green to red (Logstream 3 set to 80 to reflect this change) before the end of the previous event.		
SCENARIO	DESCRIPTION	IDENTIFIER	UNITS

Urban Event 105: Left Turn			
PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	Light turns green at 11.5 sec TTA (time to arrival to intersection)	E105_change_to_green	binary 1=yes, 0 = no
	Length of gaps	E105_gap_d_X (where X is the gap number, 1 to 8)	ft
	Length of gaps	E105_gap_t_X (where X is the gap number, 1 to 8)	sec
	Other scenario cars in front go through light		
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES ACCORDING TO THE ASSUMPTIONS)	DESCRIPTION	IDENTIFIER	UNITS
	Speed (average, min, and max) as participant approaches intersection	E105_sp_avg E105_sp_min E105_sp_max	mph
	Turn left	E105_nav_error	binary 1=yes, 0 = no
	Accelerator release	E105_accel_release	binary 1=yes, 0 = no
	Brake press	E105_brake_press	binary 1=yes, 0 = no
	Mean brake force		
	Complete stop before turn (min speed less than 1 mph)	E105_complete_stop	binary 1=yes, 0 = no
	Stop distance from stop line	E105_stop_pos	ft
	Lane position at stop	E105_stop_lp	ft
	Heading at stop (relative to original direction of travel)	E105_stop_hdng	deg
ALCOHOL IMPAIRMENT INDICATORS (MEASURES THAT ASSESS WHETHER THE EVENT IS SENSITIVE TO ALCOHOL IMPAIRMENT)	DESCRIPTION	IDENTIFIER	UNITS
	Head turn (threshold angle that defines a turn needs TBD)	E105_head_turn	count
	Turn signal use	E105_turn_signal	binary 1=yes, 0 = no
	Time from stop until turn begins (when vehicle heading has rotated 90 deg)	E105_turn_start_t	sec
	Gap participant takes	E105_gap_taken_d E105_gap_taken_t	ft sec
	Size of gap taken relative to size of previous gaps		

Urban Event 105: Left Turn			
	Time distance of following vehicle in gap when participant releases brake and begins turn	E105_gap_t_start	sec
	TTC of oncoming vehicle when vehicle heading has rotated to 90 deg	E105_gap_t_turn	sec
	Time to complete turn (gap clearance time)	E105_turn_t	sec
	Overshoot (distance from center of lane to vehicle center when vehicle heading has rotated to 90 deg)	E105_overshoot	ft
	Lateral acceleration (max during turn)	E105_lat_acc_max	ft/s^2
	Frequency of glances to the light	E105_glance_freq_light	glances/sec
	Did participant glance toward hazard X (hazards TBD)?	E105_haz_glance_X	binary 1 = yes, 0 = no
	Smoothness of deceleration	E105_smooth_decel	
	Smoothness of acceleration	E105_smooth_acc	
	Velocity of steering wheel	E105_steer_vel	
	Jerk of steering wheel	E105_steer_jerk	
	Steering error	E105_steer_error	
	Intersection turn signal use	E105_turn_sig	
	Time to line crossing (TLC)	E105_tlc	
	Proportion of time TLC>2s	E105_tlc_2	proportion
	95% TLC	E105_tlc_95	
	Velocity of accelerator position	E105_accel_vel	
	Jerk of accelerator position	E105_accel_jerk	
	SD of accelerator position	E105_accel_sd	
	Mean brake force	E105_brake_avg	
	SD of brake force	E105_brake_sd	
	Time gap accepted	E105_time_gap	
	TTC to oncoming vehicle during turn	E105_ttc	
	Glance frequency at particular object	E105_freq_glance	
	Pressure output(global and local)	E105_out_pres	
	Pressure and force over time	E105_force_pres	
	Pressure point mapping	E105_map_pres	

Urban Event 105: Left Turn			
	PERCLOS	E105_perclos	
	Eye blink frequency	E105_blink_freq	
	Eye blink duration	E105_blink_dur	
	Percent in center based on median location of gaze	E105_gaze_center	
	Correlation between eye movements and steering	E105_eye_steer	
	Number of collisions	E105_num_col	
	Near misses	E105_num_miss	
	Degree of conflict	E105_deg_conflict	
	Delay time	E105_delay_time	
	Rise time	E105_rise_time	
	Peak time	E105_peak_time	
	Max overshoot	E105_over_max	
	Settling time	E105_set_time	
	How well it fits the model	E105_model_fit	
	Smooth pursuit velocity	E105_smpur_vel	
	Smooth pursuit duration	E105_smpur_dur	
	Smooth pursuit frequency	E105_smpur_freq	
	Smooth pursuit maximum velocity	E105_smpur_maxvel	
	Smooth pursuit gain	E105_smpur_gain	
	SD of gaze	E105_gaze_sd	
	Gaze kurtosis	E105_gaze_kurt	
	Dwell duration	E105_dwell_time	
	Frequency of side mirror glances	E105_glance_freq_side	
	Frequency of speedometer glances	E105_glance_freq_speed	
	Glance direction	E105_glance_dir	
	Head movement	E105_head_mov	
ALGORITHM INPUT (MEASURES THAT IS INPUT TO THE ALGORITHM)	DESCRIPTION	IDENTIFIER	UNITS
	Mean accelerator position		

Urban Event 105: Left Turn			

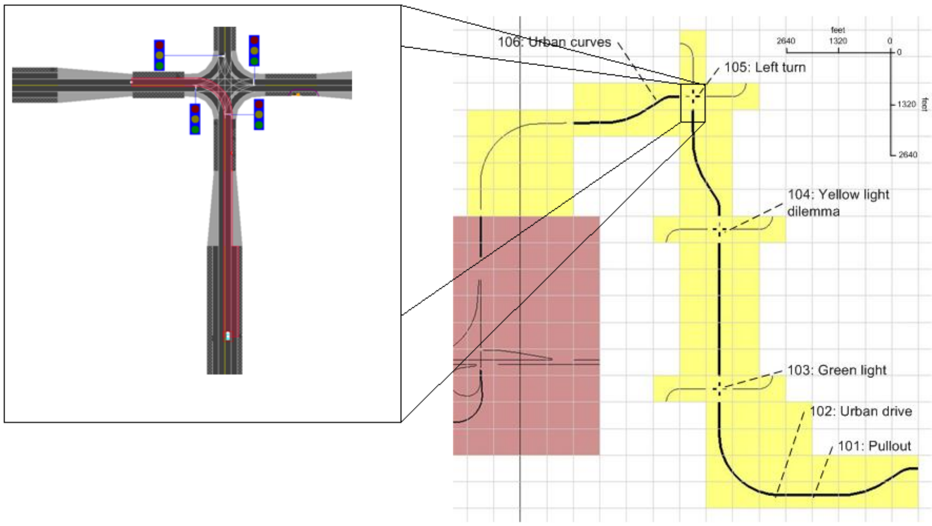

Figure F12. Left turn

- Jerk of accelerator position
- Velocity of accelerator position
- Smoothness of lane change
- Max overshoot
- Velocity of steering wheel
- Jerk of steering wheel

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when turning left are: the smoothness of pulling out, max overshoot, and jerk and velocity of accelerator position. The smoothness of lane change and max overshoot go hand in hand in the way a person pulls out of the parking space as unimpaired drivers will get into the lane fairly quickly and impaired drivers will have to adjust their position before settling on an adequate location (Struster, 1997). Jerk and velocity of accelerator position look at how smoothly the participant pulled out of the parking space in a longitudinal perspective. Alcohol impaired drivers have trouble slowing and speeding up in a smooth manner (Struster, 1997).

F.10.7 **Urban Event 106: Urban Curves**

The participant drives through a series of three curves of mixed radius of curvature (non-steady radius). The entrances of the curves is blinded (the participant's view of the rest of the curve is obstructed). Figure F13 shows a view of the urban curves.

URBAN EVENT 106: URBAN CURVES			
RATIONALE	This event involves navigating a series of curves on an urban two-lane road with cars parked on both sides and oncoming traffic approximately once every 30 seconds. The FARS rationale is the over-representation of impaired driving fatal crashes on curves, at non-junctions and on two-lane roadways. FARS driving related factors that are over-represented for impaired participants could also come into play in this scenario: e.g., steering only as a crash avoidance maneuver, running off the road, failure to keep in proper lane, driving too fast for conditions.		
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 7920 Road type (lanes, surface): 2 driving lanes with on-road parking Speed limit (in mph): 30 increasing to 45 mph for last 400 ft Curvature: Blind mixed radius (S-curve with 365 ft radius entry, 1460 ft radius exit; 90 deg curve with 1100 ft radius) Intersection type: None Time of Day/Date: Night		
PREPARATION	Just after the start of the event instruction #302 is played, instructing the participant to turn onto the interstate The participant navigates a series of curves The participant experiences oncoming traffic once per 30 seconds on average Towards the end of the event the speed limit changes from 30 mph to 45 mph.		
START CONDITIONS	Finished Left Turn onto Urban Residential Section		
ACTUAL EVENT	Logstream 1 is incremented, Logstream 2 is set to 106 (The participant is driving 25 mph.) (The participant stays in their lane.) Instruction #302 is played, instructing the participant to turn onto the interstate The participant experiences oncoming traffic once per 30 seconds on average. (The participant maintains a speed of 25 miles per hour) When parking lane ends, logstream 5 is set to 13 (after corridor). Approximately 1000 feet from the end of the curve there is a 45 mph speed limit sign. When the driver is 850 feet before the sign, logstream 5 is set to 14.		
END CONDITIONS	Start of Next Event		
CLEANUP	None		
EVENT CONTINGENCY	DESCRIPTION	IDENTIFIER	UNITS
	NONE		

URBAN EVENT 106: URBAN CURVES			
(VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)			
SCENARIO PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	DESCRIPTION	IDENTIFIER	UNITS
	Oncoming traffic every 30 seconds	E106_oncoming_freq	avg. sec between cars
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES ACCORDING TO THE ASSUMPTIONS)	DESCRIPTION	IDENTIFIER	UNITS
	Speed (average, min, and max)	E106_sp_avg E106_sp_min E106_sp_max	mph
	Lane position	E106_lp_avg	
ALCOHOL IMPAIRMENT INDICATORS (MEASURES THAT ASSESS WHETHER THE EVENT IS SENSITIVE TO ALCOHOL IMPAIRMENT)	DESCRIPTION	IDENTIFIER	UNITS
	Lane position	E106_lp_avg	ft
	SD of lane position relative to mean lane position	E106_lp_sd	ft
	SD of lane position relative to center of lane	E106_lpn_sd	ft
	Speed	E106_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E106_spn_avg	mph
	SD of speed relative to mean speed	E106_sp_sd	mph
	SD of speed relative to posted speed limit	E106_spn_sd	mph
	Number of center line crossings	E106_center_cross	count
	Number of right line crossings	E106_right_cross	count
	Glances to speed limit signs	E106_glance_sign_X	

URBAN EVENT 106: URBAN CURVES			
	SD of steering wheel position	E106_steer_sd	
	Velocity of steering wheel	E106_steer_vel	
	Jerk of steering wheel	E106_steer_jerk	
	Steering error	E106_steer_error	
	Steering wheel reversals	E106_steer_rev	
	Time to line crossing (TLC)	E106_tlc	
	Proportion of time TLC>2s	E106_tlc_2	proportion
	95% TLC	E106_tlc_95	
	Accelerator holds	E106_accel_holds	
	Velocity of accelerator position	E106_accel_vel	
	Jerk of accelerator position	E106_accel_jerk	
	SD of accelerator position	E106_accel_sd	
	Glance frequency at particular object	E106_freq_glance	
	Pressure output(global and local)	E106_out_pres	
	Pressure and force over time	E106_force_pres	
	Pressure point mapping	E106_map_pres	
	PERCLOS	E106_perclos	
	Eye blink frequency	E106_blink_freq	
	Eye blink duration	E106_blink_dur	
	Percent in center based on median location of gaze	E106_gaze_center	
	Correlation between road curvature and eye movements	E106_eye_curve	
	Correlation between steering and road curvature	E106_steer_curve	
	Correlation between eye movements and SDLP	E106_eye_sdlp	
	Correlation between eye movements and steering	E106_eye_steer	
	Correlation between head turn and steering wheel movement	E106_headturn_wheel	
	Number of collisions	E106_num_col	
	Near misses	E106_num_miss	
	Smooth pursuit velocity	E106_smpur_vel	
	Smooth pursuit duration	E106_smpur_dur	

Urban Event 106: Urban Curves			
	Smooth pursuit frequency	E106_smpur_freq	
	Smooth pursuit maximum velocity	E106_smpur_maxvel	
	Smooth pursuit gain	E106_smpur_gain	
	SD of gaze	E106_gaze_sd	
	Gaze kurtosis	E106_gaze_kurt	
	Dwell duration	E106_dwell_time	
	Frequency of side mirror glances	E106_glance_freq_side	
	Frequency of speedometer glances	E106_glance_freq_speed	
	Glance direction	E106_glance_dir	
Algorithm Input (Measures that is input to the algorithm)	Description	Identifier	Units
	SD of lane position relative to mean		
	SD of speed relative to mean		
	SD of speed relative to posted		
	Mean Speed		
	Number of center line crossings		
	Number of right line crossings		
	Steering wheel reversals		

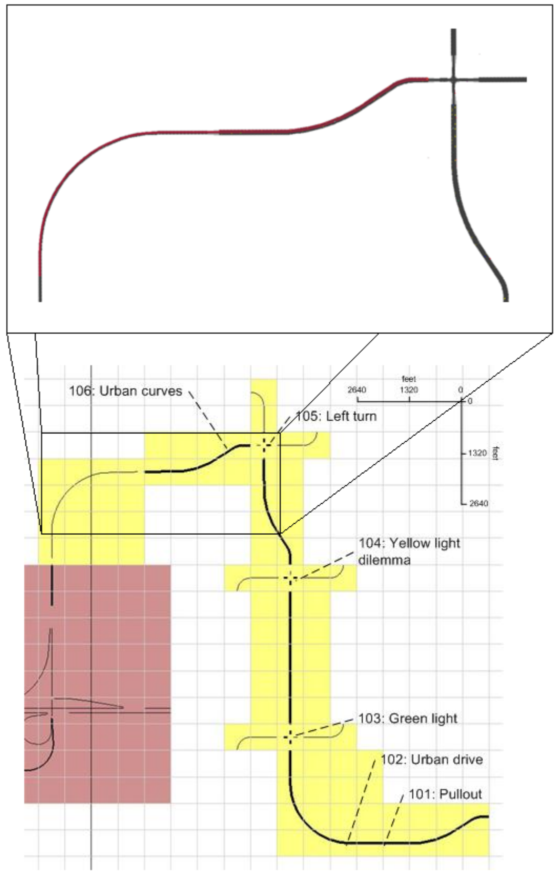

Figure F13. Urban Curves

- SD of lane position (relative to mean lane position)
- Speed (relative to posted or assumed speed limit)
- SD of speed (during "steady state") relative to mean speed
- Eye gaze distribution measures

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when driving down a road are: SDLP, SD Speed, and speed relative to the posted or assumed speed limit. One of the most widely thought of behaviors of alcohol impaired drivers is weaving around the lane. This can be represented by the variable SDLP, which has been shown to be sensitive to alcohol (Calhoun et al., 2005; Gawron & Ranney, 1988; Reed & Green, 1999). The same has been shown for variation in speed which can be measured by SD Speed (Arnedt et al., 2001; Gawron & Ranney, 1988). A standard set of qualitative behaviors for police to follow mentions that alcohol impaired drivers tend to drive slower than the speed limit by more than 10 mph (Struster, 1997).

F.10.8 Interstate Event 201: Turn On Ramp

The participant turns onto the interstate on-ramp; the turn is gentle. This ends the urban section of the drive.

INTERSTATE EVENT 201: TURN ON RAMP (TRANSITIONAL)			
RATIONALE	This event involves turning onto a ramp for transition to an interstate highway. The rationale for this event is that impaired drivers will often make driving errors such as missing a turn, inappropriate speed, or over/undershooting a turn. Some DWI detection cues could occur: e.g., turning with a wide radius, signaling intentions, accelerating and decelerating.		
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 1100 Road type (lanes, surface): 2 driving lanes Speed limit (in mph): 25 Curvature: Gentle curve to the right Intersection type: Interstate onramp Time of Day/Date: night lit		
PREPARATION	The participant turns onto the on entrance ramp (The participant correctly turns onto the ramp, and does not continue on straight)		
START CONDITIONS	The participant is 500 feet from the beginning of the on ramp		
ACTUAL EVENT	When the participant is 500 feet from the highway on ramp, logstream 1 is incremented, logstream 2 is set to 201, logstream 4 is set to 1 (The participant remembers the navigation instructions given at the end of the last turn)		
END CONDITIONS	When the participant crosses onto the on ramp		
CLEANUP	None		
EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS
SCENARIO PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	DESCRIPTION	IDENTIFIER	UNITS

Interstate Event 201: Turn On Ramp (transitional)			
Assumed Driver Behavior (Measures that indicate whether the participant behaves according to the assumptions)	Description	Identifier	Units
	Participant does not take ramp	E201_nav_error	binary 1=yes, 0 = no
	Initial speed (speed at beginning of event)	E201_sp_init	mph
	End speed (speed at end of event)	E201_sp_mavgnd	mph
	Accelerator release	E201_accel_release	binary 1=yes, 0 = no
	Brake press	E201_brake_press	binary 1=yes, 0 = no
	Acceleration (mean over entire event)	E201_acc_avg	ft/s^2
Alcohol Impairment Indicators (Measures that assess whether the event is sensitive to alcohol impairment)	Description	Identifier	Units
	Turn signal use	E201_turn_signal	binary 1=yes, 0 = no
	Smoothness of transition onto ramp (longitudinal)	E201_smooth_long	
	Smoothness of transition onto ramp (lateral)	E201_smooth_lat	
	SD of steering wheel position	E201_steer_sd	
	Velocity of steering wheel	E201_steer_vel	
	Jerk of steering wheel	E201_steer_jerk	
	Steering error	E201_steer_error	
	Steering wheel reversals	E201_steer_rev	
	Head movement		binary 1=yes, 0=no
	Lane position	E201_lp_avg	ft
	Time to line crossing (TLC)	E201_tlc	
	Proportion of time TLC>2s	E201_tlc_2	proportion
	95% TLC	E201_tlc_95	
	Accelerator holds	E201_accel_holds	
	Number of center line crossings	E201_center_cross	count
	Number of right light crossings	E201_right_cross	count
	Velocity of accelerator position	E201_accel_vel	

INTERSTATE EVENT 201: TURN ON RAMP (TRANSITIONAL)			
	Jerk of accelerator position	E201_accel_jerk	
	SD of accelerator position	E201_accel_sd	
	Mean brake force	E201_brake_avg	
	SD of brake force	E201_brake_sd	
	Speed	E201_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E201_spn_avg	mph
	Glance frequency at particular object	E201_freq_glance	
	Pressure output(global and local)	E201_out_pres	
	Pressure and force over time	E201_force_pres	
	Pressure point mapping	E201_map_pres	
	PERCLOS	E201_perclos	
	Eye blink frequency	E201_blink_freq	
	Eye blink duration	E201_blink_dur	
	Percent in center based on median location of gaze	E201_gaze_center	
	Correlation between eye movements and SDLP	E201_eye_sdlp	
	Correlation between head turn and steering wheel movement	E201_headturn_wheel	
	Number of collisions	E201_num_col	
	Near misses	E201_num_miss	
	Delay time	E201_delay_time	
	Rise time	E201_rise_time	
	Peak time	E201_peak_time	
	Max overshoot	E201_over_max	
	Settling time	E201_set_time	
	How well it fits the model	E201_model_fit	
	Smooth pursuit velocity	E201_smpur_vel	
	Smooth pursuit duration	E201_smpur_dur	
	Smooth pursuit frequency	E201_smpur_freq	
	Smooth pursuit maximum velocity	E201_smpur_maxvel	
	Smooth pursuit gain	E201_smpur_gain	

Interstate Event 201: Turn On Ramp (Transitional)			
	SD of gaze	E201_gaze_sd	
	Gaze kurtosis	E201_gaze_kurt	
	Dwell duration	E201_dwell_time	
	Frequency of side mirror glances	E201_glance_freq_side	
	Frequency of speedometer glances	E201_glance_freq_speed	
	Glance direction	E201_glance_dir	
	Head movement	E201_head_mov	
Algorithm Input (Measures that is input to the algorithm)	Description	Identifier	Units
	Mean brake force		
	Mean accelerator position		
	Steering wheel reversals		

- Jerk of accelerator position
- Velocity of accelerator position
- Velocity of steering wheel
- Jerk of steering wheel

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when turning onto a ramp are: jerk and velocity of accelerator position, and jerk and velocity of steering wheel position. Jerk and velocity of accelerator position look at how smoothly the participant pulled out of the parking space in a longitudinal perspective. Alcohol impaired drivers have trouble slowing and speeding up in a smooth manner (Struster, 1997). The jerk and velocity of the steering wheel position look at how smoothly the participant turned onto the ramp. Research has shown that alcohol impairs a person's ability to maintain lateral control (Calhoun et al., 2005).

F.10.9 **Interstate Event 202: Merge On**

The participant will merge onto the interstate. Figure F14 shows the merge onto the interstate.

Interstate Event 202: Merge On			
RATIONALE	This event involves merging onto the interstate highway from the ramp. This interchange is required to provide a transition to the higher speed interstate environment. Despite the fact that there is not a conflict situation when entering the roadway, the geometry of the interchange would require the driver to scan the visual environment to confirm this. Additionally, it provides data on driver acceleration switching between speed limits. There is no specific FARS data on which this event is based.		
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 3960 Road type (lanes, surface): Asphalt entrance ramp Speed limit (in mph): 45 (suggested) Curvature: 1100 ft radius Intersection type: on ramp		
PREPARATION	The participant approaches the interstate. (The participant is accelerating up to highway speeds) The participant merges onto the interstate (The participant safely merges without an accident.)		
START CONDITIONS	When the participant enters the on-ramp		
ACTUAL EVENT	Logstream 1 is incremented, logstream 2 is set to 202, logstream 4 is set to 0, logstream 5 is set to 21 The participant approaches the interstate; when the participant is approximately one third of the way down the onramp, a tractor trailer is created in the right lane of the interstate approximately 2300 feet ahead of the participant, a second truck will be created 1000 feet behind this truck (on the highway, not on the on-ramp). Both of these trucks will be traveling 10 miles per hour slower than the participant while the paritipcnat is on the ramp. After subject enters the interstate, the tractor trailers travel at 45 mph. Logstream 4 is set to 1. (The participant is accelerating) (The tractor trailer stays in right lane and maintains speed.) When participant begins to merge onto the interstate, logstream 4 is set to 2. (The participant safely merges onto the interstate.) Once the participant has merged onto the highway, logstream 4 is set to 100; logstream 5 is set to 22.		
END CONDITIONS	Participant merges onto the highway		
CLEANUP	None		
EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS

Interstate Event 202: Merge On			
SCENARIO PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	DESCRIPTION	IDENTIFIER	UNITS
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES ACCORDING TO THE ASSUMPTIONS)	DESCRIPTION	IDENTIFIER	UNITS
	Participant is able to successfully merge onto the highway	E202_merge_success	binary 1=yes, 0 = no
	Average acceleration	E202_acc_avg	ft/s^2
	Accelerator pedal variability	E202_accel_sd	proportion of range
ALCOHOL IMPAIRMENT INDICATORS (MEASURES THAT ASSESS WHETHER THE EVENT IS SENSITIVE TO ALCOHOL IMPAIRMENT)	DESCRIPTION	IDENTIFIER	UNITS
	Turn signal use	E202_turn_signal	binary 1=yes, 0 = no
	Lateral acceleration	E202_lat_acc	ft/sec^2
	Smoothness of transition off ramp (longitudinal)	E202_smooth_long	
	Smoothness of transition off ramp (lateral)	E202_smooth_lat	
	SD of steering wheel position	E202_steer_sd	
	Velocity of steering wheel	E202_steer_vel	
	Jerk of steering wheel	E202_steer_jerk	
	Steering error	E202_steer_error	
	Lane position	E202_lp_avg	ft
	Time to line crossing (TLC)	E202_tlc	
	Velocity of accelerator position	E202_accel_vel	
	Jerk of accelerator position	E202_accel_jerk	
	SD of accelerator position	E202_accel_sd	

Interstate Event 202: Merge On			
	Mean brake force	E202_brake_avg	
	SD of brake force	E202_brake_sd	
	Speed	E202_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E202_spn_avg	mph
	Time to collision (TTC)	E202_ttc	
	Time gap accepted	E202_time_gap	
	Timing of participant looking at rear view mirror	E202_rear_look	
	Glance frequency at particular object	E202_freq_glance	
	Pressure output(global and local)	E202_out_pres	
	Pressure and force over time	E202_force_pres	
	Pressure point mapping	E202_map_pres	
	PERCLOS	E202_perclos	
	Eye blink frequency	E202_blink_freq	
	Eye blink duration	E202_blink_dur	
	Percent in center based on median location of gaze	E202_gaze_center	
	Correlation between eye movements and SDLP	E202_eye_sdlp	
	Correlation between head turn and steering wheel movement	E202_headturn_wheel	
	Number of collisions	E202_num_col	
	Near misses	E202_num_miss	
	Degree of conflict	E202_deg_conflict	
	Delay time	E202_delay_time	
	Rise time	E202_rise_time	
	Peak time	E202_peak_time	
	Max overshoot	E202_over_max	
	Settling time	E202_set_time	
	How well it fits the model	E202_model_fit	
	Smooth pursuit velocity	E202_smpur_vel	
	Smooth pursuit duration	E202_smpur_dur	
	Smooth pursuit frequency	E202_smpur_freq	

Interstate Event 202: Merge On			
	Smooth pursuit maximum velocity	E202_smpur_maxvel	
	Smooth pursuit gain	E202_smpur_gain	
	SD of gaze	E202_gaze_sd	
	Gaze kurtosis	E202_gaze_kurt	
	Dwell duration	E202_dwell_time	
	Frequency of side mirror glances	E202_glance_freq_side	
	Frequency of speedometer glances	E202_glance_freq_speed	
	Glance direction	E202_glance_dir	
	Head movement	E202_head_mov	
	Timing of participant looking at side mirror	E202_side_time	
ALGORITHM INPUT	DESCRIPTION	IDENTIFIER	UNITS
(MEASURES THAT IS INPUT TO THE ALGORITHM)	Mean brake force		
	Mean accelerator position		
	Lateral acceleration		

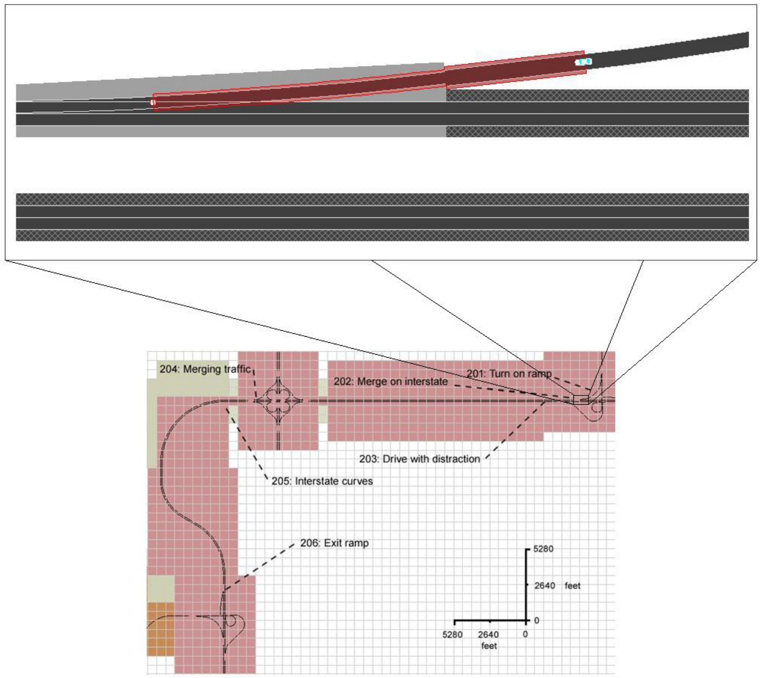

Figure F14. Merging onto highway

- Look for oncoming traffic
- Jerk of accelerator position
- Velocity of accelerator position
- Smoothness of merge on
- Max overshoot
- SDLP on ramp
- SD of acceleration to highway speed

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when merging onto a highway are: time from last glance until merging on, the smoothness of changing lanes, max overshoot, and jerk and velocity of accelerator position. As a person merges onto a highway, looking for other traffic is essential to safe driving and is something that alcohol impaired drivers tend to ignore**. The smoothness of lane change and max overshoot go hand in hand in the way a person pulls out of the parking space as unimpaired drivers will get into the lane fairly quickly and impaired drivers will have to adjust their position before settling on an adequate location (Struster, 1997). Jerk and velocity of accelerator position look at how smoothly the participant pulled out of the parking space in a longitudinal perspective. Alcohol impaired drivers have trouble slowing and speeding up in a smooth manner (Struster, 1997).

F.10.10 **Interstate Event 203: Drive with Distraction**

The participant drives on a straight section of interstate with two slow-moving trucks in the driving lane and a relatively slow-moving passenger car in the passing lane. The driver will also be instructed to interact with the CD player during this event.

INTERSTATE EVENT 203: DRIVE WITH DISTRACTION	
RATIONALE	Once the participant has merged onto the interstate, there will be a slow moving truck ahead of the driver that will maintain 45 mph. The posted speed limit of the interstate is 70 mph but with a posted truck speed limit of 65 mph. At three times during this section the driver will be instructed to interact with the CD player by turning it on and switching tracks. There is no specific FARS rationale for this event; however, it could involve a number of cues from NHTSA's DWI Detection Guide: e.g., following too close, unsafe lane change, weaving and failure to signal intentions. Some risk taking could take place when the drivers are impaired.
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 19712 Road type (lanes, surface): 2-lane interstate Speed limit (in mph): 70 mph for passenger vehicles, 65 mph for trucks Curvature: none Intersection type: none Time of Day/Date: night lit
PREPARATION	A pair of tractor-trailers are created in the previous event ahead of the participant traveling 10 miles per hour slower than the participant with a minimum speed of 35 mph. Once the driver has finished merging onto the freeway the tractor-trailers will change their speed to 45 miles per hour. When the participant is at 6500, 10000, and 15000 they will be instructed to interact with the CD player. Before the participant reaches the first off ramp, a passenger vehicle will be created 1200 feet ahead of the driver in the passing lane. In drives 1 and 2, the vehicle will be created when the driver is 500 feet from the start of the exit-ramp; in drive 3, the vehicle will be created when the participant is 2850 feet from the exit ramp. The passenger vehicle will be traveling at 66 percent of the participant's speed; this will encourage the participant change lanes into the right lane to pass the passenger vehicle.
START CONDITIONS	200 feet past the on ramp.
ACTUAL EVENT	The participant has merged onto the interstate. Logstream 1 is incremented, logstream 2 is set to 203, and Logstream 4 is set to 1. When the participant is within 5.0 seconds headway to the first heavy truck or no later than approximately 6500 ft from the end of the on-ramp. SCC_Audio_Trigger is set to 313, playing the instructions for the 1st CD interaction task: "At this time – please turn on the CD player - select track 13 - then press off." When the participant is approximately 10000 ft from the end of the on-ramp. SCC_Audio_Trigger is set to 314, playing the instructions for the 2nd CD interaction task: "At this time – please turn on the CD player - select track 8 - then press off." When the participant is approximately 15000 ft from the end of the on-ramp. SCC_Audio_Trigger is set to 315, playing the instructions for the 3rd CD interaction task: "At this time – please turn on the CD player - select track 3 - then press off." When the participant is 500 feet from the end of the off-ramp in driver 1&2, and 2850 for drive 3, a car is created in the passing lane 1200 feet ahead of the participant. It will be traveling 66 percent of t the participants speed. Logstream 4 will be set to 3

Interstate Event 203: Drive with Distraction			
End Conditions	The participant is 100 ft before the overpass.		
Cleanup	none		
Event Contingency (Variables that define dependence of the current event on the interpretation of the previous event)	Description	Identifier	Units
Scenario Performance (Measures that indicate if the event is operating as expected)	Description	Identifier	Units
	Trucks and passenger vehicle maintain speed		
	Trucks and passenger vehicle maintain lane		
	Trucks turn off exit ramp	E203_exit_X (X is truck number, 1 to 2)	binary 1=yes, 0 = no
Assumed Driver Behavior (Measures that indicate whether the participant behaves according to the assumptions)	Description	Identifier	Units
	Driver passes first truck		binary 1=yes, 0=no
	Driver passes second truck		binary 1=yes, 0=no
	Driver passes car		binary 1=yes, 0=no
	Driver performs CD task as instructed	By observation	
Alcohol Impairment Indicators	Description	Identifier	Units
	Average distance from SV to truck	E203_hdwy_avg_d	ft
	Number of lane changes during following	E203_lane_change_ct	count

Interstate Event 203: Drive with Distraction			
(Measures that assess whether the event is sensitive to alcohol impairment)	Lane position	E203_lp_avg	ft
	Head movement (during lane change if any)		binary 1=yes, 0=no
	SD of lane position from mean	E203_lp_sd	ft
	SD of lane position from center	E203_lpn_sd	ft
	Turn signal use	E203_turn_signal_ct	binary 1=yes, 0 = no
	Time to collision	E203_ttc_min E203_ttc_obj	sec name of obj
	Smoothness of lane changes		
	SD of steering wheel position	E203_steer_sd	
	Velocity of steering wheel	E203_steer_vel	
	Jerk of steering wheel	E203_steer_jerk	
	Steering error	E203_steer_error	
	Highway turn signal use	E203_highwayturn_sig	
	Proportion of time TLC>2s	E203_tlc_2	proportion
	95% TLC	E203_tlc_95	
	Lateral Acceleration	E203_lat_acc	ft/sec^2
	Accelerator holds	E203_accel_holds	
	Number of center line crossings	E203_center_cross	count
	Number of right light crossings	E203_right_cross	count
	Frequency of lane changes	E203_freq_lane	count
	Velocity of accelerator position	E203_accel_vel	
	Jerk of accelerator position	E203_accel_jerk	
	SD of accelerator position	E203_accel_sd	
	Mean brake force	E203_brake_avg	
	SD of brake force	E203_brake_sd	
	Speed	E203_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E203_spn_avg	mph
	Timing of participant looking at rear view mirror	E203_rear_look	

INTERSTATE EVENT 203: DRIVE WITH DISTRACTION			
	Glance frequency at particular object	E203_freq_glance	
	Pressure output(global and local)	E203_out_pres	
	Pressure and force over time	E203_force_pres	
	Pressure point mapping	E203_map_pres	
	PERCLOS	E203_perclos	
	Eye blink frequency	E203_blink_freq	
	Eye blink duration	E203_blink_dur	
	Percent in center based on median location of gaze	E203_gaze_center	
	Correlation between road curvature and eye movements	E203_eye_curve	
	Correlation between steering and road curvature	E203_steer_curve	
	Correlation between eye movements and SDLP	E203_eye_sdlp	
	Correlation between eye movements and steering	E203_eye_steer	
	Correlation between head turn and steering wheel movement	E203_headturn_wheel	
	Number of collisions	E203_num_col	
	Near misses	E203_num_miss	
	Degree of conflict	E203_deg_conflict	
	Delay time	E203_delay_time	
	Rise time	E203_rise_time	
	Peak time	E203_peak_time	
	Max overshoot	E203_over_max	
	Settling time	E203_set_time	
	How well it fits the model	E203_model_fit	
	Smooth pursuit velocity	E203_smpur_vel	
	Smooth pursuit duration	E203_smpur_dur	
	Smooth pursuit frequency	E203_smpur_freq	
	Smooth pursuit maximum velocity	E203_smpur_maxvel	
	Smooth pursuit gain	E203_smpur_gain	
	SD of gaze	E203_gaze_sd	
	Gaze kurtosis	E203_gaze_kurt	

INTERSTATE EVENT 203: DRIVE WITH DISTRACTION			
	Dwell duration	E203_dwell_time	
	Frequency of side mirror glances	E203_glance_freq_side	
	Frequency of speedometer glances	E203_glance_freq_speed	
	Glance direction	E203_glance_dir	
	Head movement	E203_head_mov	
	Timing of participant looking at side mirror	E203_side_time	
ALGORITHM INPUT (MEASURES THAT IS INPUT TO THE ALGORITHM)	DESCRIPTION	IDENTIFIER	UNITS
	SD of lane position relative to mean		
	Headway		
	Variation in headway		

- SD of lane position from mean
- Smoothness of lane changes
- Time headway (if participant actually follows the trucks for any length of time, which is fairly unlikely because of the speed of the trucks)
- Max overshoot
- SD of speed (during "steady state") relative to mean speed

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when driving on a highway with other traffic are: SDLP, SD Speed, smoothness of lane changes as well as maximum overshoot, and time headway. SDLP has been shown to increase significantly when drivers are under the influence of alcohol (Calhoun et al., 2005; Gawron & Ranney, 1988; Reed & Green, 1999). The same has been shown for variation in speed which can be measured by SD Speed (Arnedt et al., 2001; Gawron & Ranney, 1988). The smoothness of lane change and max overshoot go hand in hand in the way a person pulls out of the parking space as unimpaired drivers will get into the lane fairly quickly and impaired drivers will have to adjust their position before settling on an adequate location (Struster, 1997). When drivers are alcohol impaired, they tend to follow more closely behind a lead vehicle than if they weren't impaired (Strayer et al., 2006).

F.10.11 Interstate Event 204: Merging Traffic

The participant will approach a second interchange. A passenger vehicle will start to merge onto the interstate; the merge onto the interstate is timed to cause a conflict in the driving lane with the participant. This means the participant will have to either change speed or lane in order to allow the other car to merge on if they are in the driving lane. The passenger car will merge onto the interstate, but shortly thereafter will pull of onto the shoulder. Figure F15 shows a depiction of the vehicle merging onto the interstate.

INTERSTATE EVENT 204: MERGING TRAFFIC	
RATIONALE	This scenario will involve the driver approaching an interchange with a vehicle merging about 500 feet ahead of the on-ramp. The driver should keep a relatively constant speed. The FARS rationale is the over-representation of impaired drivers in fatal crashes being the striking vehicles on high speed roads. DWI detection cues that could be observed include the driver's reaction to the merge: swerving, varying speed, unsafe lane change.
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 5720 Road type (lanes, surface): 2-lane interstate Speed limit (in mph): 70 mph for passenger vehicles, 60 mph for trucks Curvature: none Intersection type: Highway Interchange Time of Day/Date: Night
PREPARATION	The participant approaches a "clover leaf" interchange. A slow moving vehicle in the passing lane from the previous event encourages the participant to pass on the right and places the participant in the driving lane. A vehicle merges onto the highway so as to create a conflict situation with the participant if they are in the driving lane. (The participant is in the driving lane) After the merging vehicle has driven in the driving lane for a short distance, it brakes and pulls off to the side of the road.
START CONDITIONS	The participant is 1070 feet before center of clover leaf interchange (merging car will come on first ramp) or between the two over passes (merging car will come on second ramp).
ACTUAL EVENT	The participant approaches a "clover leaf" interchange. (The participant is in the driving lane after passing the slow moving vehicle). The vehicle merging onto the highway is created, logstream 1 is incremented, logstream 2 is set to 204, logstream 4 is set to 1. The merging vehicle enters the driving the lane of the interstate from the last entrance ramp for scenarios 1&2, for scenario 3 the vehicle enters from the 1st on-ramp. After a short distance the merging vehicle starts to decelerate with brake lights; logstream 4 is set to 2. The merging car pulls off onto the right shoulder and brakes to a stop. Once the participant has passed the location where the merging vehicle has or will stop, logstream 4 is set to 100.
END CONDITIONS	500 ft before start of curves
CLEANUP	None

INTERSTATE EVENT 204: MERGING TRAFFIC			
EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS
SCENARIO PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	DESCRIPTION	IDENTIFIER	UNITS
	Lateral distance between SV and blocker car at time merging car crosses onto interstate	E204_blocker_lat_d	ft
	Bumper-to-bumper distance between SV and blocker car at time merging car crosses onto interstate	E204_blocker_long_d	ft
	Time SV passes blocker car relative to merging car crossing onto interstate (negative = prior)	E204_blocker_pass_t	sec
	Scenario vehicles do not drive through one another	E204_DO_col_ct E204_DO_col_tx	count of DOs that collide with each other during event names of DOs that collide
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES ACCORDING TO THE ASSUMPTIONS)	DESCRIPTION	IDENTIFIER	UNITS
	Which lane the participant is in at start of event	E204_lane_init	binary 1=right, 2=left
	Accelerator release	E204_accel_release	binary 1=yes, 0 = no
	Brake press	E204_brake_press	binary 1=yes, 0 = no
	Lane change (driver moves over for merging car)	E204_lane_change	binary 1=yes, 0 = no
	Correlation between steering and road curvature	E204_steer_curve	
	Correlation between eye movements and SDLP	E204_eye_sdlp	

Interstate Event 204: Merging Traffic			
	Correlation between eye movements and steering	E204_eye_steer	
	Correlation between head turn and steering wheel movement	E204_headturn_wheel	
	Number of collisions	E204_num_col	
	Near misses	E204_num_miss	
	Degree of conflict	E204_deg_conflict	
	Delay time	E204_delay_time	
	Rise time	E204_rise_time	
	Peak time	E204_peak_time	
	Max overshoot	E204_over_max	
	Settling time	E204_set_time	
	How well it fits the model	E204_model_fit	
	Smooth pursuit velocity	E204_smpur_vel	
	Smooth pursuit duration	E204_smpur_dur	
	Smooth pursuit frequency	E204_smpur_freq	
	Smooth pursuit maximum velocity	E204_smpur_maxvel	
	Smooth pursuit gain	E204_smpur_gain	
	SD of gaze	E204_gaze_sd	
	Gaze kurtosis	E204_gaze_kurt	
	Dwell duration	E204_dwell_time	
	Frequency of side mirror glances	E204_glance_freq_side	
	Frequency of speedometer glances	E204_glance_freq_speed	
	Glance direction	E204_glance_dir	
	Head movement	E204_head_mov	
	Percent in center based on median location of gaze	E204_gaze_center	
	Timing of participant looking at side mirror	E204_side_time	
Algorithm Input (Measures that is input to the algorithm)	Description	Identifier	Units
	Mean brake force		
	Mean accelerator position		

Interstate Event 204: Merging Traffic			

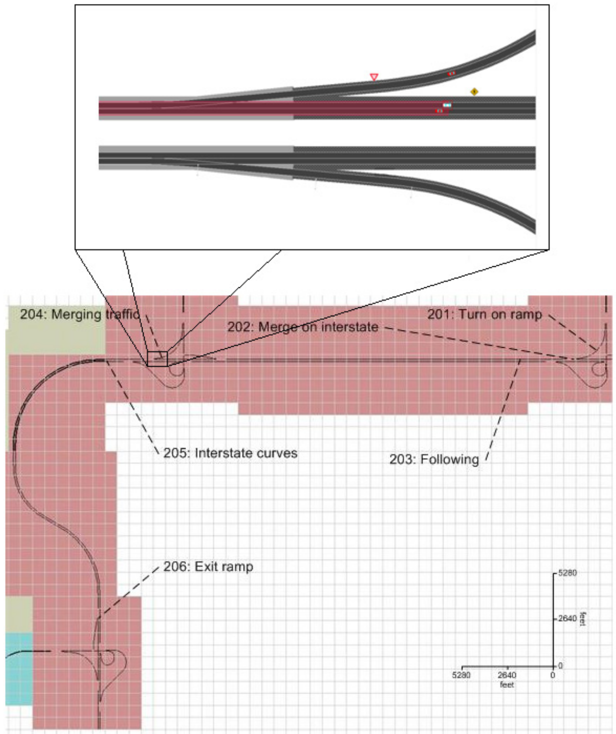

Figure F15. Merging Traffic

- Look for oncoming traffic
- Jerk of accelerator position
- Velocity of accelerator position
- Smoothness of lane change
- Max overshoot

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when encountering traffic merging onto a highway are: time from last glance until merging on, the smoothness of pulling changing lanes, max overshoot, and jerk and velocity of accelerator position. As a person merges onto a highway, looking for other traffic is essential to safe driving and is something that alcohol impaired drivers tend to ignore**. The smoothness of lane change and max overshoot go hand in hand in the way a person pulls out of the parking space as unimpaired drivers will get into the lane fairly quickly and impaired drivers will have to adjust their position before settling on an adequate location (Struster, 1997). Jerk and velocity of accelerator position look at how smoothly the participant pulled out of the parking space in a longitudinal perspective. Alcohol impaired drivers have trouble slowing and speeding up in a smooth manner (Struster, 1997).

F.10.12 Interstate Event 205: Interstate Curves

The participant will navigate a series of three curves on the interstate.

INTERSTATE EVENT 205: INTERSTATE CURVES			
RATIONALE	This scenario will involve a series of three curves the driver must negotiate on the interstate with light traffic. The FARS rationale is the over-representation of impaired driving fatal crashes on curves on dark but lighted roads. DWI detection cues that could occur include: weaving, drifting out of lane, almost striking an object, varying speed, and straddling a lane line.		
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 20020 Road type (lanes, surface): Asphalt 2-lane interstate Speed limit (in mph): 70 mph for passenger vehicles, 65 mph for trucks Curvature: 3 curves (radii of 3350, 2250, and 2925 ft) Intersection type: none Time of Day/Date: night lit		
PREPARATION	The participant navigates a series of three curves on the interstate. Audio instruction #303 plays, instructing the participant to get off at the next exit. (The participant is able to keep the vehicle on the road)		
START CONDITIONS	500 feet before the start of the first curve		
ACTUAL EVENT	Logstream 1 is incremented, logstream 2 is set to 205 The participant navigates a series of three curves on the interstate. Audio instruction number 303 plays, instructing participant to get off at the next exit. (The participant is able to keep the vehicle on the road.)		
END CONDITIONS	1000 feet before off ramp		
CLEANUP	None		
EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS
SCENARIO PERFORMANCE (MEASURES THAT	DESCRIPTION	IDENTIFIER	UNITS
	There are no scenario cars traveling in same direction as participant		

INTERSTATE EVENT 205: INTERSTATE CURVES			
INDICATE IF THE EVENT IS OPERATING AS EXPECTED)			
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES ACCORDING TO THE ASSUMPTIONS)	DESCRIPTION	IDENTIFIER	UNITS
	Road departures	E205_road_depart_ct	count
ALCOHOL IMPAIRMENT INDICATORS (MEASURES THAT ASSESS WHETHER THE EVENT IS SENSITIVE TO ALCOHOL IMPAIRMENT)	DESCRIPTION	IDENTIFIER	UNITS
	Lane position	E205_lp_avg	ft
	SD of lane position relative to mean	E205_lp_sd	ft
	SD of lane position relative to center	E205_lpn_sd	ft
	Steering wheel reversals		
	SD of speed relative to mean	E205_sp_sd	mph
	SD of speed relative to posted speed limit	E205_spn_sd	mph
	Number of center line crossings	E205_center_cross	count
	Number of right line crossings	E205_right_cross	count
	Speed	E205_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E205_spn_avg	mph
	Smoothness of lane changes (should they occur)	E205_lat_acc_avg	ft/s^2
	Lateral acceleration	E205_lat_acc	ft/s^2
	Head movement (during lane change if any)		binary 1=yes,0=no
	Turn Signal Use	E205_turn_signal	binary 1=yes, 0 = no
	SD of steering wheel position	E205_steer_sd	
	Velocity of steering wheel	E205_steer_vel	
	Jerk of steering wheel	E205_steer_jerk	

INTERSTATE EVENT 205: INTERSTATE CURVES			
	Steering error	E205_steer_error	
	Steering wheel reversals	E205_steer_rev	
	Highway turn signal use	E205_highwayturn_sig	
	Time to line crossing (TLC)	E205_tlc	
	Proportion of time TLC>2s	E205_tlc_2	proportion
	95% TLC	E205_tlc_95	
	Accelerator holds	E205_accel_holds	
	Frequency of lane changes	E205_freq_lane	count
	Velocity of accelerator position	E205_accel_vel	
	Jerk of accelerator position	E205_accel_jerk	
	SD of accelerator position	E205_accel_sd	
	Mean brake force	E205_brake_avg	
	SD of brake force	E205_brake_sd	
	Timing of participant looking at rear view mirror	E205_rear_look	
	Glance frequency at particular object	E205_freq_glance	
	Pressure output(global and local)	E205_out_pres	
	Pressure and force over time	E205_force_pres	
	Pressure point mapping	E205_map_pres	
	PERCLOS	E205_perclos	
	Eye blink frequency	E205_blink_freq	
	Eye blink duration	E205_blink_dur	
	Percent in center based on median location of gaze	E205_gaze_center	
	Correlation between road curvature and eye movements	E205_eye_curve	
	Correlation between steering and road curvature	E205_steer_curve	
	Correlation between eye movements and SDLP	E205_eye_sdlp	
	Correlation between eye movements and steering	E205_eye_steer	
	Correlation between head turn and steering wheel movement	E205_headturn_wheel	
	Number of collisions	E205_num_col	
	Near misses	E205_num_miss	

INTERSTATE EVENT 205: INTERSTATE CURVES			
	Delay time	E205_delay_time	
	Rise time	E205_rise_time	
	Peak time	E205_peak_time	
	Max overshoot	E205_over_max	
	Settling time	E205_set_time	
	How well it fits the model	E205_model_fit	
	Smooth pursuit velocity	E205_smpur_vel	
	Smooth pursuit duration	E205_smpur_dur	
	Smooth pursuit frequency	E205_smpur_freq	
	Smooth pursuit maximum velocity	E205_smpur_maxvel	
	Smooth pursuit gain	E205_smpur_gain	
	SD of gaze	E205_gaze_sd	
	Gaze kurtosis	E205_gaze_kurt	
	Dwell duration	E205_dwell_time	
	Frequency of side mirror glances	E205_glance_freq_side	
	Frequency of speedometer glances	E205_glance_freq_speed	
	Glance direction	E205_glance_dir	
	Head movement	E205_head_mov	
ALGORITHM INPUT	DESCRIPTION	IDENTIFIER	UNITS
(MEASURES THAT IS INPUT TO THE ALGORITHM)	SD of lane position relative to mean		
	SD of speed relative to mean		
	Steering wheel reversals		
	Lateral acceleration		

- SD of lane position (relative to mean lane position)
- Speed (relative to posted or assumed speed limit)
- SD of speed (during "steady state") relative to mean speed

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when driving down a road are: SDLP, SD Speed, and speed relative to the posted or assumed speed limit. One of the most widely thought of behaviors of alcohol impaired drivers is weaving around the lane. This can be represented by the variable SDLP, which has been shown to be sensitive to alcohol (Calhoun et al., 2005; Gawron & Ranney, 1988; Reed & Green, 1999). The same has been shown for variation in speed which can be measured by SD Speed (Arnedt et al., 2001; Gawron & Ranney, 1988). A standard set of qualitative behaviors for police to follow mentions that alcohol impaired drivers tend to drive slower than the speed limit by more than 10 mph (Struster, 1997).

F.10.13 **Interstate Event 206: Exit Ramp**

The participant will take the next exit ramp off the interstate. Figure F16 shows the exit ram off of the interstate. The off-ramp includes an elevation change. The beginning of the ramp starts at zero feet and increases to thirty feet by the end of the ramp. The elevation then decreases back to zero feet after the participant turns right.

Interstate Event 206: Exit Ramp	
RATIONALE	The participant will get off at the exit. This will involve going from two lanes to one lane, slowing from 70 mph to about 35 mph on a gentle curve. The FARS rationale is the over-representation of impaired participant crashes on curves. The DWI detection cues to observe could be: decelerating or braking in a jerky manner, drifting out of the proper lane, and failure to signal intentions.
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 1540 Road type (lanes, surface): 2-lane interstate to single lane exit ramp Speed limit (in mph): 70 to 35 (assumed) mph Curvature: 3600 ft radius, 2816 ft radius s-curve off ramp Intersection type: exit ramp Time of Day/Date: lit night Elevation: 0 ft at beginning of ramp to 30 ft at end of ramp
PREPARATION	The participant pulls off interstate onto the off-ramp As the participant approaches the intersection, some cross traffic passes from both directions in the oncoming intersection The participant takes the exit ramp (The participant may or may not actually stop fully at the turn)
START CONDITIONS	1000 feet from start of off ramp

Interstate Event 206: Exit Ramp			
ACTUAL EVENT	When the participant is 500 feet from the start of the off ramp, Logstream 1 is incremented, Logstream 2 is set to 206, Logstream 4 is set to 1. The participant pulls off onto the off ramp, Logstream 5 is set to 23, Logstream 4 is set to 100 (The participant remembers the audio instructions to pull off at the given exit) When the participant is 21 seconds from the stop line at the end of the ramp, two cars are created to pass through the intersection of the off ramp with the perpendicular rural roadway. A cargo truck crosses from the left and a car from the right. Logstream 3 is set to 1. 3 seconds later, another car is created to pass through the intersection from the right. Logstream 3 is set to 2.		
END CONDITIONS	Participant is at the stop line.		
CLEANUP	None		
EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS
SCENARIO PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	DESCRIPTION	IDENTIFIER	UNITS
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES ACCORDING TO THE ASSUMPTIONS)	DESCRIPTION	IDENTIFIER	UNITS
	Driver does not take the ramp	E206_nav_error	binary 1=yes, 0 = no
	Accelerator release	E206_accel_release	binary 1=yes, 0 = no
	Brake press	E206_brake_press	binary 1=yes, 0 = no
ALCOHOL	DESCRIPTION	IDENTIFIER	UNITS

Interstate Event 206: Exit Ramp			
IMPAIRMENT INDICATORS (MEASURES THAT ASSESS WHETHER THE EVENT IS SENSITIVE TO ALCOHOL IMPAIRMENT)	Speed	E206_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E206_spn_avg	mph
	Mean acceleration	E206_acc_avg	ft/s^2
	Number of center line crossings	E206_center_cross	count
	Number of right line crossings	E206_right_cross	count
	Turn signal use	E206_turn_signal	binary 1=yes, 0 = no
	Smoothness of transition onto the exit ramp (lateral)	E206_smooth_lat	
	Smoothness of transition onto the exit ramp (longitudinal)	E206_smooth_long	
	Head movement		binary 1=yes, 0 = no
	Lateral acceleration	E204_lat_acc	ft/s^2
	SD of steering wheel position	E206_steer_sd	
	Velocity of steering wheel	E206_steer_vel	
	Jerk of steering wheel	E206_steer_jerk	
	Steering error	E206_steer_error	
	Velocity of accelerator position	E206_accel_vel	
	Jerk of accelerator position	E206_accel_jerk	
	SD of accelerator position	E206_accel_sd	
	Mean brake force	E206_brake_avg	
	SD of brake force	E206_brake_sd	
	Glance frequency at particular object	E206_freq_glance	
	Pressure output(global and local)	E206_out_pres	
	Pressure and force over time	E206_force_pres	
	Pressure point mapping	E206_map_pres	
	PERCLOS	E206_perclos	
	Eye blink frequency	E206_blink_freq	
	Eye blink duration	E206_blink_dur	
	Percent in center based on median location of gaze	E206_gaze_center	

Interstate Event 206: Exit Ramp			
	Correlation between head turn and steering wheel movement	E206_headturn_wheel	
	Number of collisions	E206_num_col	
	Near misses	E206_num_miss	
	Delay time	E206_delay_time	
	Rise time	E206_rise_time	
	Peak time	E206_peak_time	
	Max overshoot	E206_over_max	
	Settling time	E206_set_time	
	How well it fits the model	E206_model_fit	
	Smooth pursuit velocity	E206_smpur_vel	
	Smooth pursuit duration	E206_smpur_dur	
	Smooth pursuit frequency	E206_smpur_freq	
	Smooth pursuit maximum velocity	E206_smpur_maxvel	
	Smooth pursuit gain	E206_smpur_gain	
	SD of gaze	E206_gaze_sd	
	Gaze kurtosis	E206_gaze_kurt	
	Dwell duration	E206_dwell_time	
	Frequency of side mirror glances	E206_glance_freq_side	
	Frequency of speedometer glances	E206_glance_freq_speed	
	Glance direction	E206_glance_dir	
	Head movement	E206_head_mov	
ALGORITHM INPUT (MEASURES THAT IS INPUT TO THE ALGORITHM)	DESCRIPTION	IDENTIFIER	UNITS
	Lateral acceleration		
	Mean brake force		
	Number of center line crossings		
	Number of right line crossings		

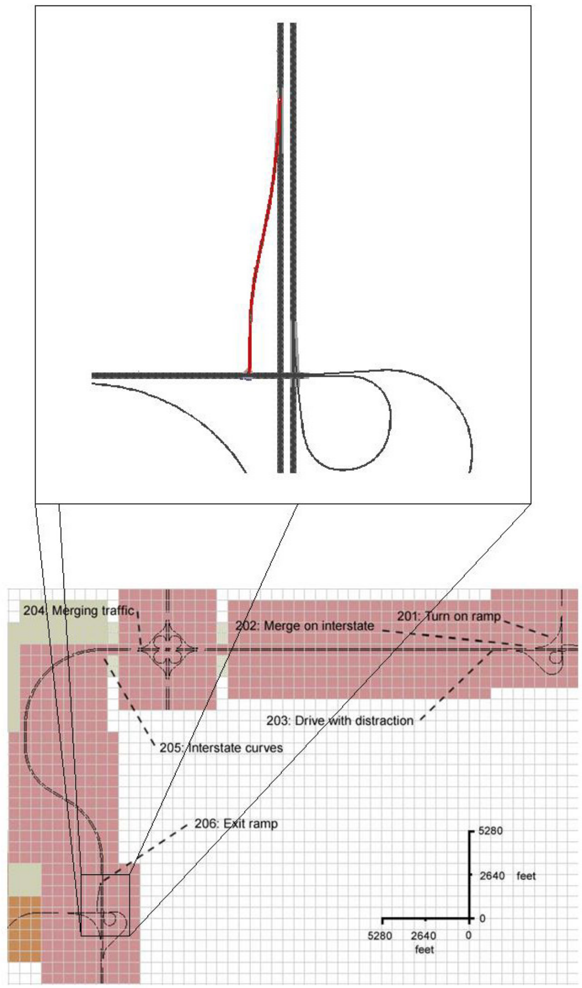

Figure F16. Interstate off-ramp.

- Jerk of accelerator position
- Velocity of accelerator position
- Velocity of steering wheel
- Jerk of steering wheel

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when turning onto a ramp are: jerk and velocity of accelerator position, and jerk and velocity of steering wheel position. Jerk and velocity of accelerator position look at how smoothly the participant pulled out of the parking space in a longitudinal perspective. Alcohol impaired drivers have trouble slowing and speeding up in a smooth manner (Struster, 1997). The jerk and velocity of the steering wheel position look at how smoothly the participant turned onto the ramp. Research has shown that alcohol impairs a person's ability to maintain lateral control (Calhoun et al., 2005).

F.10.14 Rural Event 301: Turn Off Ramp (Transitional)

The driver is at a stop sign at the end of an exit ramp. They will have been given an instruction to turn right at the intersection. The participant will make a right hand turn onto a rural highway and accelerate up to speed.

RURAL EVENT 301: TURN OFF RAMP (TRANSITIONAL)	
RATIONALE	The driver is required to make a right turn from the off-ramp onto a rural two-lane undivided road with a speed limit of 55 mph. There is no traffic for this transition scenario. The FARS rationale is the over-representation of impaired driving fatal crashes on dark, but lighted, undivided two-lane roads, involving a slight curve. DWI detection cues that could emerge include: turning with a wide radius, weaving across lanes, speed variation problems, and driving in the opposing lane.
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 1500 Road type (lanes, surface): 1-lane asphalt to 2-lane asphalt Speed limit (in mph): 35 mph (assumed) exit ramp to 55 mph highway Curvature: Approximate radius is 1900 ft Intersection type: Exit ramp to 2-lane rural road Time of Day/Date: Night, lighted Elevation: 30 ft to 0 ft
PREPARATION	The participant nears the stop line (The participant may or may not come to a complete stop) The participant turns right onto the 2-lane lit rural highway (The participant makes the correct turn) When the participant has driven 400 feet after making the turn, an audio instruction (304-turn left, 326 turn right) informing them of their next turn plays. (The participant makes the correct turn) The participant speeds up and matches the speed limit (The participant accelerates after the turn)
START CONDITIONS	The participant is 12 feet in front of the stop line
ACTUAL EVENT	The participant slows to a very low speed or come to a complete stop near the stop line. Logstream 1 is set to incremented, Logstream 2 is set to 301. (The participant may or may not come to a complete stop) The participant turns right onto the 2-lane lit rural highway. As the participant crosses the stop line logstream 4 is set to 1. As the participant finishes the turn and is on the rural highway, logstream 5 is set to 31 (The participant makes the correct turn) When the participant has driven 400 feet after making the turn, an audio instruction (304-turn left, 326 turn right) plays informing them of their next turn. (The participant makes the correct turn) The participant speeds up and matches the speed limit (The participant accelerates after the turn)
END CONDITIONS	The participant has traveled 1500 feet from the turn
CLEANUP	None

Rural Event 301: Turn Off Ramp (Transitional)			
Event Contingency (Variables that define dependence of the current event on the interpretation of the previous event)hn thought to CC me on that email this time	Description	Identifier	Units
Scenario Performance (Measures that indicate if the event is operating as expected)	Description	Identifier	Units
	Crossing vehicles pass through intersection	Observation variable	
Assumed Driver Behavior (Measures that indicate whether the participant behaves according to the assumptions)	Description	Identifier	Units
	Acceleration rate at beginning of task	E301_acc_init	ft/s^2
	Complete stop	E301_complete_stop	binary 1=yes, 0 = no
	Minimum speed	E301_sp_min	mph
	Driver does not turn right at end of the ramp	E301_nav_error	binary 1=yes, 0 = no
	Acceleration rate at end of event	E301_acc_end	ft/s^2
	Done accelerating	E301_acc_done	binary 1=yes, 0 = no
	Average acceleration rate on ramp	E301_acc_avg_ramp	ft/s^2
	Average acceleration rate on rural road	E301_acc_avg_rural	ft/s^2
	Acceleration distance on rural road	E301_acc_done_d	ft
	Speed at the end of event	E301_sp_mavgnd	mph
Alcohol Impairment Indicators	Description	Identifier	Units
	Smooth pursuit duration		sec
	Smooth pursuit frequency		pursuits/sec

Rural Event 301: Turn Off Ramp (Transitional)			
(Measures that assess whether the event is sensitive to alcohol impairment)	Smooth pursuit maximum velocity		deg/sec
	Smooth pursuit gain		
	S.D. of accelerations	E301_acc_sd	ft/s^2
	Turn signal use	E301_turn_signal	binary 1=yes, 0 = no
	Head movement		binary 1=yes, 0 = no
	Deviation around the Line of Best fit for speed during acceleration (Robertson, 1996)		
	Number of center line crossings	E301_center_cross	count
	Number of right line crossings	E301_right_cross	count
	Smoothness of transition (longitudinal)	E301_smooth_long	
	Smoothness of transition (lateral)	E301_smooth_lat	
	Complete stop	E301_complete_stop	binary 1=yes, 0 = no
	Location of stop (relative to stop line)	E301_stop_pos	ft
	Heading at stop	E301_stop_hdng	deg
	Frequency of glances to traffic on left	E301_glance_freq_left	glances/sec
	Mean brake force		
	Intersection turn signal use	E301_turn_sig	
	Velocity of accelerator position	E301_accel_vel	
	Jerk of accelerator position	E301_accel_jerk	
	SD of accelerator position	E301_accel_sd	
	Mean brake force	E301_brake_avg	
	SD of brake force	E301_brake_sd	
	Speed	E301_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E301_spn_avg	mph
	Glance frequency at particular object	E301_freq_glance	
	Pressure output(global and local)	E301_out_pres	
	Pressure and force over time	E301_force_pres	
	Pressure point mapping	E301_map_pres	

Rural Event 301: Turn Off Ramp (Transitional)			
	PERCLOS	E301_perclos	
	Eye blink frequency	E301_blink_freq	
	Eye blink duration	E301_blink_dur	
	Percent in center based on median location of gaze	E301_gaze_center	
	Correlation between road curvature and eye movements	E301_eye_curve	
	Correlation between steering and road curvature	E301_steer_curve	
	Correlation between eye movements and SDLP	E301_eye_sdlp	
	Correlation between eye movements and steering	E301_eye_steer	
	Number of collisions	E301_num_col	
	Near misses	E301_num_miss	
	Delay time	E301_delay_time	
	Rise time	E301_rise_time	
	Peak time	E301_peak_time	
	Max overshoot	E301_over_max	
	Settling time	E301_set_time	
	How well it fits the model	E301_model_fit	
	Smooth pursuit velocity	E301_smpur_vel	
	Smooth pursuit duration	E301_smpur_dur	
	Smooth pursuit frequency	E301_smpur_freq	
	Smooth pursuit maximum velocity	E301_smpur_maxvel	
	Smooth pursuit gain	E301_smpur_gain	
	SD of gaze	E301_gaze_sd	
	Gaze kurtosis	E301_gaze_kurt	
	Dwell duration	E301_dwell_time	
	Frequency of side mirror glances	E301_glance_freq_side	
	Frequency of speedometer glances	E301_glance_freq_speed	
	Glance direction	E301_glance_dir	
	Head movement	E301_head_mov	
Algorithm Input	Description	Identifier	Units

RURAL EVENT 301: TURN OFF RAMP (TRANSITIONAL)			
(MEASURES THAT IS INPUT TO THE ALGORITHM)	Mean accelerator position		
	Lateral acceleration		
	Smoothness of acceleration		
	Mean speed		
	Smooth pursuit eye movements		

- Jerk of accelerator position
- Velocity of accelerator position
- Smoothness of lane change
- Max overshoot
- Velocity of steering wheel
- Jerk of steering wheel

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when turning left are: the smoothness of pulling out, max overshoot, and jerk and velocity of accelerator position. The smoothness of lane change and max overshoot go hand in hand in the way a person pulls out of the parking space as unimpaired drivers will get into the lane fairly quickly and impaired drivers will have to adjust their position before settling on an adequate location (Struster, 1997). Jerk and velocity of accelerator position look at how smoothly the participant pulled out of the parking space in a longitudinal perspective. Alcohol impaired drivers have trouble slowing and speeding up in a smooth manner (Struster, 1997).

F.10.15 **Rural Event 302: Lighted Rural**

The participant will follow a lighted two-lane road with a speed limit of 55 mph.

RURAL EVENT 302: LIGHTED RURAL	
RATIONALE	The driver is required to drive for a few minutes on a lighted two-lane rural road with a speed limit of 55 mph with oncoming traffic about once every 60 seconds. The FARS rationale includes the over-representation on rural two-lane undivided roads with a speed limit of 55 mph. DWI detection cues could be: weaving, drifting, lane maintenance problems, accelerating or decelerating for no good reason, varying speed, and driving in opposing lanes

Rural Event 302: Lighted Rural			
Road Network Requirements	Overall length/distance needed to support event (in feet): 750 Road type (lanes, surface): 2-lane asphalt Speed limit (in mph): 55 mph Curvature: None Intersection type: None Time of Day/Date: Night, lighted		
Preparation	The participant follows this lighted two-lane road with a speed limit of 55 mph. (The participant has finished accelerating and is traveling 55 mph) The participant sees oncoming traffic on average once per 60 seconds		
Start Conditions	The participant has traveled 1500 feet after turning onto the rural highway		
Actual Event	Logstream 1 is incremented, logstream 2 is set to 302, logstream 3 is set to 0, logstream 4 is set to 100. The participant follows this lighted two-lane road with a speed limit of 55 mph. (The participant is traveling 55 mph) The participant sees oncoming traffic on average once per 60 seconds		
End Conditions	The participant has passed the last lamp post		
Cleanup			
Event Contingency (Variables that define dependence of the current event on the interpretation of the previous event)	Description	Identifier	Units
	Done accelerating	E301_acc_done	binary 1=yes, 0 = no
Scenario Performance (Measures that indicate if the event is operating as expected)	Description	Identifier	Units
	Oncoming traffic present on average every 60 seconds	E302_oncoming_freq	avg. sec between cars
	Lighting present on road	observation	
Assumed Driver Behavior (Measures that indicate whether the participant behaves	Description	Identifier	Units
	Average speed during event	E302_sp_avg	mph
	Average speed relative to speed limit	E302_spn_avg	mph
	SD speed during event relative to mean	E302_sp_sd	mph

Rural Event 302: Lighted Rural			
according to the assumptions)	SD speed during event relative to speed limit	E302_spn_sd	mph
Alcohol Impairment Indicators (Measures that assess whether the event is sensitive to alcohol impairment)	Description	Identifier	Units
	Average lane position	E302_lp_avg	ft
	SD of lane position relative to mean	E302_lp_sd	ft
	SD of lane position relative to center of lane	E302_lpn_sd	ft
	Speed	E302_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E302_spn_avg	mph
	SD speed during event relative to mean	E302_sp_sd	mph
	SD speed during event relative to speed limit	E302_spn_sd	mph
	Number of center line crossings	E302_center_cross	count
	Number of right line crossings	E302_right_cross	count
	Frequency of glances to rear view mirror	E302_glance_freq_rear	glances/sec
	Steering wheel reversals	E302_steer_rev	
	SD of steering wheel position	E302_steer_sd	
	Velocity of steering wheel	E302_steer_vel	
	Jerk of steering wheel	E302_steer_jerk	
	Steering error	E302_steer_error	
	Time to line crossing (TLC)	E302_tlc	
	Proportion of time TLC>2s	E302_tlc_2	proportion
	95% TLC	E302_tlc_95	
	Accelerator holds	E302_accel_holds	
	Velocity of accelerator position	E302_accel_vel	
	Jerk of accelerator position	E302_accel_jerk	
	SD of accelerator position	E302_accel_sd	
	Glance frequency at particular object	E302_freq_glance	
	Pressure output(global and local)	E302_out_pres	
	Pressure and force over time	E302_force_pres	

Rural Event 302: Lighted Rural			
	Pressure point mapping	E302_map_pres	
	PERCLOS	E302_perclos	
	Eye blink frequency	E302_blink_freq	
	Eye blink duration	E302_blink_dur	
	Percent in center based on median location of gaze	E302_gaze_center	
	Correlation between road curvature and eye movements	E302_eye_curve	
	Correlation between steering and road curvature	E302_steer_curve	
	Correlation between eye movements and SDLP	E302_eye_sdlp	
	Correlation between eye movements and steering	E302_eye_steer	
	Number of collisions	E302_num_col	
	Near misses	E302_num_miss	
	Smooth pursuit velocity	E302_smpur_vel	
	Smooth pursuit duration	E302_smpur_dur	
	Smooth pursuit frequency	E302_smpur_freq	
	Smooth pursuit maximum velocity	E302_smpur_maxvel	
	Smooth pursuit gain	E302_smpur_gain	
	SD of gaze	E302_gaze_sd	
	Gaze kurtosis	E302_gaze_kurt	
	Dwell duration	E302_dwell_time	
	Frequency of side mirror glances	E302_glance_freq_side	
	Frequency of speedometer glances	E302_glance_freq_speed	
	Glance direction	E302_glance_dir	
Algorithm Input (Measures that is input to the algorithm)	Description	Identifier	Units
	Lane position		
	Speed		
	SD of lane position relative to mean		
	SD of speed relative to mean		
	Steering wheel reversals		
	Number of center line crossings		

RURAL EVENT 302: LIGHTED RURAL			
	Number of right line crossings		

- SD of lane position (relative to mean lane position)
- Speed (relative to posted or assumed speed limit)
- SD of speed (during "steady state") relative to mean speed

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver are driving down a road are: SDLP, SD Speed, and speed relative to the posted or assumed speed limit. One of the most widely thought of behaviors of alcohol impaired drivers is weaving around the lane. This can be represented by the variable SDLP, which has been shown to be sensitive to alcohol (Calhoun et al., 2005; Gawron & Ranney, 1988; Reed & Green, 1999). The same has been shown for variation in speed which can be measured by SD Speed (Arnedt et al., 2001; Gawron & Ranney, 1988). A standard set of qualitative behaviors for police to follow mentions that alcohol impaired drivers tend to drive slower than the speed limit by more than 10 mph (Struster, 1997).

F.10.16 Rural Event 303: Transition to Dark Rural

The road will transition to an unlighted two-lane road. The center and road edge markings are faded, and the road will have a grayish surface.

RURAL EVENT 303: TRANSITION TO DARK RURAL	
RATIONALE	The driver is required to transition to a segment of the rural road that is unlighted. The center and edge lines is faded and the road will have a grayish surface. There is no specific FARS rationale, but this transition is typical and could involve some challenging visual problems. DWI detection cues that could occur include: swerving, drifting, varying speed, and straddling the lane lines.
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet):1500 ft Road type (lanes, surface): 2-lane asphalt Speed limit (in mph): 55 mph Curvature: None Intersection type: None Time of Day/Date: Night, transition from lit to dark
PREPARATION	The participant is driving on the lighted two-lane road with a speed limit of 55 mph. (The participant is traveling 55 mph)
START CONDITIONS	Event starts at the last lamp post
ACTUAL EVENT	The participant enters the unlighted portion of the rural road. Logstream 1 is incremented, logstream 2 is set to 303, logstream 4 is set to 32. (The participant maintains speed or slows slightly.)
END CONDITIONS	Event ends 1500 feet past the last lamp post.
CLEANUP	None

Rural Event 303: Transition to Dark Rural			
Event Contingency (Variables that define dependence of the current event on the interpretation of the previous event)	Description	Identifier	Units
Scenario Performance (Measures that indicate if the event is operating as expected)	Description	Identifier	Units
	Lighted road ends—dark begins		
	Oncoming traffic every 60 seconds	E303_oncoming_freq	avg. sec between cars
Assumed Driver Behavior (Measures that indicate whether the participant behaves according to the assumptions)	Description	Identifier	Units
	Beginning speed	E303_sp_init	mph
	Ending speed	E303_sp_mavgnd	mph
	Average speed	E303_sp_avg	mph
	Average speed relative to speed limit	E303_spn_avg	mph
	SD speed relative to mean speed	E303_sp_sd	mph
	SD speed relative to speed limit	E303_spn_sd	mph
Alcohol Impairment Indicators (Measures that assess whether the event is sensitive to alcohol impairment)	Description	Identifier	Units
	Average lane position	E303_lp_avg	ft
	SD of lane position relative to mean lane position	E303_lp_sd	ft
	SD of lane position relative to center of lane	E303_lpn_sd	ft
	SD speed relative to mean speed	E303_sp_sd	mph
	SD speed relative to speed limit	E303_spn_sd	mph
	Number of center line crossings	E303_center_cross	count
	Number of right line crossings	E303_right_cross	count
	Frequency of glances to rear view mirror	E303_glance_freq_rear	glances/sec
	Steering wheel reversals	E303_steer_rev	

RURAL EVENT 303: TRANSITION TO DARK RURAL			
	SD of steering wheel position	E303_steer_sd	
	Velocity of steering wheel	E303_steer_vel	
	Jerk of steering wheel	E303_steer_jerk	
	Steering error	E303_steer_error	
	Time to line crossing (TLC)	E303_tlc	
	Proportion of time TLC>2s	E303_tlc_2	proportion
	95% TLC	E303_tlc_95	
	Accelerator holds	E303_accel_holds	
	Velocity of accelerator position	E303_accel_vel	
	Jerk of accelerator position	E303_accel_jerk	
	SD of accelerator position	E303_accel_sd	
	Speed	E303_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E303_spn_avg	mph
	Glance frequency at particular object	E303_freq_glance	
	Pressure output(global and local)	E303_out_pres	
	Pressure and force over time	E303_force_pres	
	Pressure point mapping	E303_map_pres	
	PERCLOS	E303_perclos	
	Eye blink frequency	E303_blink_freq	
	Eye blink duration	E303_blink_dur	
	Percent in center based on median location of gaze	E303_gaze_center	
	Correlation between road curvature and eye movements	E303_eye_curve	
	Correlation between steering and road curvature	E303_steer_curve	
	Correlation between eye movements and SDLP	E303_eye_sdlp	
	Correlation between eye movements and steering	E303_eye_steer	
	Number of collisions	E303_num_col	
	Near misses	E303_num_miss	
	Smooth pursuit velocity	E303_smpur_vel	
	Smooth pursuit duration	E303_smpur_dur	

Rural Event 303: Transition to Dark Rural			
	Smooth pursuit frequency	E303_smpur_freq	
	Smooth pursuit maximum velocity	E303_smpur_maxvel	
	Smooth pursuit gain	E303_smpur_gain	
	SD of gaze	E303_gaze_sd	
	Gaze kurtosis	E303_gaze_kurt	
	Dwell duration	E303_dwell_time	
	Frequency of side mirror glances	E303_glance_freq_side	
	Frequency of speedometer glances	E303_glance_freq_speed	
	Glance direction	E303_glance_dir	
Algorithm Input (Measures that is input to the algorithm)	Description	Identifier	Units
	Lane position		
	Speed		
	SD lane position relative to mean		
	SD speed relative to mean		
	Steering wheel reversals		
	Number of center line crossings		
	Number of right line crossings		

- Change in speed (from beginning of the event to the end)
- SDLP
- Maximum brake pressure

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver with a lit to unlit roadway transition are: SDLP, the change in speed from the beginning of the event to the end, and the maximum brake pressure. One of the most widely thought of behaviors of alcohol impaired drivers is weaving around the lane. This can be represented by the variable SDLP, which has been shown to be sensitive to alcohol (Calhoun et al., 2005; Gawron & Ranney, 1988; Reed & Green, 1999). Maximum brake pressure and change in speed both look at a participant's ability to control velocity in a changing environment. It is known that alcohol impaired drivers have trouble slowing and speeding up in a smooth manner (Struster, 1997).

F.10.17 **Rural Event 304: Dark Rural**

The road has transitioned to an unlighted two-lane road. The center and road edge markings are faded, and the road has a grayish surface. Figure F17 depicts the dark rural segment. There is an elevation change for the rural curves that increases from zero feet to fifty, then decreases back to zero feet.

RURAL EVENT 304: DARK RURAL			
RATIONALE	This segment involves a few minutes of driving on this rural, two-lane, unlighted 55 mph road with faded lane lines involving some curves. Curve radii range from 456 ft to 5500 ft. The FARS rationale includes the over-representation of impaired driving fatal crashes occurring under just these conditions. DWI cues that could emerge include: weaving across lanes, drifting, varying speed, driving in opposing lane, and running off the road.		
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 14510 Road type (lanes, surface): 2-lane asphalt with faded pavement markings Speed limit (in mph): 55 mph initially, 45 mph on curves, 55 mph at end of event Curvature: Varying straight and curved sections including approximately 45 deg left turn with radius of 1525 ft and hairpin curve, approximately 135 deg, radius of 456 ft. Intersection type: None Time of Day/Date: Night, dark Elevation: Event contains a hill approximately 55 ft high		
PREPARATION	The participant follows an unlighted two-lane road with a speed limit of 55 mph. (The participant is traveling 55 mph) The participant experiences oncoming traffic on average every 60 seconds. The participant experiences a series of curves. (The participant is traveling 45 mph) The participant experiences an oncoming car timed such that it meets the participant near the apex of one of the curves		
START CONDITIONS	The participant has passed the geometric point defining the end of the transition to the dark rural road segment (1500 ft after lighted rural roadway segment ends).		
ACTUAL EVENT	Logstream 1 is incremented, logstream 2 is set to 304. The participant follows an unlighted two-lane road with a speed limit of 55 mph. (The participant is traveling 55 mph) The participant navigates through a series of curves. (The participant is traveling 45 mph, maintains lane position, and does not crash.) Traffic frequency in oncoming lane is 1 vehicle/60 sec. The participant encounters an oncoming vehicle on a curve. When the oncoming vehicle is 800 feet from the participant, logstream 3 is set to 1 (The participant does not crash) When the oncoming vehicle is has passed the participant, logstream 3 is set to 0 (The participant does not crash)		
END CONDITIONS	500 ft before Y-intersection with transition to gravel road		
CLEANUP	None		
EVENT CONTINGENCY	DESCRIPTION	IDENTIFIER	UNITS

Rural Event 304: Dark Rural			
(Variables that define dependence of the current event on the interpretation of the previous event)			
Scenario Performance (Measures that indicate if the event is operating as expected)	Description	Identifier	Units
	No lights	Observation	
	Oncoming traffic (1 car/60 sec)	E304_oncoming_freq	avg. sec between cars
	Meet conflict car on apex of curve		
Assumed Driver Behavior (Measures that indicate whether the participant behaves according to the assumptions)	Description	Identifier	Units
	Speed (average, min, and max)	E304_sp_avg E304_sp_min E304_sp_max	mph
Alcohol Impairment Indicators (Measures that assess whether the event is sensitive to alcohol impairment)	Description	Identifier	Units
	Lane position	E304_lp_avg	ft
	SD of lane position (relative to mean lane position)	E304_lp_sd	ft
	SD of lane position (relative to center of lane)	E304_lpn_sd	ft
	Speed	E304_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E304_spn_avg	mph
	SD of speed (relative to mean speed)	E304_sp_sd	mph
	SD of speed (relative to posted or assumed speed limit)	E304_spn_sd	mph
	Number of center line crossings	E304_center_cross	count

RURAL EVENT 304: DARK RURAL			
	Number of right line crossings	E304_right_cross	count
	Frequency of glances to rear view mirror	E304_glance_freq_rear	glances/sec
	Mean speed during hairpin turn	E302_spn_avg_hp	mph
	Steering wheel reversals	E304_steer_rev	
	SD of steering wheel position	E304_steer_sd	
	Velocity of steering wheel	E304_steer_vel	
	Jerk of steering wheel	E304_steer_jerk	
	Steering error	E304_steer_error	
	Time to line crossing (TLC)	E304_tlc	
	Proportion of time TLC>2s	E304_tlc_2	proportion
	95% TLC	E304_tlc_95	
	Accelerator holds	E304_accel_holds	
	Velocity of accelerator position	E304_accel_vel	
	Jerk of accelerator position	E304_accel_jerk	
	SD of accelerator position	E304_accel_sd	
	Glance frequency at particular object	E304_freq_glance	
	Pressure output(global and local)	E304_out_pres	
	Pressure and force over time	E304_force_pres	
	Pressure point mapping	E304_map_pres	
	PERCLOS	E304_perclos	
	Eye blink frequency	E304_blink_freq	
	Eye blink duration	E304_blink_dur	
	Percent in center based on median location of gaze	E304_gaze_center	
	Correlation between road curvature and eye movements	E304_eye_curve	
	Correlation between steering and road curvature	E304_steer_curve	
	Correlation between eye movements and SDLP	E304_eye_sdlp	
	Correlation between eye movements and steering	E304_eye_steer	
	Number of collisions	E304_num_col	
	Near misses	E304_num_miss	

Rural Event 304: Dark Rural			
	Degree of conflict	E304_deg_conflict	
	Smooth pursuit velocity	E304_smpur_vel	
	Smooth pursuit duration	E304_smpur_dur	
	Smooth pursuit frequency	E304_smpur_freq	
	Smooth pursuit maximum velocity	E304_smpur_maxvel	
	Smooth pursuit gain	E304_smpur_gain	
	SD of gaze	E304_gaze_sd	
	Gaze kurtosis	E304_gaze_kurt	
	Dwell duration	E304_dwell_time	
	Frequency of side mirror glances	E304_glance_freq_side	
	Frequency of speedometer glances	E304_glance_freq_speed	
	Glance direction	E304_glance_dir	
Algorithm Input (Measures that is input to the algorithm)	Description	Identifier	Units
	Lane position		
	Speed		
	SD of lane position relative to mean		
	SD of speed relative to mean		
	Number of center line crossings		
	Number of right line crossings		
	Steering wheel reversals		

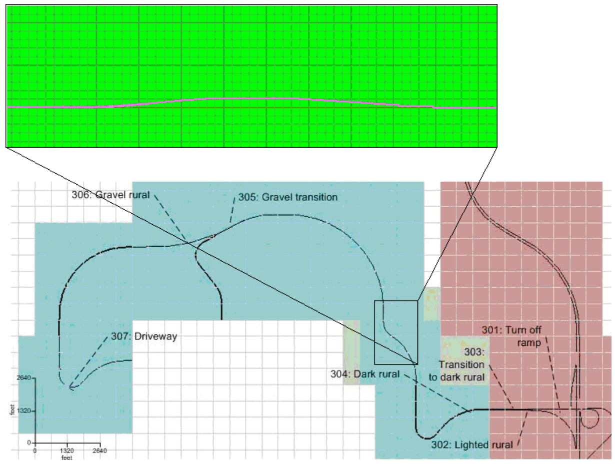

Figure F17. Elevation change in rural curves

- SD of lane position (relative to mean lane position)
- Speed (relative to posted or assumed speed limit)
- SD of speed (during "steady state") relative to mean speed

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver are driving down a road are: SDLP, SD Speed, and speed relative to the posted or assumed speed limit. One of the most widely thought of behaviors of alcohol impaired drivers is weaving around the lane. This can be represented by the variable SDLP, which has been shown to be sensitive to alcohol (Calhoun et al., 2005; Gawron & Ranney, 1988; Reed & Green, 1999). The same has been shown for variation in speed which can be measured by SD Speed (Arnedt et al., 2001; Gawron & Ranney, 1988). A standard set of qualitative behaviors for police to follow mentions that alcohol impaired drivers tend to drive slower than the speed limit by more than 10 mph (Struster, 1997).

F.10.18 **Rural Event 305: Gravel Transition**

The participant will come upon a fork in the road. The main road will curve to the left, and a gravel road will veer to the right. The participants will veer to the right (see Figure F18). The participant is instructed through an audio queue to continue in either direction.

RURAL EVENT 305: GRAVEL TRANSITION	
RATIONALE	In this segment, the driver will come to a fork in the road, turn slightly to the right on a gravel road and continue straight. The FARS rationale is the over-representation of high BAC crashes on gravel roads. DWI cues could be driving too fast for conditions, swerving, running off the road edge, and stopping for no apparent reason.

<table>
<tr><th colspan="4">RURAL EVENT 305: GRAVEL TRANSITION</th></tr>
<tr><td>ROAD NETWORK REQUIREMENTS</td><td colspan="3">Overall length/distance needed to support event (in feet): 2420
Road type (lanes, surface): Transition from faded asphalt to 2-lane gravel
Speed limit (in mph): 55 mph to an assumed speed of 45 mph
Curvature: None
Intersection type: Y, gravel road straight ahead, asphalt road curving away
Time of Day/Date: Night, dark</td></tr>
<tr><td>PREPARATION</td><td colspan="3">The participant approaches a Y intersection (gravel road going straight ahead, asphalt road curving away to the left)
(The participant is driving on the road and in the correct lane)
The following vehicles(approximately 500 feet behind) veer left at the intersection and not follow the onto the gravel road</td></tr>
<tr><td>START CONDITIONS</td><td colspan="3">500 ft before the Y-intersection</td></tr>
<tr><td>ACTUAL EVENT</td><td colspan="3">Logstream 1 is incremented, logstream 2 is set to 305, logstream 4 is set to 1
Once the participant has crossed into the gravel road, logstream 4 is set to 100, and logstream 5 is set to 33
The participant continues straight onto the gravel road section
(The participant veers off the paved road onto the gravel road.)
(The participant adjusts their speed appropriately for the gravel road surface (no posted speed limit).
The following vehicles veer left at the intersection and not follow the participant onto the gravel road</td></tr>
<tr><td>END CONDITIONS</td><td colspan="3">The participant has traveled 1500 ft past the start of the gravel road.</td></tr>
<tr><td>CLEANUP</td><td colspan="3">None</td></tr>
<tr><td rowspan="5">EVENT CONTINGENCY
(VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)</td><td>DESCRIPTION</td><td>IDENTIFIER</td><td>UNITS</td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
<tr><td rowspan="6">SCENARIO PERFORMANCE
(MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)</td><td>DESCRIPTION</td><td>IDENTIFIER</td><td>UNITS</td></tr>
<tr><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td></tr>
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<tr><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td></tr>
</table>

Rural Event 305: Gravel Transition			
Assumed Driver Behavior (Measures that indicate whether the participant behaves according to the assumptions)	Description	Identifier	Units
	Participant does not take turn	E305_nav_error	binary 1=yes, 0 = no
	Initial speed (speed at beginning of event)	E305_sp_init	mph
	End speed (speed at end of event)	E305_sp_mavgnd	mph
	Accelerator release	E305_accel_release	binary 1=yes, 0 = no
	Brake press	E305_brake_press	binary 1=yes, 0 = no
Alcohol Impairment Indicators (Measures that assess whether the event is sensitive to alcohol impairment)	Description	Identifier	Units
	SD of speed relative to mean	E305_sp_sd	mph
	SD of speed relative to posted or assumed speed limit	E305_spn_sd	mph
	Speed	E305_sp_avg	mph
	Speed (relative to posted or assumed speed limit)	E305_spn_avg	mph
	S.D. of steering wheel angle	E305_steer_sd	deg
	Smoothness of transition onto gravel (longitudinal)	E305_smooth_long	
	Smoothness of transition onto gravel (lateral)	E305_smooth_lat	
	Turn signal use	E305_turn_signal	binary 1=yes, 0 = no
	Steering wheel reversals	E305_steer_rev	
	SD of steering wheel position	E305_steer_sd	
	Velocity of steering wheel	E305_steer_vel	
	Jerk of steering wheel	E305_steer_jerk	
	Steering error	E305_steer_error	
	Frequency of glances to rear view mirror	E305_glance_freq_rear	glances/sec
	Accelerator holds	E305_accel_holds	
	Number of left line crossings	E305_left_cross	count
	Number of right line crossings	E305_right_cross	count

RURAL EVENT 305: GRAVEL TRANSITION			
	Velocity of accelerator position	E305_accel_vel	
	Jerk of accelerator position	E305_accel_jerk	
	SD of accelerator position	E305_accel_sd	
	Mean brake force	E305_brake_avg	
	SD of brake force	E305_brake_sd	
	Glance frequency at particular object	E305_freq_glance	
	Pressure output(global and local)	E305_out_pres	
	Pressure and force over time	E305_force_pres	
	Pressure point mapping	E305_map_pres	
	PERCLOS	E305_perclos	
	Eye blink frequency	E305_blink_freq	
	Eye blink duration	E305_blink_dur	
	Percent in center based on median location of gaze	E305_gaze_center	
	Correlation between road curvature and eye movements	E305_eye_curve	
	Correlation between steering and road curvature	E305_steer_curve	
	Correlation between eye movements and SDLP	E305_eye_sdlp	
	Correlation between eye movements and steering	E305_eye_steer	
	Number of collisions	E305_num_col	
	Near misses	E305_num_miss	
	Delay time	E305_delay_time	
	Rise time	E305_rise_time	
	Peak time	E305_peak_time	
	Max overshoot	E305_over_max	
	Settling time	E305_set_time	
	How well it fits the model	E305_model_fit	
	Smooth pursuit velocity	E305_smpur_vel	
	Smooth pursuit duration	E305_smpur_dur	
	Smooth pursuit frequency	E305_smpur_freq	
	Smooth pursuit maximum velocity	E305_smpur_maxvel	

RURAL EVENT 305: GRAVEL TRANSITION			
	Smooth pursuit gain	E305_smpur_gain	
	SD of gaze	E305_gaze_sd	
	Gaze kurtosis	E305_gaze_kurt	
	Dwell duration	E305_dwell_time	
	Frequency of side mirror glances	E305_glanceglance_freq_side_side	
	Frequency of speedometer glances	E305_glance_freq_speed	
	Glance direction	E305_glance_dir	
ALGORITHM INPUT (MEASURES THAT IS INPUT TO THE ALGORITHM)	DESCRIPTION	IDENTIFIER	UNITS
	Mean brake force		
	Mean accelerator position		

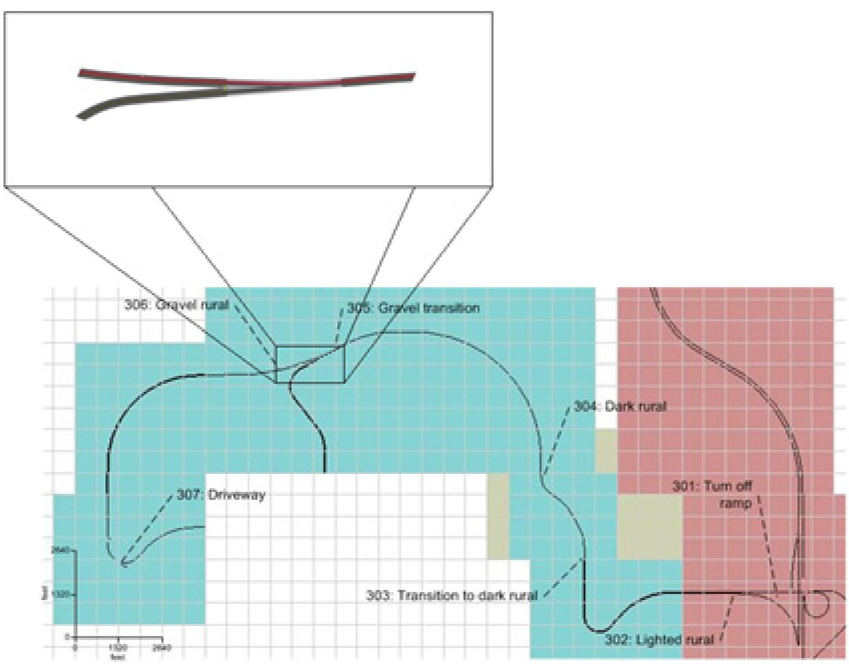


Figure F18. Rural Event 3: Entering gravel road

- Change in speed (from beginning of the event to the end)
- Maximum brake pressure
- SDLP

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver with a pavement to gravel road transition are: SDLP, the change in speed from the beginning of the event to the end, and the maximum brake pressure. One of the most widely thought of behaviors of alcohol impaired drivers is weaving around the lane. This can be represented by the variable SDLP, which has been shown to be sensitive to alcohol (Calhoun et al., 2005; Gawron & Ranney, 1988; Reed & Green, 1999). Maximum brake pressure and change in speed both look at a participant's ability to control velocity in a changing environment. It is known that alcohol impaired drivers have trouble slowing and speeding up in a smooth manner (Struster, 1997).

F.10.19 Rural Event 306: Gravel Rural

At distance of 1500 ft. after the transition to the gravel road, the participant will experience a series of curves and straight-aways.

RURAL EVENT 306: GRAVEL RURAL	
RATIONALE	In this segment, the driver will navigate on an unlighted gravel rural road that contains a series of curves and has no posted speed limit. The FARS rationale includes an over-representation of impaired driving fatal crashes on curves and unlighted rural gravel roads. The DWI cues that could be observed include: running off the road, almost striking objects, varying speed, and driving in the opposing lane.
ROAD NETWORK REQUIREMENTS	Overall length/distance needed to support event (in feet): 11880 Road type (lanes, surface): 2-lane gravel with little or no shoulder Speed limit (in mph): Not posted (assumed 45 mph) Curvature: Varying straight and curved sections Intersection type: None Time of Day/Date: Night, dark
PREPARATION	At the start of the event, instruction #305 is played, informing them to pull into the first driveway on the right. The participant navigates an unlighted two-lane rural gravel road that contains a series of curves and has no posted speed limit. (The participant is assumed to travel at approximately 45 mph.)
START CONDITIONS	The participant has traveled 1670 ft past the transition to gravel at the Y-intersection.
ACTUAL EVENT	Logstream 1 is incremented; logstream 2 is set to 306. Instruction #305 is played. The participant continues along the gravel road section. The participant navigates a series of curves. (The participant adjusts their speed appropriately for the gravel road surface and curves.)
END CONDITIONS	The participant is 550 feet before driveway
CLEANUP	None

RURAL EVENT 306: GRAVEL RURAL			
EVENT CONTINGENCY (VARIABLES THAT DEFINE DEPENDENCE OF THE CURRENT EVENT ON THE INTERPRETATION OF THE PREVIOUS EVENT)	DESCRIPTION	IDENTIFIER	UNITS
SCENARIO PERFORMANCE (MEASURES THAT INDICATE IF THE EVENT IS OPERATING AS EXPECTED)	DESCRIPTION	IDENTIFIER	UNITS
	No cars in either direction		
	Dark gravel road		
	No oncoming traffic	E306_oncoming_freq	avg. sec between cars
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES ACCORDING TO THE ASSUMPTIONS)	DESCRIPTION	IDENTIFIER	UNITS
	Initial speed (speed at beginning of event)	E306_sp_init	mph
	End speed (speed at end of event)	E306_sp_mavgnd	mph
ALCOHOL IMPAIRMENT INDICATORS (MEASURES THAT ASSESS WHETHER THE EVENT IS SENSITIVE TO ALCOHOL IMPAIRMENT)	DESCRIPTION	IDENTIFIER	UNITS
	SD of lane position relative to mean lane position	E306_lp_sd	ft
	SD of lane position relative to center of lane	E306_lpn_sd	ft
	Lane position	E306_lp_avg	ft
	SD of speed (relative to mean speed)	E306_sp_sd	mph
	SD of speed (relative to assumed or posted speed limit)	E306_spn_sd	mph
	Speed	E306_sp_avg	mph
	Speed relative to assumed speed	E306_spn_avg	mph

Rural Event 306: Gravel Rural			
	Frequency of glances to rear view mirror	E306_glance_freq_rear	glances/sec
	Steering wheel reversals	E303_steer_rev	
	SD of steering wheel position	E306_steer_sd	
	Velocity of steering wheel	E306_steer_vel	
	Jerk of steering wheel	E306_steer_jerk	
	Steering error	E306_steer_error	
	Time to line crossing (TLC)	E306_tlc	
	Proportion of time TLC>2s	E306_tlc_2	proportion
	95% TLC	E306_tlc_95	
	Accelerator holds	E306_accel_holds	
	Number of left line crossings	E306_left_cross	count
	Number of right linet crossings	E306_right_cross	count
	Velocity of accelerator position	E306_accel_vel	
	Jerk of accelerator position	E306_accel_jerk	
	SD of accelerator position	E306_accel_sd	
	Glance frequency at particular object	E306_freq_glance	
	Pressure output(global and local)	E306_out_pres	
	Pressure and force over time	E306_force_pres	
	Pressure point mapping	E306_map_pres	
	PERCLOS	E306_perclos	
	Eye blink frequency	E306_blink_freq	
	Eye blink duration	E306_blink_dur	
	Percent in center based on median location of gaze	E306_gaze_center	
	Correlation between road curvature and eye movements	E306_eye_curve	
	Correlation between steering and road curvature	E306_steer_curve	
	Correlation between eye movements and SDLP	E306_eye_sdlp	
	Correlation between eye movements and steering	E306_eye_steer	
	Number of collisions	E306_num_col	
	Near misses	E306_num_miss	

Rural Event 306: Gravel Rural			
	Smooth pursuit velocity	E306_smpur_vel	
	Smooth pursuit duration	E306_smpur_dur	
	Smooth pursuit frequency	E306_smpur_freq	
	Smooth pursuit maximum velocity	E306_smpur_maxvel	
	Smooth pursuit gain	E306_smpur_gain	
	SD of gaze	E306_gaze_sd	
	Gaze kurtosis	E306_gaze_kurt	
	Dwell duration	E306_dwell_time	
	Frequency of side mirror glances	E306_glance_freq_side	
	Frequency of speedometer glances	E306_glance_freq_speed	
	Glance direction	E306_glance_dir	
Algorithm Input (Measures that is input to the algorithm)	Description	Identifier	Units
	Mean lane position		
	Mean speed		
	SD of lane position relative to mean		
	SD of speed relative to mean		
	Steering wheel reversals		

- SD of speed (during "steady state") relative to mean speed
- Speed
- SDLP (relative to mean lane position)

The major variables to take into consideration when comparing an alcohol impaired driver and an unimpaired driver when driving on a gravel road are: SDLP, SD of speed relative to the mean speed, and mean speed. One of the most widely thought of behaviors of alcohol impaired drivers is weaving around the lane. This can be represented by the variable SDLP, which has been shown to be sensitive to alcohol (Calhoun et al., 2005; Gawron & Ranney, 1988; Reed & Green, 1999). The same has been shown for variation in speed which can be measured by SD Speed (Arnedt et al., 2001; Gawron & Ranney, 1988). A standard set of qualitative behaviors for police to follow mentions that alcohol impaired drivers tend to drive slower than the speed limit by more than 10 mph (Struster, 1997).

F.10.20 Rural Event 307: Driveway

The drive will end with the participant pulling into a gravel driveway. The participant is instructed through an audio queue to pull off on the gravel driveway. The turn is gradual. Figure F19 shows an illustration of the driveway event.

Rural Event 307: Driveway			
Rationale	The drive will end with the driver pulling into a gravel driveway. The turn is gradual. This is the typical end of a trip from the bar. No FARS rationale, but could involve DWI cues such as: turning with a wide radius, almost striking an object, and stopping problems (too far, too short, etc.).		
Road Network Requirements	Overall length/distance needed to support event (in feet): 660 Road type (lanes, surface): 2-lane gravel to 1-lane gravel Speed limit (in mph): Assumed 45 mph to a stop Curvature: 1800ft radius intersection corridor to 510ft radius driveway Intersection type: None Time of Day/Date: Night, dark		
Preparation	The participant slows and turns into the drive way (The participant turns into the driveway) The participant is instructed to stop the car, ending the drive (The participant stops the car)		
Start Conditions	The participant is 550 ft before driveway.		
Actual Event	The participant makes the turn onto the drive way, logstream 5 changes to 34. (The participant makes the turn) When the participant has pulled onto the driveway an audio message instructs (306) them that they have reached their destination. In-cab researcher instructs participant to brake to a stop and shift into park. (The participant stops)		
End Conditions	The participant brakes to a complete stop.		
Cleanup	None		
Event Contingency (Variables that define dependence of the current event on the interpretation of the previous event)	Description	Identifier	Units
Scenario Performance (Measures that	Description	Identifier	Units

Rural Event 307: Driveway			
INDICATE IF THE EVENT IS OPERATING AS EXPECTED)			
ASSUMED DRIVER BEHAVIOR (MEASURES THAT INDICATE WHETHER THE PARTICIPANT BEHAVES ACCORDING TO THE ASSUMPTIONS)	DESCRIPTION	IDENTIFIER	UNITS
	Initial speed	E307_sp_init	mph
	End speed	E307_sp_mavgnd	mph
	Deceleration rate	E307_acc_avg	ft/s^2
	Maximum steering angle (assuming positive indicates right turn)	E307_steer_max	deg
ALCOHOL IMPAIRMENT INDICATORS (MEASURES THAT ASSESS WHETHER THE EVENT IS SENSITIVE TO ALCOHOL IMPAIRMENT)	DESCRIPTION	IDENTIFIER	UNITS
	Turn signal use	E307_turn_signal	binary 1=yes, 0 = no
	Speed variance	E307_sp_sd	mph
	Mean brake force	E104_brake_avg	
	Smoothness of deceleration		
	Frequency of glances to rear view mirror	E307_glance_freq_rear	glances/sec
	Glance frequency at particular object	E307_freq_glance	
	Pressure output(global and local)	E307_out_pres	
	Pressure and force over time	E307_force_pres	
	Pressure point mapping	E307_map_pres	
	PERCLOS	E307_perclos	
	Eye blink frequency	E307_blink_freq	
	Eye blink duration	E307_blink_dur	
	Percent in center based on median location of gaze	E307_gaze_center	
	Correlation between head turn and steering wheel movement	E307_headturn_wheel	
	Number of collisions	E307_num_col	
	Near misses	E307_num_miss	

Rural Event 307: Driveway			
	Delay time	E307_delay_time	
	Rise time	E307_rise_time	
	Peak time	E307_peak_time	
	Max overshoot	E307_over_max	
	Settling time	E307_set_time	
	How well it fits the model	E307_model_fit	
	Smooth pursuit velocity	E307_smpur_vel	
	Smooth pursuit duration	E307_smpur_dur	
	Smooth pursuit frequency	E307_smpur_freq	
	Smooth pursuit maximum velocity	E307_smpur_maxvel	
	Smooth pursuit gain	E307_smpur_gain	
	SD of gaze	E307_gaze_sd	
	Gaze kurtosis	E307_gaze_kurt	
	Dwell duration	E307_dwell_time	
	Frequency of side mirror glances	E307_glance_freq_side	
	Frequency of speedometer glances	E307_glance_freq_speed	
	Glance direction	E307_glance_dir	
ALGORITHM INPUT (MEASURES THAT IS INPUT TO THE ALGORITHM)	DESCRIPTION	IDENTIFIER	UNITS
	Mean brake force		

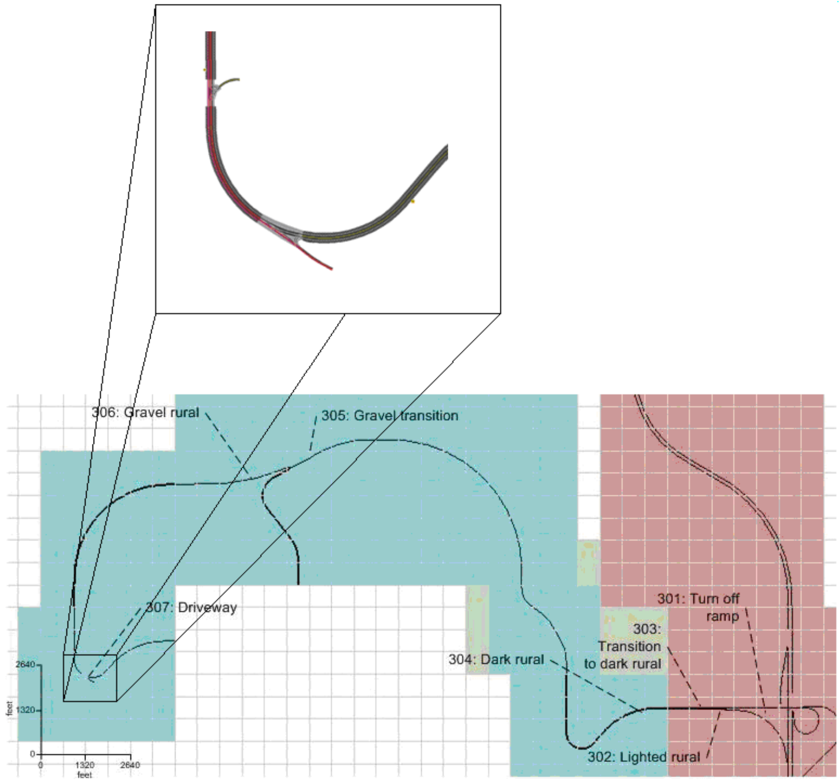


Figure F19. Driveway

- Max brake pressure
- Variation in brake pressure

Maximum brake pressure and variation in brake pressure look at a participant's ability to control velocity in a changing environment. It is known that alcohol impaired drivers have trouble slowing and speeding up in a smooth manner (Struster, 1997).

F.11 Potential Hazards in Urban Scenario Events

The urban scenario events contain a number of potential hazards in the form of pedestrians and vehicles whose behavior might give the participants the impression that they need to react to the hazard in order to avoid collision. The location and timing of these potential hazards is catalogued so that the participants' responses may be evaluated. Each of the three scenarios contains equal numbers of each kind of hazard and to the extent possible the environment near the hazard is equivalent.

Table F11. Potential Hazards

Hazard number	Name	Description
1	Walker3DRR1_01	Three dimensional pedestrian on the right in the parking lane walking in same direction as the driver.

2	Walker3DLR5_02	Two dimensional pedestrian on the left in the parking lane walking towards the driver.
3	Walker2DRS7_03	Two dimensional pedestrian on the right on the sidewalk walking toward the road.
4	Walker3DLR1_04	Three dimensional pedestrian on the left in the parking lane walking in the same direction as the driver.
5	Walker3DRS1_05	Three dimensional pedestrian on the right on the sidewalk walking in the same direction as the driver.
6	Walker3DLS5_06	Three dimensional pedestrian on the left on the sidewalk walking towards the driver.
7	Walker2DRS8_07	Two dimensional pedestrian on the right on the sidewalk walking towards the road and in the same direction as the driver.
8	Walker3DRS5_08	Three dimensional pedestrian on the right on the sidewalk walking towards the driver.
9	Walker3DRR1_09	Three dimensional pedestrian on the right in the parking lane walking away from the driver.
10	Walker3DLS5_10	Three dimensional pedestrian on the left on the sidewalk walking towards the driver.
11	Walker2DLS2_11	Two dimensional pedestrian on the left on the sidewalk walking towards the road in the same direction as the driver.
12	Walker3DLR5_12	Three dimensional pedestrian on the left on the parking lane walking away from the driver.
13	PullOutVespaRight	Vespa moped coming from an alley on the right pulls out into the parking lane approximately 75 ft in front of the driver and parks after traveling a short distance.
14	PullOutVespaLeft	Vespa moped coming from an ally on the left pulls out onto the parking lane approximately 18 ft in front of the driver and parks after traveling a short distance.
15	AllyTaxi	Taxi coming from an alley on the left created approximately 650 ft in front of the driver pulls through the parking lane as if it is going to turn and join the roadway but does not enter the oncoming traffic lane.
16	TaxiPullOut	Taxi parked in the opposite parking lane pulling out into the roadway and joining oncoming traffic approximately 100 ft in front of the driver.

17	PullOutCar1	Parked car in the oncoming lane pulling out into oncoming traffic 8 seconds in front of the driver.
18	FakeCrosser	Three dimensional pedestrian in parking lane on the left waiting for a car to pass before walking onto oncoming lane towards driver and then walking around a parked car.
19	StreetCrosser	As driver approaches intersection for E105: Left Turn, a pedestrian walks across the perpendicular street from the far corner on the right toward the driver in the crosswalk.

F.12 Motion Pre-positions and Washouts

Each scenario specifies pre-position points for the motion base. Whenever one is encountered, the motion slowly ramps to the new position so that it is favorably positioned for an upcoming event. Similarly, the washout parameters are dynamically changed from one set to another when requested by the scenario. There is a washout set for turns, one for highways, and another for curves.

The three figures that follow have each Pre-position and washout trigger called out on the figure. The Pre-position call-out consists of three position numbers corresponding to X, Y, and turntable angle respectively. The washout call-outs will show the text 'Turn','Hwy2', or 'Curve' to denote which washout file is loaded at that point.

Finally, each scenario has an initial position that controls where the simulator motion base starts at the beginning of the scenario. These positions are given in text boxes inset into each figure. The practice drive is based on scenario 1, and therefore the practice drive initial position is given in the Scenario 1 figure.

Table F12. List of motion pre-position points with markers

Preposition	Crossbeam X	Carriage Y	Turntable Angle
A	150 in	150 in	45 deg
B	0 in	0 in	45 deg
C	200 in	0 in	90 deg
D	200 in	0 in	90 deg
E	0 in	0 in	90 deg
F	250 in	0 in	90 deg
G	100 in	0 in	90 deg
H	100 in	0 in	90 deg

Table F13. List of motion washout files with markers

Washout	Name
1	Turn.mda
2	Hwy2.mda
3	Curve.mda

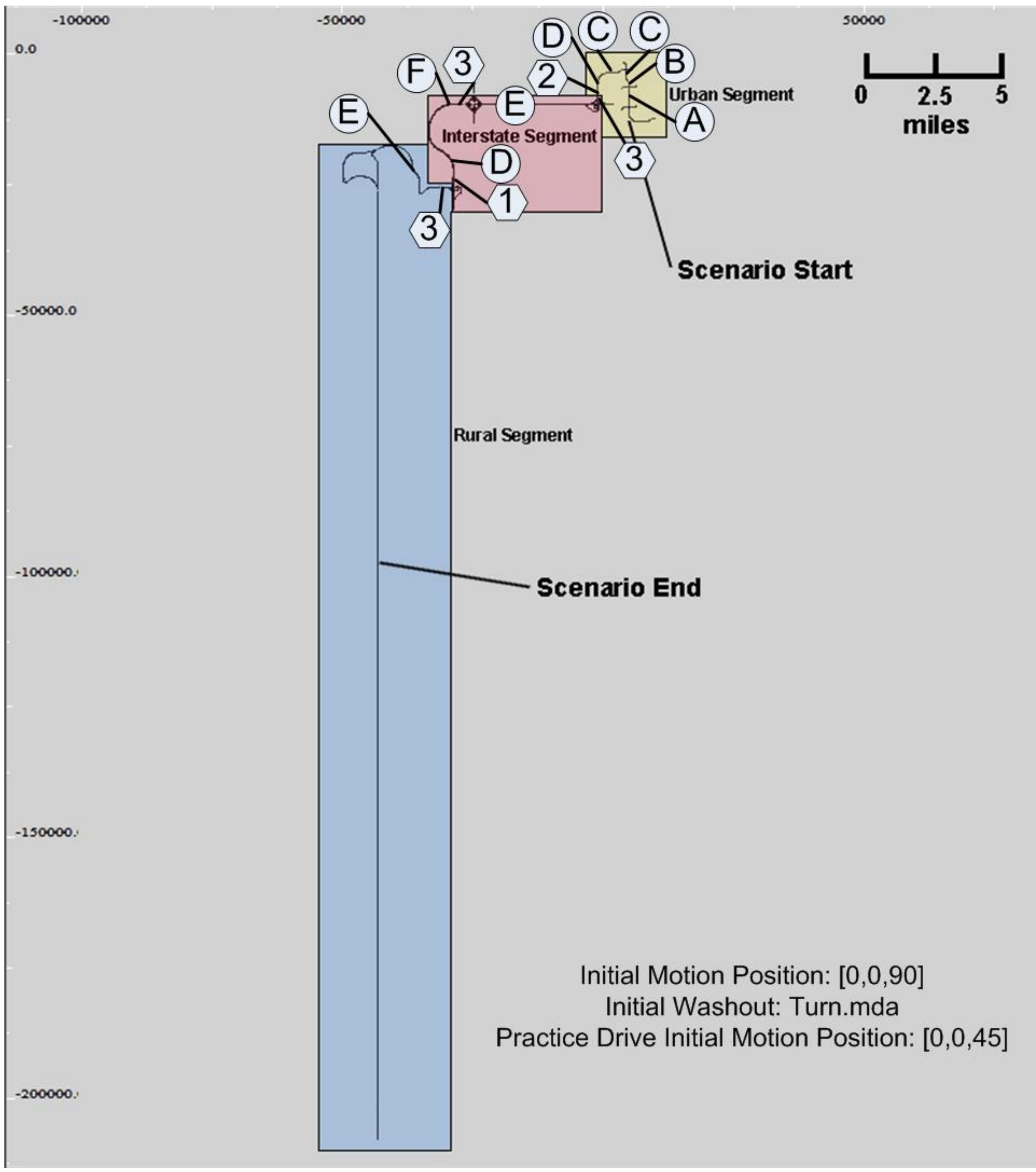


Figure F20. Scenario 1 Pre-positions and Washouts

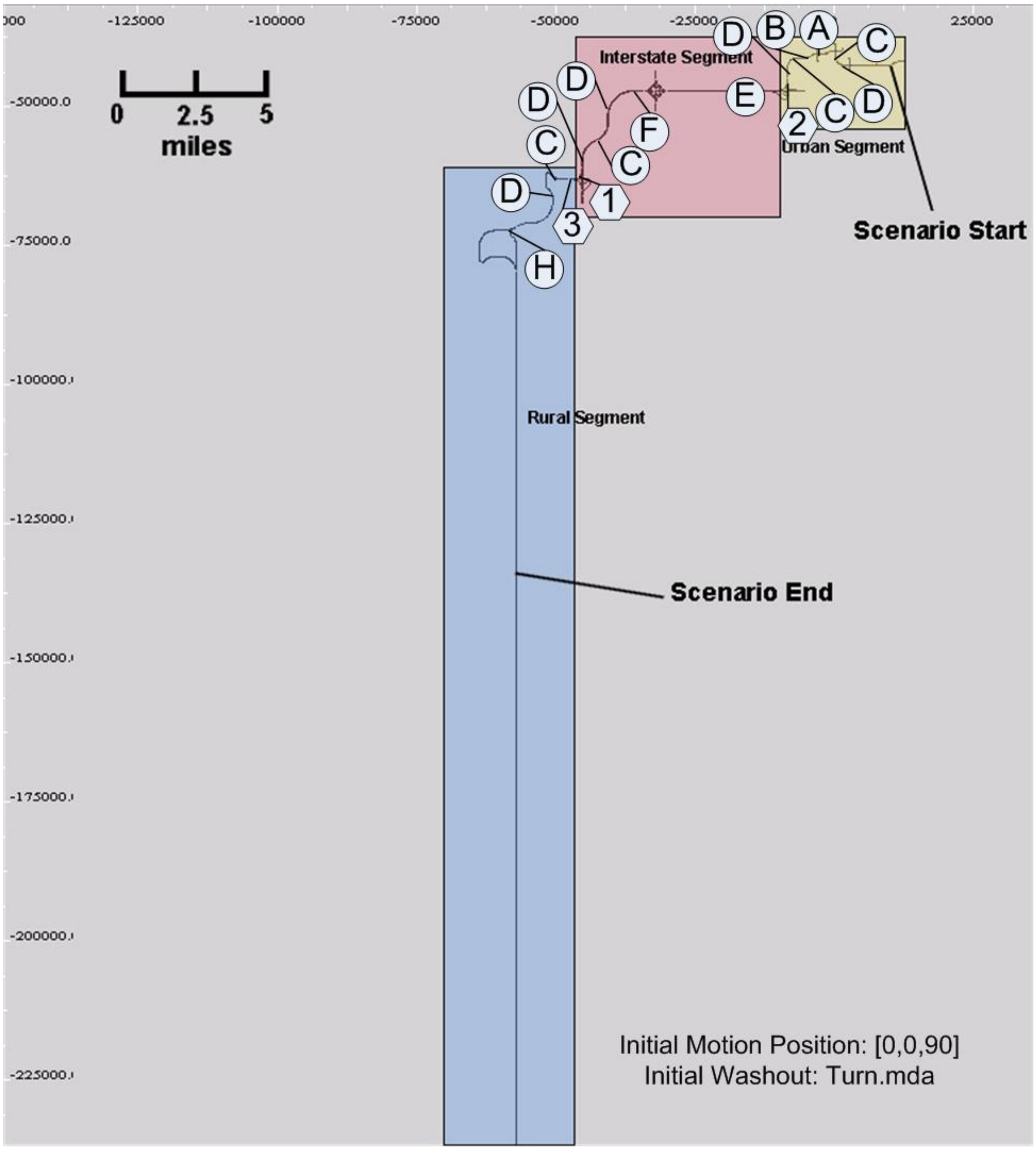


Figure F21. Scenario 2 Pre-positions and Washouts

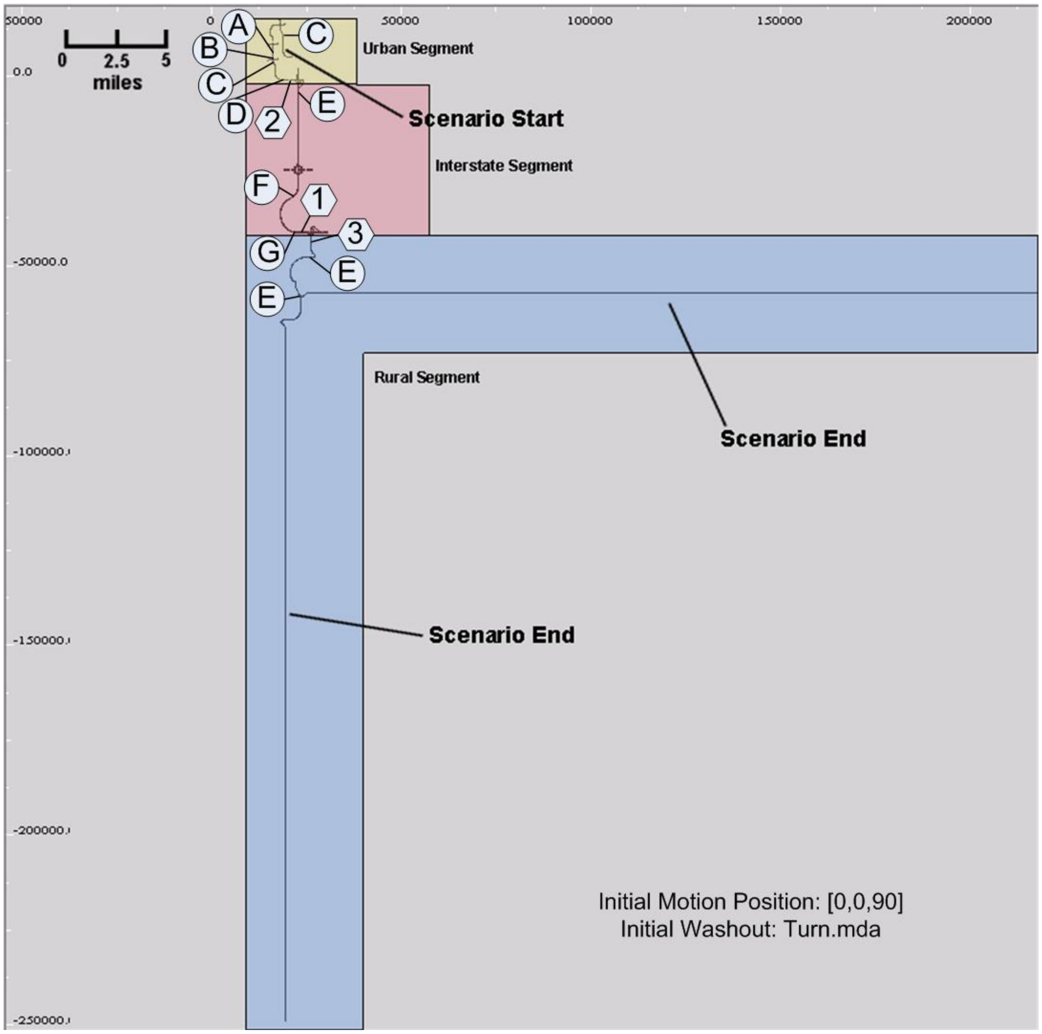


Figure F22. Scenario 3 Pre-positions and Washouts

F.13 Data Reduction Routine

The data from the NADS is saved in DAQ files. When each of these files is written from temporary storage to long-term storage, a report is generated. This report contains the name and size of the DAQ file. Names of valid DAQ files are copied from the report and appended to an Excel spreadsheet. The first few rows of this Excel spreadsheet for Task 1 Pilot 3 are shown below. An "X" is placed in the Analyze column for the DAQ files that need to be reduced. Each time the reduction scripts are run, this Excel spreadsheet is read in and only the DAQ files specified in the Analyze column are reduced. If the eye data collected during the drives are too poor to be used for analysis, an "X" is placed in the Bad Eye column. When these DAQ files with poor eye data are reduced, a null value of 99 is given to any eye movement dependent measures. In addition, the spread sheet contains the Run Name (which identifies the directory on the data storage server where the DAQ file is saved), the name of the DAQ file (timestamp when file was created), the date the data was collected (extracted from timestamp), the participant number, the name of the drive, the participant's age group (Y=young, M=middle, O=old), gender, and which combination of dose order and scenario order the participant was assigned to (18 possible combinations counterbalanced across age and gender).

Analyze	Ignore	Reduced	**Eye** (Place 'X' in column if eye data is **bad**)	Run Name	DAQ File	Date	Part Num	Drive	Age	Gender	Order
	X			P304YF01_1PRACT	20080919184353	09/19/2008	P304YF01	1PRACT	Y	F	01
X				P304YF01_1S1RNA	20080919185511	09/19/2008	P304YF01	1S1RNA	Y	F	01
	X			P303OM01_1PRACT	20080919193422	09/19/2008	P303OM01	1PRACT	O	M	01
X				P303OM01_1S1RNA	20080919194410	09/19/2008	P303OM01	1S1RNA	O	M	01
X				P303OM01_1S1RS5	20080919201433	09/19/2008	P303OM01	1S1RS5	O	M	01

DAQ files will be reduced as frequently as possible during main data collection (ideally, daily, but no less than three times a week).

MATLAB is used to perform the data reduction. During data reduction, each DAQ file indicated in the spreadsheet is individually opened and the required variables are read into the MATLAB workspace. Some raw values, e.g., lane deviation, need to be cleaned in order to calculate the specified dependent measures. Once the raw data is cleaned for the entire file, dependent measures are calculated for each of the scenario events.

F.14 Data Reduction Output File Layout

The data reduction procedure creates two output data files. The first file contains all of the dependent measures specified in Section 14.8, including scenario performance measures, measures of assumed driver behavior, and measures of alcohol impairment. Each row in this file contains the reduced data from one scenario event. Not all dependent measures are applicable to all events. Thus, this output file is very sparse with only a few columns containing values for a given event. Columns that are not applicable to a given event contain "NaN". A portion of this file is shown in Table F14.

The second file contains all of the dependent measures that are thought to be indicative of driver impairment due to alcohol. Each row in this file contains the reduced data from one experimental drive. Thus, each dependent measure is identified by the number of the scenario event they are associated with. For example, all dependent measures associated with the pullout event begin with "E101." Cells without data are left blank. A portion of this file is shown in Table F15.

Table F14. Data reduction output file sample – first 13 columns

Subject	RunName	Drive	Event	acc_avg	acc_end	acc_end_d	acc_end_t	acc_init	accel_release	accel_sd	accelerate	brake_press
001	20080528131249	1	E101	NaN	NaN	425.6597667	7.933333333	NaN	NaN	NaN	NaN	NaN
001	20080528131249	1	E102	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
001	20080528131249	1	E103	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0
001	20080528131249	1	E104	NaN	NaN	NaN	NaN	NaN	1	NaN	-1	0
001	20080528131249	1	E105	NaN	NaN	NaN	NaN	NaN	1	NaN	NaN	1
001	20080528131249	1	E106	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
001	20080528131249	1	E201	-1	NaN	NaN	NaN	NaN	0	NaN	NaN	0
001	20080528131249	1	E202	-1	NaN	NaN	NaN	NaN	0	-1	NaN	0
001	20080528131249	1	E203	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
001	20080528131249	1	E204	NaN	NaN	NaN	NaN	NaN	0	NaN	NaN	0
001	20080528131249	1	E205	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
001	20080528131249	1	E206	NaN	NaN	NaN	NaN	NaN	1	NaN	NaN	1
001	20080528131249	1	E301	NaN	-1	-1	NaN	-1	NaN	NaN	NaN	NaN
001	20080528131249	1	E302	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
001	20080528131249	1	E303	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
001	20080528131249	1	E304	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
001	20080528131249	1	E305	NaN	NaN	NaN	NaN	NaN	0	NaN	NaN	0
001	20080528131249	1	E306	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
001	20080528131249	1	E307	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Table F15. Sample of second data reduction output file – first 12 columns

Subject	Drive	E101_head_turn	E101_side_mirror	E101_rear_mirror	E101_last_glance	E101_gap	E101_collision	E101_collision_obj	E101_turn_signal	E102_done_acc
1	1	-2	-2	-2	-2	-1	-1	-1	-1	0
1	2	-2	-2	-2	-2	-1	-1	-1	-1	0
1	3	-2	-2	-2	-2	-1	-1	-1	-1	0
2	1	-2	-2	-2	-2	-1	-1	-1	-1	0
2	2	-2	-2	-2	-2	-1	-1	-1	-1	0
2	3	-2	-2	-2	-2	-1	-1	-1	-1	0

APPENDIX G: EXPERIMENTAL PROCEDURES SUMMARY

Phone Screening

- Complete the telephone screening as outlined in **Screening Procedures**.

<u>SCREENING VISIT</u>

Screening (Visit 1)

- Upon arriving at NADS, review elements of informed consent either verbally, encouraging participant to ask questions.
- Have participant sign and date **Informed Consent Document. (Visit 1 Only)**
- Have participant sign and date **Video Release Statement (Visit 1 Only)**
- Have the participant fill out the **Payment Voucher**. **(Visit 1 Only)**
- Verify that participant has a valid driver's license.
- Escort participant to restroom so that urine sample can be collected.
- Participant asked to rest for 5 minutes. Urine drug screen and pregnancy test performed on urine sample during this time.
- Take participant's blood pressure and heart rate
- If drug and (females pregnancy screen), blood pressure or heart rate does not meet study requirements, participant will be sent home. If passed, participant will complete a **Breath alcohol test**.
- Have participant fill out **Sleep & Intake Questionnaire**.
- If participant remains eligible, continue with **Driving Survey (Visit 1 Only)**. If not, participant is released to go home
- Watch training video.

Driving (Visit 1 Only)

- Introduce in-vehicle experimenter, who takes over at this point.
- Escort participant to the vehicle and allow him/her to be seated.
- Ask the participant if he/she has any questions.
- Calibrate Eye Tracker.
- Brief the participant on the practice drive and ask if there are any questions.
- After completing practice drive, advise participant to shift into PARK.

End of Driving (Visit 1 Only)

- After the practice drive is complete and the participant has shifted into PARK, administer the **Wellness Survey**.
- When the simulator has docked, escort the participant to the participant prep area and make sure that prep area experimenter knows he/she is there. The prep area experimenter will review **Wellness Survey** for eligibility to continue. If participant remains eligible, continue with scheduling next two appointments. Experimenter will confirm date, time & transportation arrangements for next 2 visits and make arrangements for receiving activity monitor and activity log if necessary. Participant will then complete the EEG baseline session. If not eligible to continue, participant is released to go home and paid for their time and effort.

<u>Daytime Visit (Alert)</u>

Daytime Visit (Visit 2or 3)

- Upon arrival at NADS, the activity monitor and activity log will be collected.
- While reviewing monitor log data, participant asked to complete the **Sleep & Intake Questionnaire**.
- If participant remains eligible, administer a **Breath Alcohol Test**. If not, send home.

Driving (Alert Visit Only)

- Introduce in-vehicle experimenter, who takes over at this point.
- Escort participant to the vehicle and allow him/her to be seated.
- Fit subject with EEG monitoring device
- Calibrate Eye Tracker.
- Brief the participant on the study drive and ask if there are any questions.
- Administer **Psychomotor Vigilance Test** and **Stanford Sleepiness Scale**.
- Drive.
- After completing study drive, advise participant to shift into PARK.

End of Driving (Alert Visit Only)

- After the study drive is complete and the participant has shifted into PARK.
- Administer the **Stanford Sleepiness Scale, Wellness Survey** and **Psychomotor Vigilance Test**
- When the simulator has docked, escort the participant to the participant prep area and make sure that prep area experimenter knows he/she is there. The prep area experimenter takes over at this point.

Wrap-Up (Alert Visit Only)

- Offer participant beverage.
- Ask if participant has any questions.
- Allow participant to complete **Wellness Survey** if not finished in vehicle.
- Administer **Retrospective Sleepiness Survey.**
- Administer **Realism Survey**.
- (If third visit, participant will be interviewed using **Debriefing Interview**)
- Confirm date, time & transportation arrangements for next visit and return activity monitor and activity log if necessary
- Participant goes home

<u>Nighttime/Overnight Visit (Drowsy)</u>

Nighttime/Overnight Visit (Visit 2or 3)

- Arrangements made to pick up participant at home

- Upon arrival at NADS, the activity monitor and activity log will be collected.
- While reviewing monitor log data, participant asked to complete the **Sleep & Intake Questionnaire**.
- If participant remains eligible, administer a **Breath Alcohol Test**. If not, take home.
- If participant remains eligible, make participant comfortable in large waiting room. Movies, games, TV, books will be provided for activities while waiting Staff stays in room to monitor that participant does not sleep or talk with other participants.
- Participants will complete **Stanford Sleepiness Scale** every 30 minutes until drive.
- 1 hour prior to drive participant is escorted to private secluded room to wait. He/she completes **Psychomotor Vigilance Test** at 1 hour prior to drive and at 30 minutes prior to drive.

First Drive (Nighttime/Overnight Visit Only)

- Between 10pm and 2am, introduce in-vehicle experimenter, who takes over at this point.
- Escort participant to the vehicle through dimly lit hallway and allow him/her to be seated.
- Fit participant with EEG monitoring device
- Calibrate Eye Tracker
- Brief the participant on the study drive and ask if there are any questions.
- Administer **Psychomotor Vigilance Test** and **Stanford Sleepiness Scale**.
- Drive
- After completing the study drive, advise participant to shift into PARK.

End of First Drive (Nighttime/Overnight Visit Only)

- After the study drive is complete and the participant has shifted into PARK.
- Administer the **Stanford Sleepiness Scale and Wellness Survey** and **Psychomotor Vigilance Test.**
- When the simulator has docked, escort the participant to the participant prep area and make sure that prep area experimenter knows he/she is there. The prep area experimenter takes over at this point.
- Administer **Retrospective Sleepiness Survey.**
- Make participant comfortable in large waiting room. Movies, games, TV, books will be provided for activities while waiting. Staff stays in room to monitor that participant does not sleep or talk with other participants.
- Participants will complete **Stanford Sleepiness Scale** every 30 minutes until drive.
- 1 hour prior to drive participant is escorted to private secluded room to wait. He/she completes **Psychomotor Vigilance Test** at 1 hour prior to drive and at 30 minutes prior to drive.

Second Drive (Nighttime/Overnight Visit Only)

- Between 2am and 6am, introduce in-vehicle experimenter, who takes over at this point.
- Escort participant to the vehicle through dimly lit hallway and allow him/her to be seated.
- Fit subject with EEG monitoring device
- Calibrate Eye Tracker.
- Brief the participant on the study drive and ask if there are any questions.
- Administer **Psychomotor Vigilance Test** and **Stanford Sleepiness Scale**.
- Drive
- After completing study drive, advise participant to shift into PARK.

End of Second Drive (Nighttime/Overnight Visit Only)

- After the study drive is complete and the participant has shifted into PARK.
- Administer the **Stanford Sleepiness Scale and Wellness Survey** and **Psychomotor Vigilance Test**
- When the simulator has docked, escort the participant to the participant prep area and make sure that prep area experimenter knows he/she is there. The prep area experimenter takes over at this point.

Wrap-Up (Nighttime/Overnight Visit Only)

- Offer participant beverage and ask if participant has any questions.
- Allow participant to complete **Wellness Survey** if not finished in vehicle.
- Administer **Retrospective Sleepiness Survey.**
- Administer **Realism Survey**.
- (If third visit, participant will be interviewed using **Debriefing Interview**)
- Administer **Debriefing Statement**
- Confirm date and time for next visit and return activity monitor and sleep log if necessary and arrange for transportation home. If third visit, finalize payment.

APPENDIX H: INFORMED CONSENT DOCUMENT

INFORMED CONSENT DOCUMENT

Project Title: **Advanced Vehicle-Based Countermeasures for Multiple Impairments**

Principal Investigator: **Timothy Brown**

Research Team Contact: **Cheryl Roe, 319-335-4775**

This consent form describes the research study to help you decide if you want to participate. This form provides important information about what you will be asked to do during the study, the risks and benefits of the study, and your rights as a research subject.

- If you have any questions about or do not understand something in this form, you should ask the research team for more information.
- You should discuss your participation with anyone you choose such as family or friends.
- Do not agree to participate in this study unless the research team has answered your questions and you decide that you want to be part of this study.

WHAT IS THE PURPOSE OF THIS STUDY?

This is a research study. We are inviting you to participate in this research study because you are between the ages of 21-34, 38-51, and 55-68, with a valid driver's license for at least two years, drive a minimum of 10,000 miles per year, and are in good general health.

The purpose of this research study is to evaluate algorithms designed to detect drowsy driving.

HOW MANY PEOPLE WILL PARTICIPATE?

Approximately 115 people will take part in this study at the University of Iowa.

HOW LONG WILL I BE IN THIS STUDY?

If you agree to take part in this study, your involvement will require 3 visits. The screening visit will take approximately 1 ½ hours in length, one daytime study drive visit of approximately 1 ½ hours in length and one night-time study drive visit which could last up to 11 hours.

WHAT WILL HAPPEN DURING THIS STUDY?

Visit 1 (Screening Visit)

Upon arrival at NADS, study staff will verbally review this document with you, answer any questions you may have about the study, provide you time to read this document and then obtain your written consent. You will receive a copy of this signed Informed Consent Document. Then you will be asked to provide a urine sample and a urine drug screen test will be performed. Female subjects' urine specimen will additionally be tested and screened to determine if they are pregnant. Then you will be asked to sit quietly and rest 5 minutes followed by staff obtaining your blood pressure and heart rate. Your participation in the study will end if your drug screen test is positive, your blood pressure and/or heart rate do not meet the study requirements, and if female, you test positive for pregnancy. Results from the drug screen, blood pressure, heart rate, and for females, pregnancy test will remain confidential and your eligibility status will be documented as either a yes or no. No other information will be recorded. Then you will be asked to complete a breath alcohol test. If you meet study criteria, you will complete a questionnaire that asks you questions about your driving record, driving behavior, and driving history. If you fail to meet study criteria, you will be paid for your time and effort.

You will then be asked to watch an overview presentation of the simulator cab and staff will train you on an in-vehicle task involving changing CD tracks. Next, you will be escorted into the simulator, provided with an overview of the simulator cab and asked to drive a 5-8 minute practice drive in order for you to be comfortable with driving the simulator. After the practice drive, you will be asked to fill out a questionnaire about how you currently feel and then escorted back to the waiting room. This questionnaire will determine if you are eligible to continue in the study.

For the next two study visits, one will be conducted during daytime hours and the other will be in the evening and throughout the night. Staff will determine which order you will complete these visits. In this document we will refer to the daytime visit as Visit 2 and the nighttime visit as Visit 3 regardless of the order you will complete these. After staff confirms your next two study visits and review the instructions for receiving and wearing your activity monitor and completing your activity log, you will be free to go.

Visit 2 (Daytime Visit)

Two days prior to this visit you will receive an activity monitor, which is similar to wearing a wrist watch that will record your activity and sleep. You will be instructed to wear this monitor on your wrist until your last study visit. You will also be asked to complete an activity log for the two days prior to your appointment. The activity log will ask you to keep information about your sleep, your food and beverage consumption and the activities you engaged in.

For this visit you will report to the NADS facility and staff will first collect your activity wrist monitor and your activity log. While data is collected from your monitor, you will be asked to complete a survey about your sleep and food intake over the last 24 hours.

Next you will be asked to complete a breath alcohol test. If your participation is ended, you will be paid for your time and effort. If you continue to meet study criteria you will be escorted into the simulator, and you will be fitted with an EEG monitoring device. This device is a non-intrusive wireless recording device that is worn on your head. Then eye tracking procedures will be conducted and you will be asked to complete a brief test and a questionnaire about your current sleepiness level. Then you will drive for approximately 30 minutes. Your drive will consist of 3 segments, each 10 minutes in length which includes urban, freeway, and rural roadways. After your study drive you will be asked to complete a test about your current sleepiness level, a questionnaire about your current sleepiness level, a questionnaire about how you feel, and a questionnaire about the simulator.

Staff will confirm your next study visit and review the instructions for receiving and wearing an activity wrist monitor and completing your activity log. This will complete your daytime study drive visit.

Visit 3 (Nighttime/Overnight Visit)

Two days prior to this visit you will receive an activity wrist monitor that will record your activity and sleep. You will also complete and activity log.

Arrangements will be made to transport you to and from the National Advanced Driving Simulator (NADS) via taxi or shuttle. We ask that you have finished your dinner and are ready for transportation in order to arrive by 7pm to the study facility for the nighttime visit.

After your arrival, staff will collect your activity wrist monitor and activity log. While data is collected from your monitor, you will be asked to complete a survey about your sleep and food intake over the last 24 hours. Next you will be asked to complete a breath alcohol test. If your participation is ended, you will be paid for your time and effort and transported home.

If you continue to meet study criteria, you will be escorted to a large waiting room with other participants where you will be provided with activates to do while you are waiting to drive (watching movies, TV, games, read book). While you are waiting you will not be allowed to converse with other participants. Staff will monitor you while waiting. You will be asked to complete a questionnaire about your current sleepiness level every 30 minutes prior to your drive. One hour preceding your first drive you will be escorted to a secluded private room where you will be asked to complete a test to measure your current sleepiness level. This test will last for about 10 minutes. You will complete the test again 30 minutes prior to your drive.

You will then be escorted into the simulator, and you will be fitted with an EEG monitoring device. Then eye tracking procedures will be conducted and you will be asked to complete a brief test and a questionnaire about your current sleepiness level. You will then be asked to drive for approximately 30 minutes. Your drive will consist of 3 segments, each 10 minutes in length which includes urban, freeway, and rural roadways. After your study drive, you will be asked to complete a test about your current sleepiness level, a questionnaire about your current sleepiness level, and a questionnaire about how you feel. Then you will be escorted back to the large waiting with other participants where you will be provided with activates to do while you are waiting to complete your second drive (watching movies, TV, games, read book).

Your second drive will be approximately 3 ½ to 4 hours after your first drive. You will also complete questionnaires about your current sleepiness level every 30 minutes. One hour preceding your first drive you will be escorted to a secluded private room where you will be asked to complete a test to measure your current sleepiness level. This test will last for about 10 minutes. You will complete the test again 30 minutes prior to your drive.

You will then be escorted into the simulator, and you will be fitted with an EEG monitoring device. Then eye tracking procedures will be conducted and you will be asked to complete a brief test and a questionnaire about your current sleepiness level. Then you will be asked to drive for approximately 30 minutes. Your drive will consist of 3 segments, each 10 minutes in length which includes urban, freeway, and rural roadways. After your study drive, you will be asked to complete a test about your current sleepiness level, a questionnaire about your current sleepiness level, a questionnaire about how you feel and a questionnaire about the simulator.

After completion of the third visit, you will be asked a series of questions about your experience while participating in the study and staff will finalize your payment voucher and transportation will be arranged to take you home and you will be asked to avoid driving until you are well rested.

You may skip any questions that you do not wish to answer on the questionnaires.

<u>All driving trials will be recorded on video.</u>

The simulator contains sensors that measure vehicle operation, vehicle motion, and your driving actions. The system also contains video cameras that capture images of you while driving (e.g., driver's hand position on the steering wheel, forward road scene). These sensors and video cameras are located in such a manner that they will not affect you or obstruct your view while driving. The information collected using these sensors and video cameras are recorded for analysis by research staff and may be used as described in the Confidentiality section below.

We will keep your name and information about you, including birth date, contact phone numbers and the annual mileage you drive each year on file. In the future, we may contact you to see if you would be willing to complete questionnaires, interviews, or drives relating the data from this study to future studies. Agreeing to participate in this study does not obligate you to participate in future studies. You will be asked to give a separate consent for any future studies.

<u>WHAT ARE THE RISKS OF THIS STUDY?</u>

You may experience one or more of the risks indicated below from being in this study. In addition to these, there may be other unknown risks, or risks that we did not anticipate, associated with being in this study. The risk involving driving the simulator is possible discomfort associated with simulator disorientation. Previous studies with similar driving intensities and simulator setups produced few disorientation effects. When effects were reported, they were usually mild to moderate and consisted of slight uneasiness, warmth, or eyestrain for a small number of participants. These effects typically last for only a short time, usually 10-15 minutes, after leaving the simulator. You may quit driving at any time if you experience any discomfort.

If you ask to quit driving as a result of discomfort, you will be allowed to quit at once. If you ask to quit driving due to discomfort, you will be escorted to a room, asked to sit and rest, and offered a beverage and snack. A trained staff member will determine if and when you will be allowed to leave. If you show few or no signs of discomfort, you will be transported home.

If you experience anything other than slight effects, a follow-up call will be made to you 24 hours later to ensure you're not feeling ill effects.

An experimenter will be in the back seat of the simulator cab to ensure your safety while you drive.

As all of the participants for the evening drives will be waiting in a single room, it is possible that you may know or be known by another participant. Interactions between participants while waiting will be minimal.

Drowsy driving is dangerous, and participants need to refrain from driving until they are sufficiently rested.

WHAT ARE THE BENEFITS OF THIS STUDY?

You will not benefit from being in this study.

However, we hope that, in the future, other people might benefit from this study because the information gathered in this research study might benefit society by obtaining a better understanding of how drowsy driving impairs specific driving performance which may allow the development of new technologies that could minimize drowsy driving related crashes in the future.

WILL IT COST ME ANYTHING TO BE IN THIS STUDY?

You will not have any costs for being in this research study.

WILL I BE PAID FOR PARTICIPATING?

You will be paid for being in this research study. You will need to provide your social security number (SSN) in order for us to pay you. You may choose to participate without being paid if you do not wish to provide your social security number (SSN) for this purpose. You may also need to provide your address if a check will be mailed to you. If your social security number is obtained for payment purposes only, it will not be retained for research purposes.

If you agree to participate in this study, you will be paid $250 if you complete all study visits and procedures. If you withdraw or your participation ends, your compensation will be pro-rated as follows:

Visit 1 (Screening)	$ 10
Visit 2	$ 90
Visit 3	$ 150
Total (complete all visits)	$ 250

In the event that you fail to meet the study criteria (drug screen, pregnancy screen, breath alcohol test, and activity level requirements) you will be paid only $5 for the visit.

WHO IS FUNDING THIS STUDY?

The National Highway Traffic and Safety Administration (NHTSA) is the study sponsor and is funding this research study. This means that the University of Iowa is receiving payments from them to support the activities that are required to conduct the study. No one on the research team will receive a direct payment or increase in salary from NHTSA for conducting this study.

WHAT IF I AM INJURED AS A RESULT OF THIS STUDY?

- If you are injured or become ill from taking part in this study, medical treatment is available at the University of Iowa Hospitals and Clinics.
- No compensation for treatment of research-related illness or injury is available from the University of Iowa unless it is proven to be the direct result of negligence by a University employee.
- If you experience a research-related illness or injury, you and/or your medical or hospital insurance carrier will be responsible for the cost of treatment.

WHAT ABOUT CONFIDENTIALITY?

We will keep your participation in this research study confidential to the extent described in this document and permitted by law. However, it is possible that other people such as those indicated below may become aware of your participation in this study and may inspect and copy records pertaining to this research. Some of these records could contain information that personally identifies you.

- federal government regulatory agencies,
- auditing departments of the University of Iowa, and
- the University of Iowa Institutional Review Board (a committee that reviews and approves research studies)

You will be assigned a study number which will be used instead of your name to identify all data collected for the study. The list linking your study number and your name will be stored in a secure location and will be accessible only to the researchers at the University of Iowa. All records and data containing confidential information will be maintained in locked offices or on secure password protected computer systems that are accessible to the researchers, the study sponsor, and its agents. It is possible that persons viewing the video data may be able to identify you. If we write a report or article about this study, we typically describe the study results in a summarized manner so that you cannot be identified by name.

The **engineering data** collected and recorded in this study (including any performance scores based on these data) will be analyzed along with data gathered from other participants. These data may be publicly released in final reports or other publications or media for scientific (e.g., professional society meetings), regulatory (e.g., to assist in regulating devices), educational (e.g., educational campaigns for members of the general public), outreach (e.g., nationally televised programs highlighting traffic safety issues), legislative (e.g., data provided to the U.S. Congress to assist with law-making activities), or research purposes (e.g., comparison analyses with data from other studies). Engineering data may also be released individually or in summary with that of other participants, but will not be presented publicly in a way that permits personal identification, except when presented in conjunction with video data.

The **video data** (video image data recorded during your drive) recorded in this study includes your video-recorded likeness and all in-vehicle audio including your voice (and may include, in some views, superimposed performance information). Video and in-vehicle sounds will be used to examine your driving performance and other task performance while driving. Video image data (in continuous video or still formats) and associated audio data may be publicly released, either separately or in association with the appropriate engineering data for scientific, regulatory, educational, outreach, legislative, or research purposes (as noted above).

The **simulator data** is captured and stored on hard drives located within a limited access area of the NADS facility. Access to simulator data is controlled through permissions established on a per-study basis.

If we write a report or article about this study or share the study data set with others, we will do so in such a way that you cannot be directly identified.

WILL MY HEALTH INFORMATION BE USED DURING THIS STUDY?

The Federal Health Insurance Portability and Accountability Act (HIPAA) requires your health care provider to obtain your permission for the research team to access or create "protected health information" about you for purposes of this research study. Protected health information is information that personally identifies you and relates to your past, present, or future physical or mental health condition or care. We will access or create health information about you, as described in this document, for purposes of this research study. Once your health care provider has disclosed your protected health information to us, it may no longer be protected by the Federal HIPAA privacy regulations, but we will continue to protect your confidentiality as described under "Confidentiality."

We may share your health information related to this study with other parties including federal government regulatory agencies, the University of Iowa Institutional Review Boards and support staff, and the National Highway Traffic and Safety Administration.

You cannot participate in this study unless you permit us to use your protected health information. If you choose *not* to allow us to use your protected health information, we will discuss any non-research alternatives available to you. Your decision will not affect your right to medical care that is not research-related. Your signature on this Consent Document authorizes your health care provider to give us permission to use or create health information about you.

Although you may not be allowed to see study information until after this study is over, you may be given access to your health care records by contacting your health care provider. Your permission for us to access or create protected health information about you for purposes of this study has no expiration date. You may withdraw your permission for us to use your health information for this research study by sending a written notice to Dr. Timothy Brown, National Advanced Driving Simulator, 2401 Oakdale Blvd., University of Iowa. However, we may still use your health information that was collected before withdrawing your permission. Also, if we have sent your health information to a third party, such as the study sponsor, or we have removed your identifying information, it may not be possible to prevent its future use. You will receive a copy of this signed document.

IS BEING IN THIS STUDY VOLUNTARY?

Taking part in this research study is completely voluntary. You may choose not to take part at all. If you decide to be in this study, you may stop participating at any time. If you decide not to be in this study, or if you stop participating at any time, you won't be penalized or lose any benefits for which you otherwise qualify.

What if I Decide to Drop Out of the Study?

If you decide to leave the study early, we ask you to contact Cheryl Roe 319-335-4775 as soon as you decide not to participate.

Can Someone Else End my Participation in this Study?

Under certain circumstances, the researchers or NHTSA might decide to end your participation in this research study earlier than planned. This might happen because you fail the drug screen testing, for females, you are pregnant while participating, or if you do not meet the activity requirements for the study, additionally, your participation may end if you fail to operate the research vehicle in accordance with the instructions provided or if there are technical difficulties with the driving simulator.

WHAT IF I HAVE QUESTIONS?

We encourage you to ask questions. If you have any questions about the research study itself, please contact: Dr. Timothy Brown, (319) 335-4785. If you experience a research-related injury, please contact: Dr. Timothy Brown (319) 335-4785.

If you have questions, concerns, or complaints about your rights as a research subject or about research related injury, please contact the Human Subjects Office, 340 College of Medicine Administration Building, The University of Iowa, Iowa City, Iowa, 52242, (319) 335-6564, or e-mail irb@uiowa.edu. General information about being a research subject can be found by clicking "Info for Public" on the Human Subjects Office web site, http://research.uiowa.edu/hso. To offer input about your experiences as a research subject or to speak to someone other than the research staff, call the Human Subjects Office at the number above.

This Informed Consent Document is not a contract. It is a written explanation of what will happen during the study if you decide to participate. You are not waiving any legal rights by signing this Informed Consent Document. Your signature indicates that this research study has been explained to you, that your questions have been answered, and that you agree to take part in this study. You will receive a copy of this form.

Subject's Name (printed): ____

Do not sign this form if today's date is on or after $STAMP_EXP_DT

_______________________________ _______________________
(Signature of Subject) (Date)

Statement of Person Who Obtained Consent

I have discussed the above points with the subject or, where appropriate, with the subject's legally authorized representative. It is my opinion that the subject understands the risks, benefits, and procedures involved with participation in this research study.

_______________________________ _______________________
(Signature of Person who Obtained Consent) (Date)

APPENDIX I: DRIVING SURVEY

ACMI Driving Survey

As part of this study, it is useful to collect information describing each participant. The following questions ask about you and your health, your driving patterns, and your alcohol consumption. Please read each question carefully. If something is unclear, ask the researcher for help. Your participation is voluntary and you have the right to omit questions if you choose. Please remember that all of your answers will be kept confidential.

Background Information

1) What is your birth date? ________ / ________ / ______________

Month Day Year

2) What age are you today? ___________

3) What is your gender?

❒ Male

❒ Female

4) What is your marital status? (Check only one)

❒ Single, never married

❒ Married

❒ Domestic Partnership

❒ Separated or Divorced

❒ Widowed

5) What was your total household income last year? (Check only one)

❐ $0- $24,999
❐ $25,000- $29,999
❐ $30,000 - $34,999
❐ $35,000 - $39,999
❐ $40,000 - $49,999
❐ $50,000 - $59,999
❐ $60,000 - $69,999
❐ $70,000 - $79,999
❐ $80,000 - $89,999
❐ $90,000 - $99,999
❐ $100,000 or more

6) What is your present employment status? (Check only one)

❐ Unemployed
❐ Retired
❐ Work part-time
❐ Work full-time
❐ None of the above

7) What type of work do you do (e.g., teacher, homemaker)?

____

8) How many children do you have? ________

9) How many children under the age of 18 live at home? _______

10) How many children under the age of 14 live at home? _______

11) Of which ethnic origin(s) do you consider yourself? (Check all that apply)

❒ American Indian/Alaska Native
❒ Asian
❒ Black/African American
❒ Hispanic/Latino
❒ Native Hawaiian/Other Pacific Islander
❒ White/Caucasian
❒ Other

12) What is the highest level of education that you have completed? (Check only one)

❒ Primary School
❒ High School Diploma or equivalent
❒ Technical School or equivalent
❒ Some College or University
❒ Associate's Degree
❒ Bachelor's Degree
❒ Some Graduate or Professional School
❒ Graduate or Professional Degree

Driving Experience

13) How old were you when you started to drive? ________ years of age

14) For which of the following do you currently hold a valid driver's license within the United States? (Check all that apply)

	Vehicle Type	Year When FIRST Licensed (May be Approximate)
❒	Passenger Vehicle License	____ ____ ____ ____
❒	Commercial Truck License	____ ____ ____ ____
❒	Motorcycle License	____ ____ ____ ____
❒	Other: ______________________	____ ____ ____ ____
❒	Other: ______________________	____ ____ ____ ____

15) How often do you drive? (Check the most appropriate category)

❒ Less than once weekly
❒ At least once weekly
❒ At least once daily

16) Approximately how many miles do you drive per year in each vehicle type, excluding miles driven for work-related activities? (Check only one for each vehicle)

Car	Motorcycle	Truck	Other: ____________
❒ Do not drive	❒ Do not drive	❒ Do not drive	❒ Do not drive
❒ Under 2,000	❒ Under 2,000	❒ Under 2,000	❒ Under 2,000
❒ 2,000 - 7,999	❒ 2,000 - 7,999	❒ 2,000 - 7,999	❒ 2,000 - 7,999
❒ 8,000 - 12,999	❒ 8,000 - 12,999	❒ 8,000 - 12,999	❒ 8,000 - 12,999
❒ 13,000 - 19,999	❒ 13,000 - 19,999	❒ 13,000 - 19,999	❒ 13,000 - 19,999
❒ 20,000 or more	❒ 20,000 or more	❒ 20,000 or more	❒ 20,000 or more

17) Is any driving you do work-related? (Check only one)

❒ No (Go to question # 18)
❒ Yes (please complete question 17a below)

17a) How many work-related miles do you drive per year? (Check only one)

❒ Under 2,000

❒ 2,000 - 7,999

❒ 8,000 - 12,999

❒ 13,000 - 19,999

❒ 20,000 or more

18) How frequently do you drive in the following environments? (Check only one for each environment)

	Never	Yearly	Monthly	Weekly	Daily
Residential	❒	❒	❒	❒	❒
Business District	❒	❒	❒	❒	❒
Rural Highway (e.g., Route 6)	❒	❒	❒	❒	❒
Interstate (e.g., Interstate 80)	❒	❒	❒	❒	❒
Gravel Roads	❒	❒	❒	❒	❒

19) What speed do you typically drive in a **residential area** when the speed limit is **25**? __________mph

20) What speed do you typically drive in a **business district** when the speed limit is **35**? ________mph

21) What speed do you typically drive on a **rural highway** when the speed limit is **55**? __________mph

22) What speed do you typically drive on the **Interstate** when the speed limit is **65?** __________mph

23) What speed do you typically drive on a **gravel road**? ___________mph

24) Have you ever had to participate in any driver improvement courses due to moving violations?

❒ No

❒ Yes (Please describe)

____

25) When driving, how frequently do you perform each of the following tasks/maneuvers?

(Check the most appropriate answer for each task/maneuver)

	Never	Rarely	Occasionally	Frequently	Always	Not Applicable
Change lanes on Interstate or freeway	❒	❒	❒	❒	❒	❒
Keep up with traffic in town	❒	❒	❒	❒	❒	❒
Keep up with traffic on two-lane highway	❒	❒	❒	❒	❒	❒
Keep up with traffic on Interstate or freeway	❒	❒	❒	❒	❒	❒
Pass other cars on Interstate or freeway	❒	❒	❒	❒	❒	❒
Exceed speed limit	❒	❒	❒	❒	❒	❒
Wear a safety belt	❒	❒	❒	❒	❒	❒
Make left turns at uncontrolled intersections	❒	❒	❒	❒	❒	❒

26) How comfortable do you feel when you drive in the following conditions or perform the following maneuvers? (Check the most appropriate answer for each condition)

	Very Uncomfortable	Slightly Uncomfortable	Slightly Comfortable	Very Comfortable	Not Applicable
Highway/freeway	❐	❐	❐	❐	❐
After drinking alcohol	❐	❐	❐	❐	❐
With children	❐	❐	❐	❐	❐
High-density traffic	❐	❐	❐	❐	❐
Passing other cars	❐	❐	❐	❐	❐
Changing lanes	❐	❐	❐	❐	❐
Making left turns at uncontrolled intersections	❐	❐	❐	❐	❐

Violations

27) Within the past five years, how many tickets have you received for the following? (Please check a response for each ticket)

	0	1	2	3+
Speeding	❐	❐	❐	❐
Going too slowly	❐	❐	❐	❐
Failure to yield right of way	❐	❐	❐	❐
Disobeying traffic lights	❐	❐	❐	❐
Disobeying traffic signs	❐	❐	❐	❐
Improper passing	❐	❐	❐	❐
Improper turning	❐	❐	❐	❐
Reckless driving	❐	❐	❐	❐
Following another car too closely	❐	❐	❐	❐
Operating While Intoxicated (OWI) or Driving Under the influence (DUI)	❐	❐	❐	❐
Other (please specify **type** and **frequency** of violation) ____ __________				

Accidents

28) In the past five years, how many times have you been the driver of a car involved in an accident?

❒ 0 (Go to question # 29 on page 7)

❒ 1

❒ 2

❒ 3

❒ 4 or more

Please provide the following information for each accident on the next page.

Accident 1

Was another vehicle involved?	❒ No	❒ Yes
Was a pedestrian involved?	❒ No	❒ Yes
Were you largely responsible for this accident?	❒ No	❒ Yes
Did you go to driver's rehabilitation?	❒ No	❒ Yes
Weather Condition: ____________________ Month/Year: ____________________		
Description: ____ ____		

Accident 2

Was another vehicle involved?	❒ No	❒ Yes
Was a pedestrian involved?	❒ No	❒ Yes
Were you largely responsible for this accident?	❒ No	❒ Yes
Did you go to driver's rehabilitation?	❒ No	❒ Yes
Weather Condition: ____________________ Month/Year: ____________________		
Description: ____ ____		

Accident 3

Was another vehicle involved?	❒ No	❒ Yes
Was a pedestrian involved?	❒ No	❒ Yes
Were you largely responsible for this accident?	❒ No	❒ Yes
Did you go to driver's rehabilitation?	❒ No	❒ Yes
Weather Condition: _________________________ Month/Year: ______________________________		
Description:____ __________ ____ __________		

Health Status

29) How often do you experience motion sickness? (Circle only one)

0 1 2 3 4 5 6 7 8 9 10

Never Always

30) How severe are your symptoms when you experience motion sickness (Circle only one)

0 1 2 3 4 5 6 7 8 9 10

None Severe

31) Have you taken any medication in the past 48 hours? (Check only one)

- ❒ No
- ❒ Yes (Please list all)

____

____

32) What is your normal bedtime (hour of the day)?

____

Continue to the next page

Drowsy Driving History

33) Have you ever fallen asleep or nodded off even for a moment while driving?

❒ Yes **(Continue with 33A)**

❒ No (**IF NO, GO TO QUESTION 34 on page 9)**

33A) If you answered **yes** to number 33, thinking of the most recent time that you fell asleep or nodded off even for a moment while driving, how long ago was that?

❒ In the last week

❒ In the last month

❒ In the last 6 months

❒ In the last year

❒ Longer than an year ago

33B) If you answered **yes** to number 33, on this most recent time, which, if any of the following happened when you fell asleep or nodded off even for a moment while driving? (check all that apply)

❒ Ran off road

❒ Crossed centerline

❒ Wandered into other lane or onto the shoulder

❒ Got in a crash

❒ Someone honked at you

❒ Startled awake

❒ Other/Anything else:

____

33C) If you answered **yes** to number 33, thinking of the most recent time that this has occurred, what time of day was it?

❒ Midnight to 6am

❒ 6:00am-11:00am

❒ Noon-5:00pm

❒ 5:00pm-9:00pm

❒ 9:00pm-Midnight

33D) If you answered **yes** to number 33, how many hours had you been driving (the most recent time you fell asleep or nodded off even for a moment while driving)?

❒ <1 hour

❒ 1 hour

❒ 2 hours

❒ 3 hours

❒ 4 hours

❒ 5 hours

❒ 6+ hours

33E) If you answered **yes** to number 33, what type of road were you driving on (the most recent time you fell asleep or nodded off even for a moment while driving)?

❒ Multi-lane interstate-type highway with posted speed limit of 55mph or above

❒ Two-lane road with one lane of traffic traveling in each direction, with posted speed limit of 45 mph or higher

❒ City, town, or neighborhood street with posted speed limit of 35mph or higher

❒ Non-interstate, multi-lane road with posted speed limit of 40-50mph

33F) If you answered **yes** to number 33, how many hours did you sleep the night before (the most recent time you fell asleep or nodded off even for a moment while driving)?

❒ 8+ hours

❒ 7 hours

❒ 6 hours

❒ 5 hours

❒ 4 hours or less

33G) If you answered **yes** to number 33, did you have any alcoholic beverages within 2 hours prior to the trip (the most recent time you fell asleep or nodded off even for a moment while driving)?

❒ Yes

❒ No

33H) If you answered **yes** to number 33, did you take any allergy or other medications prior to the trip (the most recent time you fell asleep or nodded off even for a moment while driving)?

❒ Yes

❒ No

34) If you feel sleepy while driving, what if anything, do you do to stop it? (check all that apply)

❒ Pull over and take a nap

❒ Open the window

❒ Get coffee/soda/caffeine

❒ Pull over/get off road

❒ Turn on radio loud

❒ Get out/stretch/exercise

❒ Change drivers

❒ Eat

❒ Sing or talk to yourself/passenger

❒ Call and talk to someone on your cell phone

35) In the past five years, have you been involved in a crash while driving a motor vehicle in which there was damage to your vehicle or another vehicle?

❒ Yes **(Continue with 35A)**

❒ No (**IF NO, GO TO QUESTION 36 on page 10)**

35A) If you answered **yes** to number 35, were any of these crashes a result of you nodding off or having to greatly struggle to keep your eyes open?

❒ Yes

❒ No

36) In your opinion, how much of a threat is it to the personal safety of you and your family if other drivers do the following?

36A) Use a wireless phone while driving

❒ Not a threat

❒ Minor threat

❒ Major threat

36B) Eat or drink while driving

❒ Not a threat

❒ Minor threat

❒ Major threat

36C) Drive while sleepy or drowsy

❒ Not a threat

❒ Minor threat

❒ Major threat

36D) Look at maps or directions while driving

❒ Not a threat

❒ Minor threat

❒ Major threat

36E) Weaving in and out of traffic

❒ Not a threat

❒ Minor threat

❒ Major threat

36F) Running red lights

❒ Not a threat

❒ Minor threat

❒ Major threat

36G) Not coming to a complete stop at stop signs

❒ Not a threat

❒ Minor threat

❒ Major threat

Continue to the next page

Other Studies

37) Have you participated in other driving studies?

❐ No (End of questionnaire)
❐ Yes (please provide details for each study you have participated in below)

Study 1

What vehicle was used for this study? (Check only one)

❐ Actual car - only
❐ Another simulator - only
❐ National Advanced Driving Simulator (Motion Simulator)
❐ National Advanced Driving Simulator (Static Simulator)
❐ Both - actual car and another simulator
❐ Both - actual car and the National Advanced Driving Simulator (Motion Simulator)

Brief Description:

____

____

Study 2

What vehicle was used for this study? (Check only one)

❐ Actual car - only
❐ Another simulator - only
❐ National Advanced Driving Simulator (Motion Simulator)
❐ National Advanced Driving Simulator (Static Simulator)
❐ Both - actual car and another simulator
❐ Both - actual car and the National Advanced Driving Simulator (Motion Simulator)

Brief Description:

____

____

Study 3

What vehicle was used for this study? (Check only one)

❒ Actual car - only

❒ Another simulator - only

❒ National Advanced Driving Simulator (Motion Simulator)

❒ National Advanced Driving Simulator (Static Simulator)

❒ Both - actual car and another simulator

❒ Both - actual car and the National Advanced Driving Simulator (Motion Simulator)

Brief Description:

____

____

The End

APPENDIX J: TRAINING PRESENTATION

Drowsy Driving

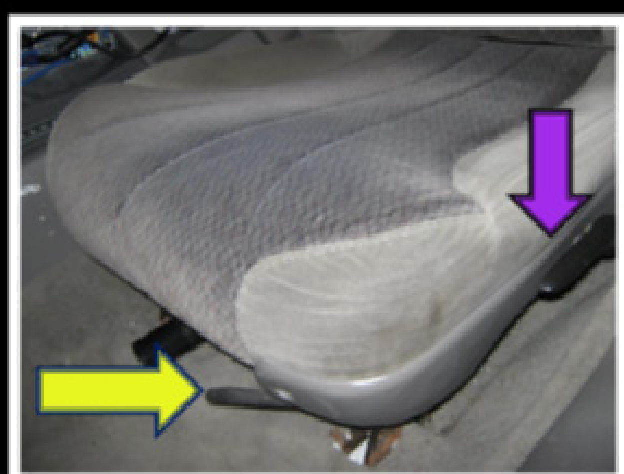
Orientation to the Simulator Cab and Study Requirements

Press the space bar to advance slides.

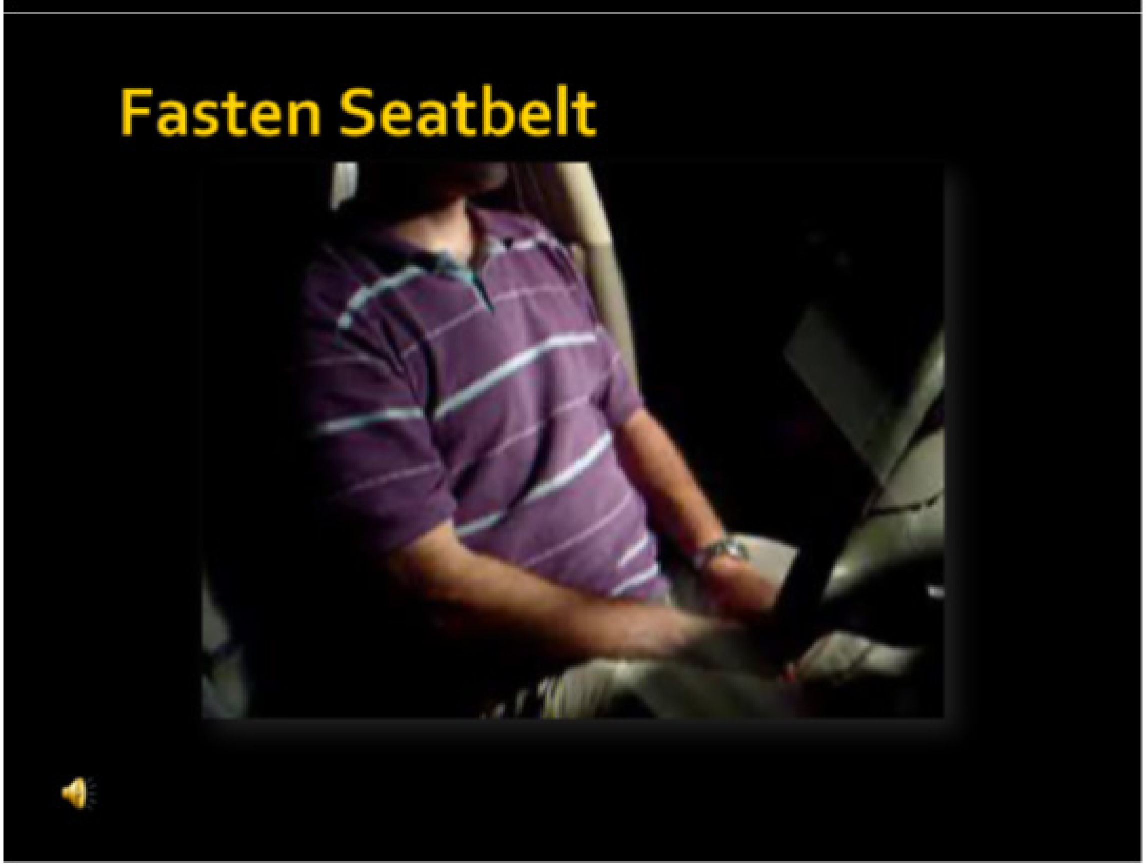
Chevy Malibu

Malibu Interior

Seat Adjustments




Steering Wheel Adjustments


Fasten Seatbelt

Resting Position

Intercom System

The cab has an intercom system which allows the researchers to hear you. It is already adjusted for the drive today. If for any reason you want to stop driving, please tell us. The operator will hear you and can end the drive in just a few seconds. The driving instructions will be given through the intercom system as well.

Eye Tracking Cameras

Mirrors

You will need to use the side and rear view mirrors for the drives today. The mirrors can be adjusted by using the control panel on the door. Set the side mirrors in much the same way as you would set the mirrors on your car. Wait to adjust the mirrors until after the eye tracking cameras have been calibrated. The control panel should be pressed firmly. If you need assistance, please ask the researcher in the simulator for some help.

Practice Drive

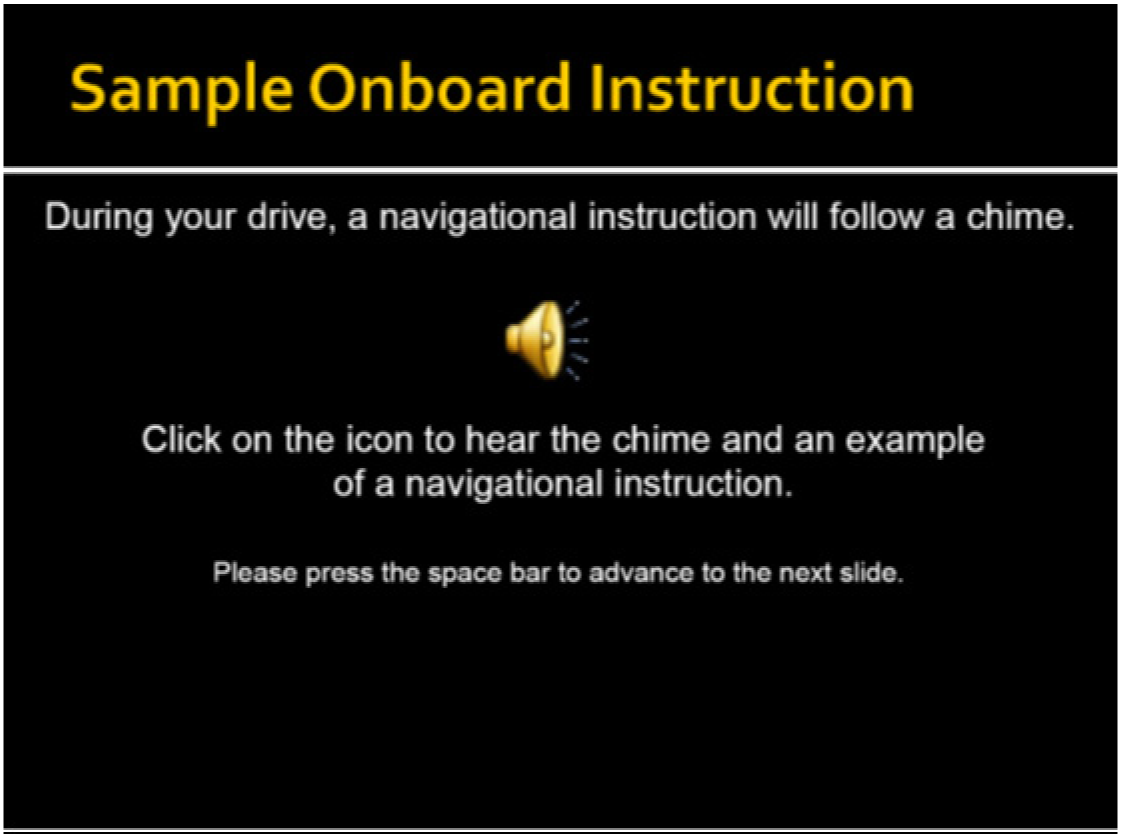
Your drive today will be a practice drive. It is designed to help you get used to the simulator. Please become familiar with driving at the speed limits and recognizing traffic control devices. You will be asked to adjust the CD player while you drive. The CD player is described in a later slide.

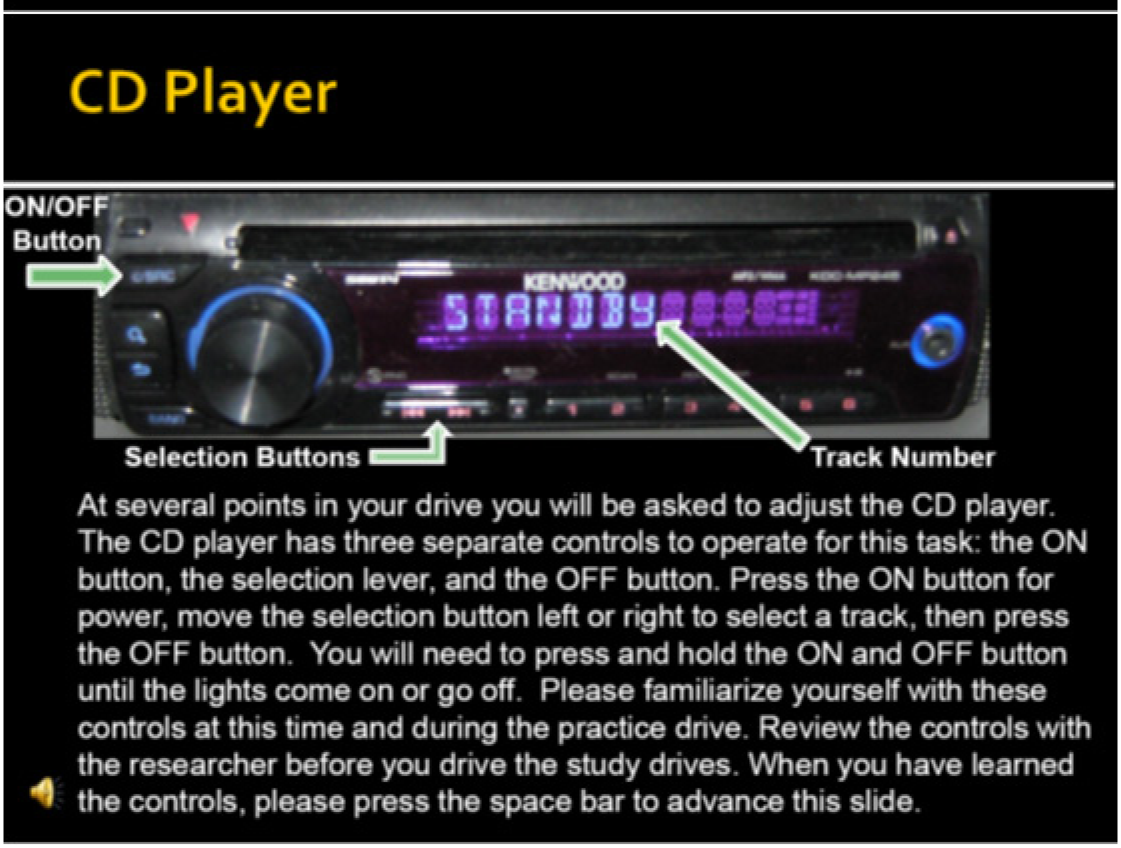
The practice drive starts with your vehicle parked along a city street. When it is time to begin, shift into Drive, then enter into traffic when it is safe to do so. Stay on the original road. You will drive to an interstate where you should merge and accelerate to the speed limit. Onboard instructions will guide you to the interstate. A recording will tell you when it is time to stop.

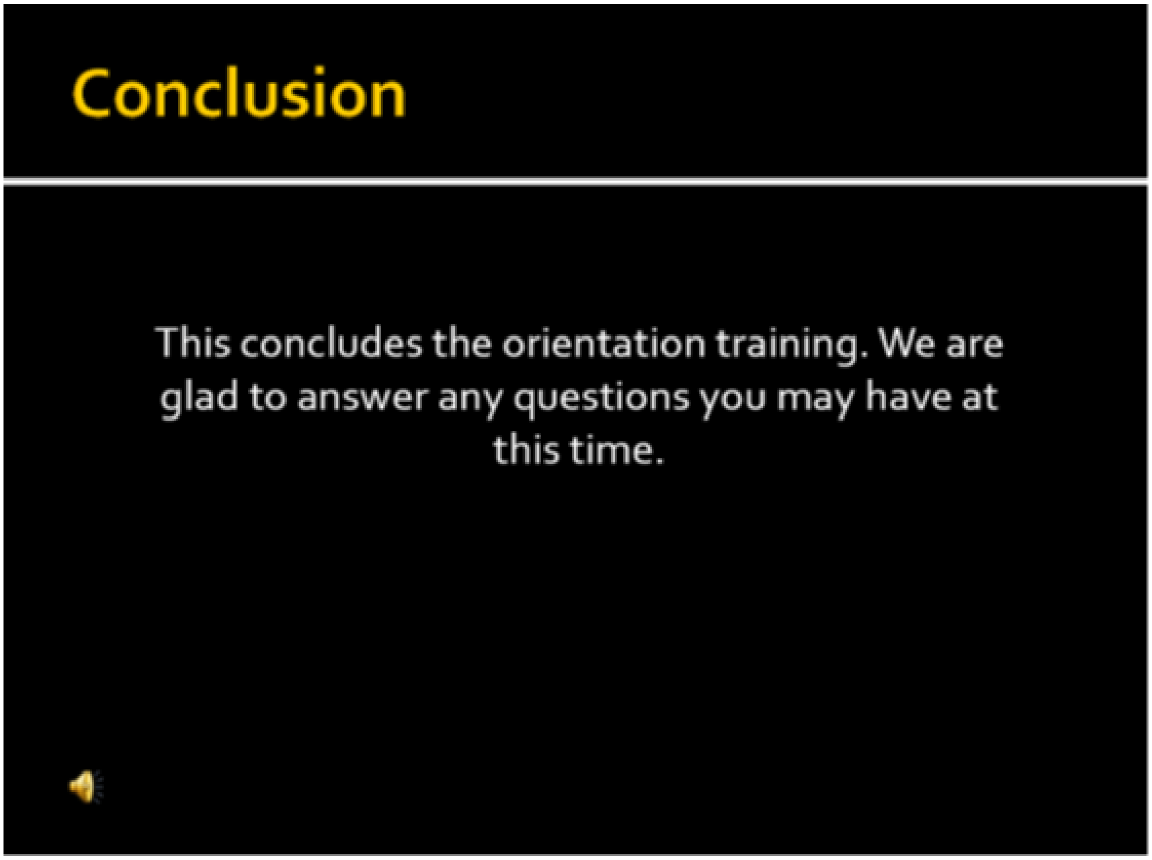
Study Drives

The study drives are designed such that you will be driving on city streets, an interstate, and country roads. Each drive has a similar route. Speed limits are posted. Navigational instructions will be played as you drive to your destination. The drive is about 30 minutes long. You will be asked to adjust the CD player several times during each drive.

The drive starts in a parking lane in the city's business district. When it is time to begin, shift into Drive, and merge into traffic when it is safe to do so. Continue driving until you enter the driveway of the residence, at which time you should park near the garage.


Sample Onboard Instruction
During your drive, a navigational instruction will follow a chime.
Click on the icon to hear the chime and an example
of a navigational instruction.
Please press the space bar to advance to the next slide.


CD Player
ON/OFF
Button
KENWOOD
Selection Buttons
Track Number
At several points in your drive you will be asked to adjust the CD player. The CD player has three separate controls to operate for this task: the ON button, the selection lever, and the OFF button. Press the ON button for power, move the selection button left or right to select a track, then press the OFF button. You will need to press and hold the ON and OFF button until the lights come on or go off. Please familiarize yourself with these controls at this time and during the practice drive. Review the controls with the researcher before you drive the study drives. When you have learned the controls, please press the space bar to advance this slide.


Conclusion
This concludes the orientation training. We are glad to answer any questions you may have at this time.

APPENDIX K: IN-CAB PROTOCOL

CAB ORIENTATION
[Participant has viewed an introductory PPT about the study and the Malibu adjustments during a screening visit.]
[open car door] **(RAS): This is your mirror adjustment.** *[Show mirror control panel]*
(RAS): Please be seated and make the adjustments so you are in a comfortable driving position. If you need any help, please let me know. *[go to passenger side]*
[Turn cabin speaker ON] *[make sure seatbelt gets fastened.]*
(RAS): *[from passenger side]* **We are going to set the cameras for eye tracking so please look straight ahead at this time.** *[Align cameras]* *[**Control room** assists] [Have driver look forward for picture]*
Plug in Dongle and inform operator when the light on the headset is solid green
(RAS): Review the CD player (ON/OFF(middle blue button) **and the track forward and track back buttons.)**
Have participant RESET CD PLAYER TO TRACK 1 AND TURN OFF. ***Turn on map light.*** *[RAS enters back seat at this time]*
GET OKAY FROM OPERATOR THAT THE IMPEDANCE IS GOOD FOR THE EEG
[reminder of "resting position"] [If there is time to start mirrors, they may, however, if Control Room comes back for eye tracking, ignore mirrors from this point until after "Start-up Bump".]
*[**Control room** calibrates the gaze into each camera] [**Control room** should cue that ET is complete.] [Turn cabin speaker OFF]*
[after ET is done, during start up of sim, play file] **Sim Start: The simulator is moving towards its start position. During this time, you may hear rumbling and feel vibrations. This is perfectly normal. There are microphones in the cab so the Simulator Operator can hear you at all times. If, for any reason, you wish to stop driving, please let us know. The Operator can bring you to a stop in just a few seconds.**
[After information and start up bump...]
[Have participant finish adjusting the mirrors to their satisfaction.] .. .. Control room
.. .. RAS says
[Administer PVT (on iPad) then Sleep Scale before Main Drive]. .. .. RAS does
MAIN DRIVE
(RAS):

(RAS read): **The Main drive will start shortly. Remember to listen to the on-board instructions carefully. If you have any uncertainty about navigating during the drive, please ask. When the scenery comes on, please press on the brake, shift into drive and merge into traffic when it is safe to do so. Do you have any questions at this time?**
(RAS): No questions, we're ready. ***Operator goes to RUN*** *[Say nothing more unless: (see page 2)] Go to page 2*
(cont'd from page 1)
[RAS stays quiet but can give concise directions if asked, intervene for well-being and must provide segue during restarts]
[RAS works with Operator to coordinate going to RUN on restarts]
*[**At End**, pre-recorded destination message will play and **RAS must speak right up.]***
(RAS): Please come to a complete stop. When the speedometer indicates "zero", shift into Park. *[Seatbelt reminder]*
END MAIN DRIVE
[Administer Sleep Scale (paper), Wellness Survey(paper) and PVT(iPad)] ***[Turn off map light.]*** *[Exit Simulator]*
.. .. Control room
.. .. RAS says
.. .. RAS does

[RAS stays quiet but can give concise directions if asked, intervene for well-being and study continuity or provide segue during restarts]
[RAS works with Operator to identify correct restart if needed]
END MAIN DRIVE
[Seatbelt fastened reminder. [Administer SSQ and Sleep Scale] [Exit Simulator]

APPENDIX L: WELLNESS SURVEY

WELLNESS SURVEY

Directions: Circle one option for each symptom to indicate whether that symptom applies to you right now.

1. General Discomfort .... None............... Slight .... Moderate .... Severe
2. Fatigue .... None............... Slight .... Moderate .... Severe
3. Headache .... None............... Slight .... Moderate .... Severe
4. Eye Strain .... None............... Slight .... Moderate .... Severe
5. Difficulty Focusing .... None............... Slight .... Moderate .... Severe
6. Salivation Increased .... None............... Slight .... Moderate .... Severe
7. Sweating .... None............... Slight .... Moderate .... Severe
8. Nausea .... None............... Slight .... Moderate .... Severe
9. Difficulty Concentrating .... None............... Slight .... Moderate .... Severe
10. *"Fullness of the Head" .... None............... Slight .... Moderate .... Severe
11. Blurred Vision .... None............... Slight .... Moderate .... Severe
12. Dizziness with Eyes Open .... None............... Slight .... Moderate .... Severe
13. Dizziness with Eyes Closed ...... None............... Slight .... Moderate .... Severe
14. **Vertigo .... None............... Slight .... Moderate .... Severe
15. ***Stomach Awareness .... None............... Slight .... Moderate .... Severe
16. Burping.................................... None............... Slight .... Moderate .... Severe
17. Vomiting................................. None............... Slight .... Moderate.........Severe
18. Other ____________________ ..... None............... Slight .... Moderate.........Severe

* Fullness of the head is an awareness of pressure in the head.

**Vertigo is experienced as loss of orientation with respect to vertical upright.

***Stomach awareness is a feeling of discomfort which is just short of nausea.

APPENDIX M: ACTIVITY LOG

ACTIVITY LOG
INSTRUCTIONS TO PARTICIPANT

You will use this log to document your activity in the days preceding your study visits. You are asked to record the following types of information:

- About your sleep
- About your food and beverage consumption
- About your activities throughout the day

Asleep column: place an X in the time slots for when were sleeping. To do this, place an X in the log at the time you lay down to sleep. When you awake, place another X.

Activity column: provide brief comments about what you were doing during that time frame. For example if you went to the gym, write gym. Also record if you wake up during the night. You will need to record activity that woke you and for how long you were awake, baby crying, bathroom, let dog out, etc. You should complete this column when you complete the activity.

Food/beverage column: Provide brief comments about what food and beverages you consumed throughout the day. Please make special note of anything that you eat or drink that contains caffeine or alcohol. You should complete this column when you complete the meal/snack.

Items with caffeine include: coffee, soda, tea, energy drinks, energy bars, vitamin water, food containing chocolate, candy

Alcohol items include: beer, wine, liquor/spirits

Pages 2-3 provide you with an example of how to complete your log.

Be specific, but try to keep your answers as brief as possible. If you have questions about completing your activity log, please contact **Cheryl Roe at (319) 335-4775**.

REMEMBER:

Refrain from consuming any alcohol 24 hours prior to ALL your driving sessions

After 12:00 pm on the day of your overnight visit, restrict beverage intake to water. This does not include Vitamin Water which contains caffeine.

Refrain from taking naps on the day of your overnight visit.

Subject ID:__________

Activity Log Example: DATE: 02/25/2011

<table>
<tr><th>Time</th><th></th><th>Asleep</th><th>Activity</th><th>Food/Beverage</th></tr>
<tr><td>12:00-12:15</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>12:15-12:30</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>12:30-12:45</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>12:45-1:00</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>1:00-1:15</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>1:15-1:30</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>1:30-1:45</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>1:45-2:00</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>2:00-2:15</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>2:15-2:30</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>2:30-2:45</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>2:45-3:00</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>3:00-3:15</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>3:15-3:30</td><td>AM</td><td>X</td><td>Woke up-baby</td><td></td></tr>
<tr><td>3:30-3:45</td><td>AM</td><td>X</td><td>|</td><td></td></tr>
<tr><td>3:45-4:00</td><td>AM</td><td>X</td><td>|</td><td></td></tr>
<tr><td>4:00-4:15</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>4:15-4:30</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>4:30-4:45</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>4:45-5:00</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>5:00-5:15</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>5:15-5:30</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>5:30-5:45</td><td>AM</td><td>X</td><td>Bathroom</td><td></td></tr>
<tr><td>5:45-6:00</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>6:00-6:15</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>6:15-6:30</td><td>AM</td><td>X</td><td></td><td></td></tr>
<tr><td>6:30-6:45</td><td>AM</td><td></td><td>Gym</td><td>20 oz. PowerAde</td></tr>
<tr><td>6:45-7:00</td><td>AM</td><td></td><td>|</td><td>Energy Bar</td></tr>
<tr><td>7:00-7:15</td><td>AM</td><td></td><td>|</td><td></td></tr>
<tr><td>7:15-7:30</td><td>AM</td><td></td><td>|</td><td></td></tr>
<tr><td>7:30-7:45</td><td>AM</td><td></td><td>At work</td><td></td></tr>
<tr><td>7:45-8:00</td><td>AM</td><td></td><td>|</td><td></td></tr>
</table>

Subject ID:__________

8:00-8:15	AM		|	
8:15-8:30	AM		|	
8:30-8:45	AM		|	
8:45-9:00	AM		|	12 oz. Latte Starbucks
9:00-9:15	AM		|	
9:15-9:30	AM		|	
9:30-9:45	AM		|	
9:45-10:00	AM		|	
10:00-10:15	AM		|	
10:15-10:30	AM		|	
10:30-10:45	AM		|	
10:45-11:00	AM		|	
11:00-11:15	AM		|	
11:15-11:30	AM		|	
11:30-11:45	AM		|	
11:45-12:00	AM/PM		Lunch	Chocolate cake, turkey sandwich, Chips,
Time		Asleep	Activity	Food/Beverage
12:00-12:15	PM		|	16 oz. Pepsi
12:15-12:30	PM		|	
12:30-12:45	PM		|	
12:45-1:00	PM		At Work	
1:00-1:15	PM		|	
1:15-1:30	PM		|	
1:30-1:45	PM		|	
1:45-2:00	PM		|	
2:00-2:15	PM		|	
2:15-2:30	PM		|	
2:30-2:45	PM		|	Snickers Bar
2:45-3:00	PM		|	
3:00-3:15	PM		|	
3:15-3:30	PM		|	
3:30-3:45	PM		|	
3:45-4:00	PM		|	
4:00-4:15	PM		|	

Subject ID:__________

4:15-4:30	PM		|	
4:30-4:45	PM		Drinks	2 Red Bull and Vodka
4:45-5:00	PM		|	
5:00-5:15	PM		|	
5:15-5:30	PM		|	
5:30-5:45	PM		|	
5:45-6:00	PM		Making Dinner @ home	
6:00-6:15	PM		|	
6:15-6:30	PM		|	
6:30-6:45	PM		Eating Dinner	1 Glass of wine
6:45-7:00	PM		|	Lasagna
7:00-7:15	PM		Watching TV	Salad
7:15-7:30	PM		|	
7:30-7:45	PM		|	
7:45-8:00	PM		|	
8:00-8:15	PM		|	2 scoops Coffee ice cream
8:15-8:30	PM		|	
8:30-8:45	PM		Reading in Bed	
8:45-9:00	PM		|	
9:00-9:15	PM		|	
9:15-9:30	PM	X		
9:30-9:45	PM	X		
9:45-10:00	PM	X		
10:00-10:15	PM	X		
10:15-10:30	PM	X		
10:30-10:45	PM	X		
10:45-11:00	PM	X		
11:00-11:15	PM	X		
11:15-11:30	PM	X		
11:30-11:45	PM	X		
11:45-12:00	PM	x		

Subject ID: __________

Activity Log DATE: ___________

Time		Asleep	Activity	Food/Beverage
12:00-12:15	AM			
12:15-12:30	AM			
12:30-12:45	AM			
12:45-1:00	AM			
1:00-1:15	AM			
1:15-1:30	AM			
1:30-1:45	AM			
1:45-2:00	AM			
2:00-2:15	AM			
2:15-2:30	AM			
2:30-2:45	AM			
2:45-3:00	AM			
3:00-3:15	AM			
3:15-3:30	AM			
3:30-3:45	AM			
3:45-4:00	AM			
4:00-4:15	AM			
4:15-4:30	AM			
4:30-4:45	AM			
4:45-5:00	AM			
5:00-5:15	AM			
5:15-5:30	AM			
5:30-5:45	AM			
5:45-6:00	AM			
6:00-6:15	AM			
6:15-6:30	AM			
6:30-6:45	AM			
6:45-7:00	AM			
7:00-7:15	AM			
7:15-7:30	AM			
7:30-7:45	AM			
7:45-8:00	AM			

Subject ID:__________

8:00-8:15	AM			
8:15-8:30	AM			
8:30-8:45	AM			
8:45-9:00	AM			
9:00-9:15	AM			
9:15-9:30	AM			
9:30-9:45	AM			
9:45-10:00	AM			
10:00-10:15	AM			
10:15-10:30	AM			
10:30-10:45	AM			
10:45-11:00	AM			
11:00-11:15	AM			
11:15-11:30	AM			
11:30-11:45	AM			
11:45-12:00	AM/PM			
Time		Asleep	Activity	Food/Beverage
12:00-12:15	PM			
12:15-12:30	PM			
12:30-12:45	PM			
12:45-1:00	PM			
1:00-1:15	PM			
1:15-1:30	PM			
1:30-1:45	PM			
1:45-2:00	PM			
2:00-2:15	PM			
2:15-2:30	PM			
2:30-2:45	PM			
2:45-3:00	PM			
3:00-3:15	PM			
3:15-3:30	PM			
3:30-3:45	PM			
3:45-4:00	PM			
4:00-4:15	PM			

4:15-4:30	PM			
4:30-4:45	PM			
4:45-5:00	PM			
5:00-5:15	PM			
5:15-5:30	PM			
5:30-5:45	PM			
5:45-6:00	PM			
6:00-6:15	PM			
6:15-6:30	PM			
6:30-6:45	PM			
6:45-7:00	PM			
7:00-7:15	PM			
7:15-7:30	PM			
7:30-7:45	PM			
7:45-8:00	PM			
8:00-8:15	PM			
8:15-8:30	PM			
8:30-8:45	PM			
8:45-9:00	PM			
9:00-9:15	PM			
9:15-9:30	PM			
9:30-9:45	PM			
9:45-10:00	PM			
10:00-10:15	PM			
10:15-10:30	PM			
10:30-10:45	PM			
10:45-11:00	PM			
11:00-11:15	PM			
11:15-11:30	PM			
11:30-11:45	PM			
11:45-12:00	PM			

APPENDIX N: SLEEP AND FOOD INTAKE

As part of this study, it is useful to collect information about your sleep and food, alcohol, and caffeine intake. Please read each question carefully. If something is unclear, ask the researcher for assistance. Your participation is voluntary and you have the right to omit questions if you choose.

1) On a typical _____________, when do you normally go to bed? ______AM/ PM

2) On a typical _____________, when do you normally wake up? ______AM/ PM

3) What time did you go to sleep last night? ___________ AM/PM

4) What time did you wake today? ___________ AM/PM

5) In total, how many hours did you sleep last night? _______

6) Do you feel that you got enough sleep? ❒No ❒Yes

7) Did you take a nap today?
   - ❒ No
   - ❒ Yes, times? _____________________

8) When did you eat your last meal? _____________AM/PM
   a) What did you eat at that meal?
   ____
   ____

9) Have you had anything to eat since your last meal?
   - ❒ No
   - ❒ Yes, when? _____________AM/PM
   a) What did you eat? ____

10) Have you had any nicotine in the last 24 hours?
   - ❒ No
   - ❒ Yes, when? ______________ AM/PM
     a) How many cigarettes did you smoke? __________________________
     b) How much chewing tobacco did you use? _______________________
     c) Other forms of nicotine? (type and frequency) ____________________

10) Have you had any caffeine in the last 24 hours?
   - ❒ No
   - ❒ Yes, when? ______________ AM/PM
     a) How many cups of coffee did you drink? _______________________

b) How many cans of caffeinated soda did you drink? ________________

c) Other forms of caffeine? (type and frequency) ____________________

11) Have you had any alcohol in the last 24 hours?

❒ No

❒ Yes, when? ______________ AM/PM

a) How many cans of beer did you drink? _________________________

b) How many glasses of wine did you drink? ________________________

c) How many mixed drinks did you consume? _______________________

d) How many shots of alcohol did you consume? _____________________

12) Have you taken any prescription or over-the-counter medications in the past 24 hours?

❒ No

❒ Yes, Explain what was taken, how much was taken and when it was taken.

____

____

____

____

APPENDIX O: STANFORD SLEEPINESS SCALE

Degree of Sleepiness	**Scale Rating**
Feeling active, vital, alert, or wide awake	1
Functioning at high levels, but not at peak; able to concentrate	2
Awake, but relaxed; responsive but not fully alert	3
Somewhat foggy, let down	4
Foggy; losing interest in remaining awake; slowed down	5
Sleepy, woozy, fighting sleep; prefer to lie down	6
No longer fighting sleep, sleep onset soon; having dream-like thoughts	7
Asleep	X

APPENDIX P: RETROSPECTIVE SLEEPINESS SCALE

SCENARIO 1

Degree of Sleepiness	Scale Rating
Feeling active, vital, alert, or wide awake	1
Functioning at high levels, but not at peak; able to concentrate	2
Awake, but relaxed; responsive but not fully alert	3
Somewhat foggy, let down	4
Foggy; losing interest in remaining awake; slowed down	5
Sleepy, woozy, fighting sleep; prefer to lie down	6
No longer fighting sleep, sleep onset soon; having dream-like thoughts	7
Asleep	8

Please rate your degree of sleepiness as you began to drive: ______

Please rate your degree of sleepiness at the left turn in the urban environment: ______

Please rate your degree of sleepiness on the on-ramp to the interstate: ______

Please rate your degree of sleepiness at the interchange on the interstate: ______

Please rate your degree of sleepiness at the stop sign on the off-ramp from the interstate: ______

Please rate your degree of sleepiness as drove through the sharp curve the rural environment: ______

Please rate your degree of sleepiness as you passed the service station at the Y-intersection: ______

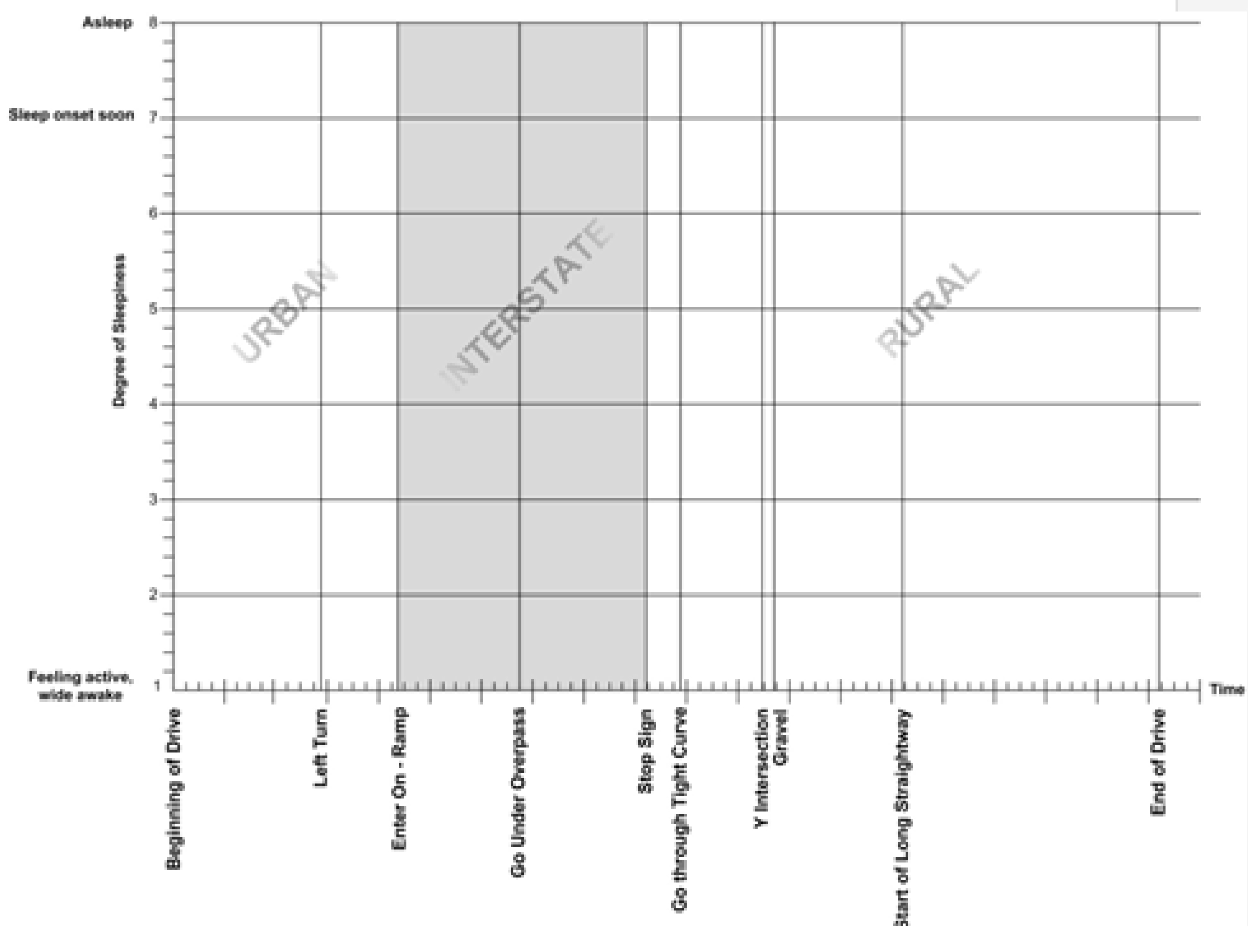
Please rate your degree of sleepiness at the start of the gravel road: ______

Please rate your degree of sleepiness at start of the long straight away: ______

Please rate your degree of sleepiness just before you were told to stop: ______

Degree of Sleepiness	Scale Rating
Feeling active, vital, alert, or wide awake	1
Functioning at high levels, but not at peak; able to concentrate	2
Awake, but relaxed; responsive but not fully alert	3
Somewhat foggy, let down	4
Foggy; losing interest in remaining awake; slowed down	5
Sleepy, woozy, fighting sleep; prefer to lie down	6
No longer fighting sleep, sleep onset soon; having dream-like thoughts	7
Asleep	8

Draw a line between the ratings to indicate your leve of sleepiness for the times between the points of intersted that are listed.



SCENARIO 2

Degree of Sleepiness	Scale Rating
Feeling active, vital, alert, or wide awake	1
Functioning at high levels, but not at peak; able to concentrate	2
Awake, but relaxed; responsive but not fully alert	3
Somewhat foggy, let down	4
Foggy; losing interest in remaining awake; slowed down	5
Sleepy, woozy, fighting sleep; prefer to lie down	6
No longer fighting sleep, sleep onset soon; having dream-like thoughts	7
Asleep	8

Please rate your degree of sleepiness as you began to drive: ______

Please rate your degree of sleepiness at the left turn in the urban environment: ______

Please rate your degree of sleepiness on the on-ramp to the interstate: ______

Please rate your degree of sleepiness at the interchange on the interstate: ______

Please rate your degree of sleepiness at the stop sign on the off-ramp from the interstate: ______

Please rate your degree of sleepiness as drove through the sharp curve the rural environment: ______

Please rate your degree of sleepiness as you passed the service station at the Y-intersection: ______

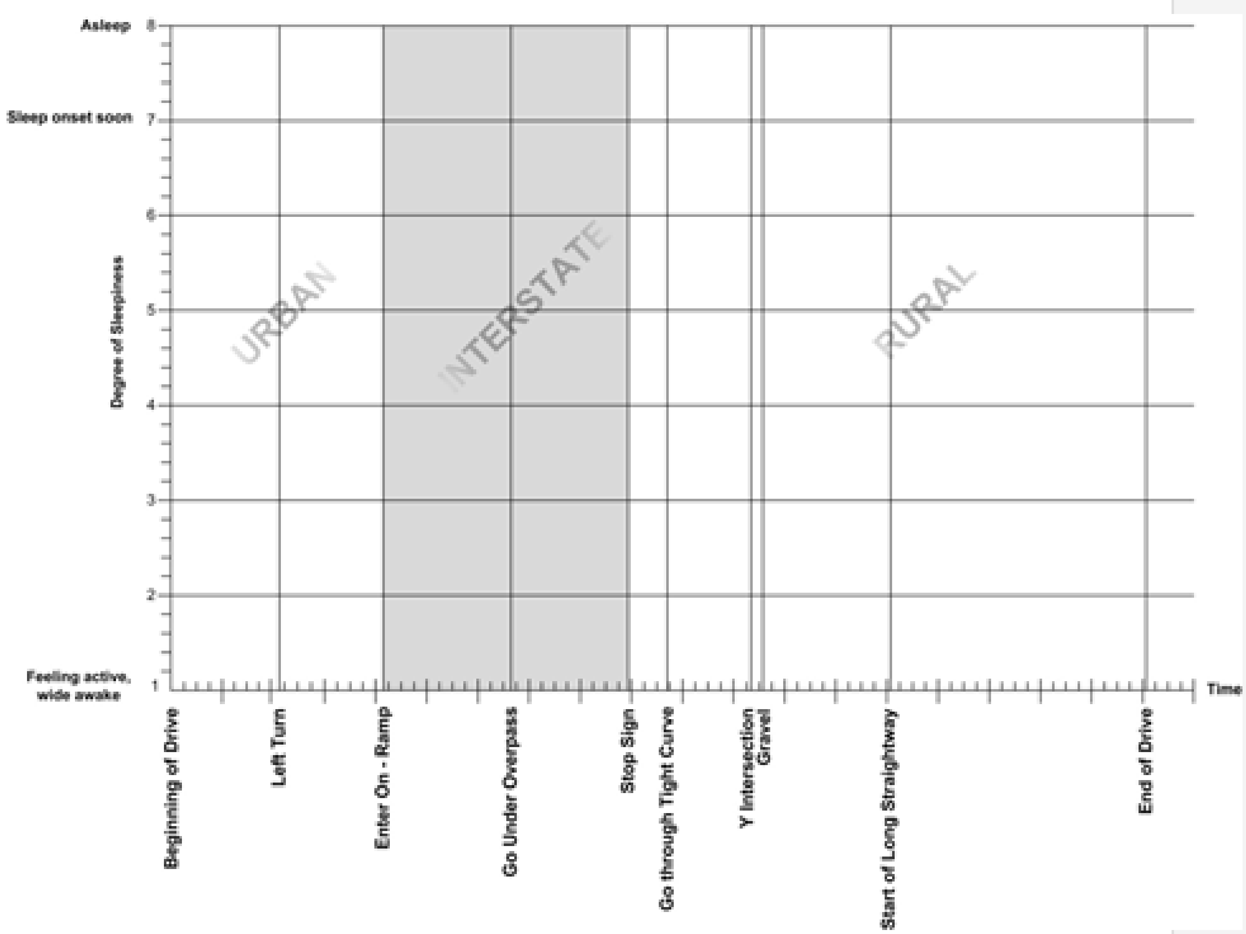
Please rate your degree of sleepiness at the start of the gravel road: ______

Please rate your degree of sleepiness at start of the long straight away: ______

Please rate your degree of sleepiness just before you were told to stop: ______

Degree of Sleepiness	Scale Rating
Feeling active, vital, alert, or wide awake	1
Functioning at high levels, but not at peak; able to concentrate	2
Awake, but relaxed; responsive but not fully alert	3
Somewhat foggy, let down	4
Foggy; losing interest in remaining awake; slowed down	5
Sleepy, woozy, fighting sleep; prefer to lie down	6
No longer fighting sleep, sleep onset soon; having dream-like thoughts	7
Asleep	8

Draw a line between the ratings to indicate your level of sleepiness for the times between the points of intersted that are listed.



SCENARIO 3

Degree of Sleepiness	Scale Rating
Feeling active, vital, alert, or wide awake	1
Functioning at high levels, but not at peak; able to concentrate	2
Awake, but relaxed; responsive but not fully alert	3
Somewhat foggy, let down	4
Foggy; losing interest in remaining awake; slowed down	5
Sleepy, woozy, fighting sleep; prefer to lie down	6
No longer fighting sleep, sleep onset soon; having dream-like thoughts	7
Asleep	8

Please rate your degree of sleepiness as you began to drive: ______

Please rate your degree of sleepiness at the left turn in the urban environment: ______

Please rate your degree of sleepiness on the on-ramp to the interstate: ______

Please rate your degree of sleepiness at the interchange on the interstate: ______

Please rate your degree of sleepiness at the stop sign on the off-ramp from the interstate: ______

Please rate your degree of sleepiness as drove through the sharp curve the rural environment: ______

Please rate your degree of sleepiness as you passed the service station at the Y-intersection: ______

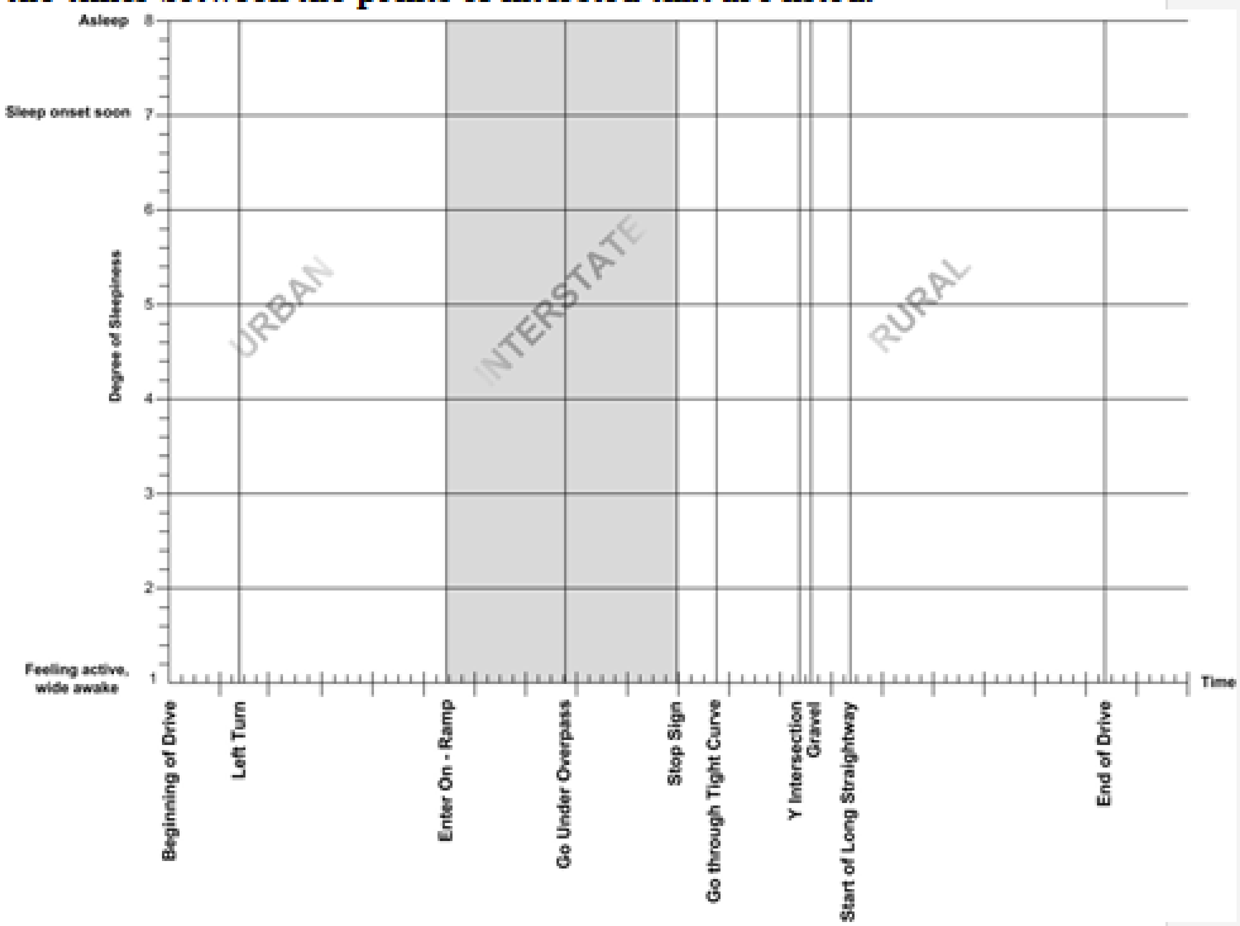
Please rate your degree of sleepiness at the start of the gravel road: ______

Please rate your degree of sleepiness at start of the long straight away: ______

Please rate your degree of sleepiness just before you were told to stop: ______

Degree of Sleepiness	Scale Rating
Feeling active, vital, alert, or wide awake	1
Functioning at high levels, but not at peak; able to concentrate	2
Awake, but relaxed; responsive but not fully alert	3
Somewhat foggy, let down	4
Foggy; losing interest in remaining awake; slowed down	5
Sleepy, woozy, fighting sleep; prefer to lie down	6
No longer fighting sleep, sleep onset soon; having dream-like thoughts	7
Asleep	8

Draw a line between the ratings to indicate your level of sleepiness for the times between the points of intersted that are listed.



APPENDIX Q: REALISM SURVEY

Date: _____

REALISM SURVEY

For each of the following items, circle the number that best indicates how closely the simulator resembles an actual car in terms of appearance, sound, and response. If an item is not applicable, circle NA.

	General Driving	Not at all realistic						Completely Realistic	
1	Response of the seat adjustment levers	0	1	2	3	4	5	6	NA
2	Response of the mirror adjustment levers	0	1	2	3	4	5	6	NA
3	Response of the door locks and handles	0	1	2	3	4	5	6	NA
4	Response of the fans	0	1	2	3	4	5	6	NA
5	Response of the gear shift	0	1	2	3	4	5	6	NA
6	Response of the brake pedal	0	1	2	3	4	5	6	NA
7	Response of accelerator pedal	0	1	2	3	4	5	6	NA
8	Response of the speedometer	0	1	2	3	4	5	6	NA
9	Response of the steering wheel while driving straight	0	1	2	3	4	5	6	NA
10	Response of the steering wheel while driving on curves	0	1	2	3	4	5	6	NA
11	Feel when accelerating	0	1	2	3	4	5	6	NA
12	Feel when braking	0	1	2	3	4	5	6	NA
13	Ability to read road and warning signs	0	1	2	3	4	5	6	NA
14	Appearance of car interior	0	1	2	3	4	5	6	NA
15	Appearance of signs	0	1	2	3	4	5	6	NA
16	Appearance of roads and road markings	0	1	2	3	4	5	6	NA
17	Appearance of urban scenery	0	1	2	3	4	5	6	NA
18	Appearance of rural scenery	0	1	2	3	4	5	6	NA
19	Appearance of freeway scenery	0	1	2	3	4	5	6	NA
20	Appearance of intersections	0	1	2	3	4	5	6	NA
21	Appearance of headlights	0	1	2	3	4	5	6	NA
22	Appearance of gravel road	0	1	2	3	4	5	6	NA
23	Appearance of other vehicles	0	1	2	3	4	5	6	NA
24	Appearance of rear-view mirror image	0	1	2	3	4	5	6	NA
25	Sound of the car	0	1	2	3	4	5	6	NA
26	Sound of other vehicles	0	1	2	3	4	5	6	NA
27	Overall feel of the car when driving	0	1	2	3	4	5	6	NA
28	Overall similarity to real driving	0	1	2	3	4	5	6	NA
29	Overall Appearance of driving scenes	0	1	2	3	4	5	6	NA

H-2

	Situational Driving	Not at all realistic						Completely Realistic	
30	Feel of driving straight while going 25 mph	0		1	2	3	4	5	6	NA
31	Feel of driving straight while going 35 mph	0		1	2	3	4	5	6	NA
32	Feel of driving straight while going 55 mph	0		1	2	3	4	5	6	NA
33	Feel of driving straight while going 65 mph	0		1	2	3	4	5	6	NA
34	Feel of driving on a curved road while going 25 mph	0		1	2	3	4	5	6	NA
35	Feel of driving on a curved road while going 55 mph	0		1	2	3	4	5	6	NA
36	Feel of driving on a curved road while going 65 mph	0		1	2	3	4	5	6	NA
37	Feel of accelerating from a stopped position	0		1	2	3	4	5	6	NA
38	Feel of braking to a stop	0		1	2	3	4	5	6	NA
39	Performing a 90 degree turn to the left while going 25 mph	0		1	2	3	4	5	6	NA
40	Performing a 90 degree turn to the right from a stopped position	0		1	2	3	4	5	6	NA
41	Feel of driving on the freeway	0		1	2	3	4	5	6	NA
42	Feel of changing lanes on the freeway	0		1	2	3	4	5	6	NA
43	Feel of driving on a freeway on/exit ramp	0		1	2	3	4	5	6	NA
44	Feel of driving on gravel road	0		1	2	3	4	5	6	NA
45	Ability to stop the vehicle	0		1	2	3	4	5	6	NA
46	Ability to respond to other vehicles	0		1	2	3	4	5	6	NA
47	Ability to keep straight in your lane	0		1	2	3	4	5	6	NA
48	Ability to respond at intersections	0		1	2	3	4	5	6	NA

APPENDIX R: DEBRIEFING INTERVIEW

ACMI Debrief Interview

[Document for research staff only. Interview will include, but is not limited to, the following questions; follow-up questions may be asked. Staff: Mark all boxes that apply for high-level analysis.]

In this interview, I'll ask you questions regarding impairment, driving, and potential future technologies that could be designed to assist drowsy drivers. Your participation is voluntary and you have the right to skip questions if you choose. All of your answers will be kept confidential.

1. Have you ever driven when you've been drowsy but believed you were still able to drive safely?

   [ ] Yes [ ] No [ ] Other

   a. What factors played a role in your decision to drive or not to drive?

IF PARTICIPANT REPORTS NEVER DRIVING WHILE BEING DROWSY, GO TO QUESTION 5.

2. Have you ever driven when you knew you were too drowsy to drive safely?

   [ ] Yes [ ] No [ ] Other

   a. What factors played a role in your decision to drive or not to drive?

   b. If there was a point where you were too drowsy to drive safely, how did you know it was not safe to drive?

3. After the occasions when you were drowsy, what differences did you notice in your driving (for example, how you control your driving speed, lane position, etc.)?

   [ ] No difference [ ] Lateral control, general
   [ ] Curves/turns
   [ ] Longitudinal control, general [ ] Speed, increase
   [ ] Speed, decrease
   [ ] Reaction time to environment [ ] Reaction time to critical event
   [ ] Other

   a. Can you describe any differences you noticed in the types of things you paid attention to, or in your ability to focus while driving?

      [ ] No difference

[ ] Reduced ability to focus or pay attention [ ] Increased ability to focus or pay attention
[ ] Other

b. In what ways did your driving or attention change based on external factors, like passengers in the vehicle or the weather?
[ ] No difference
[ ] Degraded driving performance [ ] Improved driving performance
[ ] Reduced ability to focus or pay attention [ ] Increased ability to focus or pay attention
[ ] Other

c. As your level of drowsiness increases how does it affect your driving skills or ability to focus or pay attention to the roadway?
[ ] No difference
[ ] Degraded performance with increased drowsiness
[ ] Improved performance with increased drowsiness
[ ] Reduced focus or attention with increased drowsiness
[ ] Increased focus or attention with increased drowsiness [ ] Other

4. How do you adjust your driving when you're drowsy?
[ ] No change [ ] Adjust driving when drowsy
[ ] Other

a. Do your adjustments change depending on how drowsy you are? Please describe.
[ ] Yes [ ] No [ ] Other

5. Impairment from sleep deprivation has been shown to decrease drivers' mental and physical abilities. I'd like to hear your thoughts on the role technology can play in assisting drowsy drivers or making the roadway safer for surrounding traffic.

Imagine a system in a vehicle that could detect when a driver is drowsy based on the performance or behavior of the driver and vehicle.

a. What are your thoughts about a system that detects when a driver's drowsy with 100% accuracy every time a vehicle is driven?
[ ] Positive [ ] Negative [ ] Mixed [ ] Other

b. What are your thoughts about a system that accurately identifies all drowsy drivers but also wrongly identifies some non drowsy drivers as being drowsy?
[ ] Positive [ ] Negative [ ] Mixed [ ] Other

c. What are your thoughts about a system that represents the opposite extreme – it accurately identifies all non drowsy drivers, but also wrongly identifies some drowsy drivers as not drowsy?
[ ] Positive [ ] Negative [ ] Mixed [ ] Other

d. Of the previous two examples, which is more acceptable to you?
[ ] B is more acceptable to me [ ] C is more acceptable to me [ ] Other

e. Which do you think would be more acceptable to the general public? Why?
[ ] Same as question d [ ] Different from question d [ ] Other

6. If your vehicle could detect your level of drowsiness how would you like it to respond?

Now I'd like to get your feedback on some hypothetical actions that a system designed to detect drowsiness could take. Let's assume that the drowsiness detection system is sufficiently accurate and reliable.

7. What do you think about a system that could notify you when you are drowsy with an indicator, such as a warning icon on the dash or voice alert?
   [ ] Positive [ ] Negative [ ] Mixed [ ] Other
   a. If you received this kind of alert, how would you respond?
   b. How would it affect your ability to pay attention to driving?
      [ ] No change [ ] Distraction [ ] Other

8. What do you think about a system that could give you an assessment of your driving after you return home when it detects drowsiness, like a report card?
   [ ] Positive [ ] Negative [ ] Mixed [ ] Other
   a. Would it affect your decision to drive or how you drive the next time you were drowsy, and if so, how?
      [ ] Yes [ ] No [ ] Other
   b. What do you think about a system that could give you an assessment of your driving after you return home whether it indicates drowsiness or not?
      [ ] Positive [ ] Negative [ ] Mixed [ ] Other

9. What do you think about a system that could notify a friend or relative to request help when you are drowsy?
   [ ] Positive [ ] Negative [ ] Mixed [ ] Other
   a. What about a system that could notify the police to request assistance?
      [ ] Positive [ ] Negative [ ] Mixed [ ] Other
   a. How would you respond to this system if it were in vehicles?

10. What do you think about a system that could automatically take full or partial control over certain functions, like steering or driving speed, when it detected drowsy driving?
    [ ] Positive [ ] Negative [ ] Mixed [ ] Other
    a. If you had this type of system, how would you respond?

11. What do you think about a system that could collect data in something like an airplane's black box, which could be accessed by insurance companies and/or law enforcement after a crash or serious violation to determine if drowsiness was a factor?

[ ] Positive [ ] Negative [ ] Mixed [ ] Other

a. How would you respond to this system if it were in vehicles?

12. Generally, what do you see as obstacles to implementing these types of driver assistance systems?

13. Which of the systems, if any, would make you a safer driver?
    [ ] None [ ] Warning alert [ ] Trip report [ ] Notifying friend/relative/police
    [ ] Automation [ ] Black box [ ] Other

14. Which do you think would reduce crashes?
    [ ] None [ ] Warning alert [ ] Trip report [ ] Notifying friend/relative/police
    [ ] Automation [ ] Black box [ ] Other

APPENDIX S: DEBRIEFING STATEMENT

ACMI Debriefing Statement

When is it safe to drive again?

At the time you will be transported home from completing this study visit, you will have been deprived of sleep for 20 or more hours. Although you could legally drive, we ask you to wait until you have had a full 8 hours of sleep before driving to ensure you are well rested and safe

APPENDIX T: INTERVENING VARIABLES

Several intervening variables may influence the dependent variables or mediate the influence of drowsiness on the dependent variables. Table 3 summarizes these variables and the approach to minimize any confounding they might have produced. The potential confounding of fatigue by individual differences in sleep/wake times is minimized by scheduling the drives according to the typical wake times of the participants, and suggesting that they maintain their typical sleep schedule during the study. Deviations from typical bedtimes and time since last sleep will be considered as a potential covariate depending on the range of these distributions.

Table 3 Intervening variables that might moderate the effect of drowsiness

Variable	Rationale	Mitigation
Daytime Drowsiness	Individuals who suffer from daytime drowsiness may not have significant differences in performance between their daytime and nighttime drives, as both could be classified as drowsy. This may be associated with a medical condition such OSA or narcolepsy, or could be associated with abnormal or lack of sleep the night before the daytime drive.	Participants with reported sleep disorders were excluded from the study. Participants were asked to track their sleep including the use of an activity monitor. For participants who have potentially confounding sleep, an attempt was made to reschedule.
Nighttime Alertness	Individuals who are overly alert at night, may not exhibit drowsiness at the planned data collection times.	Participants were asked to maintain a normal sleep pattern and not to nap the day of their overnight drive. Participant sleep patterns were monitored through an activity monitor and activity logs. Participants who deviated from normal sleep patterns (shift work, extreme evening people) were dropped from the study.
Physical Fatigue	Excessive physical activity may confound the effects of drowsiness, particularly if present on only one of the data collection days.	Participants were asked to maintain the same pattern of activity on data collection days.
Ambient temperature	Can impact simulator sickness	Temperature was set at 72° F.

Variable	Rationale	Mitigation
Simulator sickness score	Higher levels of simulator sickness can result in potential changes in driver behavior to counteract its effects	Participants had a practice drive during their screening. Participants with high scores (Nausea ≥ 21, Oculomoter ≥ 32, Disorientation ≥ 15, or Total ≥ 32) related to the completing the screening drive were excluded from the study.

APPENDIX U: REPEATED EXPOSURE ANALYSIS

U.1 Lane Deviation

There were statistical differences as a function of visit number for a number of events: Urban Drive (111), Green Light (103), Yellow Light (104), Interstate Merge On (202), Interstate Merging Traffic (204), Rural Transition to Dark (303), Transition to Rural (305), Gravel (306), Passing Driveway (307), Gravel Extension (308), Rural Straight (311), and the Hairpin curve (324). Figure 40 shows lane deviation by visit number across scenario events. Nine of the twelve events for which differences were found were for short duration events (< 30 seconds). Of the other three events, Urban Drive (111) had the best performance for the second visit, and Gravel (306) and Rural Straight had the best performance on the first visit. Only the event for Passing the Driveway (307) exhibited the typical learning effect with performance improving from Visit 1 to the future visits.

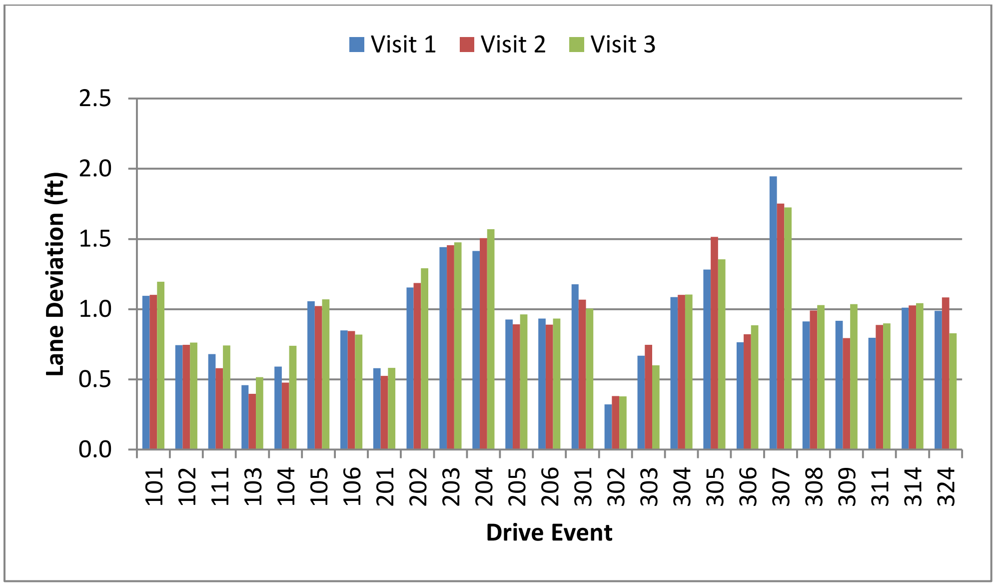


Figure U1. Lane deviation by visit number across scenario events.

U.2 Average Speed

There were statistical differences as a function of visit number for a number of events: Left Turn (105), Interstate Merge On (202), Interstate Driving with Trucks (203), Interstate Merging Traffic (204), Interstate Exit Ramp (206), Transition to Rural (305), Passing Driveway (307), Gravel Extension (308), Gravel Transition to Paved (309), and Rural Driving without hairpin Curve (314). Figure U2 shows average speed by visit number across scenario events. Eight of the ten significant differences were for short events. For 9 of the 10 events, average speed increased across visits.

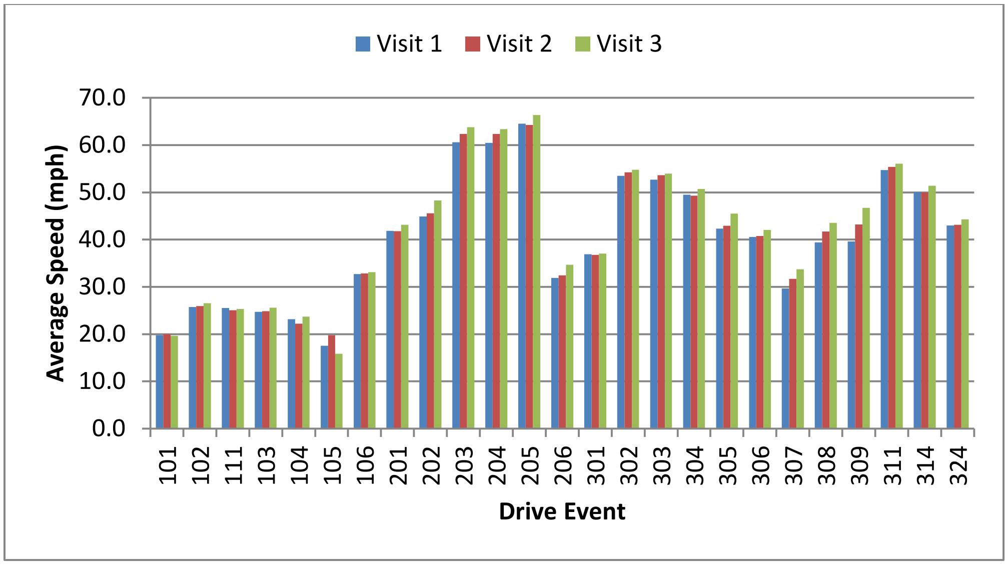


Figure U2. Average speed by visit number across scenario events.

U.3 Speed Deviation

There were statistically reliable differences as a function of visit number in the Urban Drive (111), Left Turn (105), Interstate Driving with Trucks (203), Passing Driveway (307), Gravel Transition to Paved (309), and the Hairpin curve (324). Figure U3 shows speed deviation by visit number across scenario events. Four of the 6 events where there was a significant difference were for short duration events. In 5 of the 6 events, speed deviation decreased across the visits.

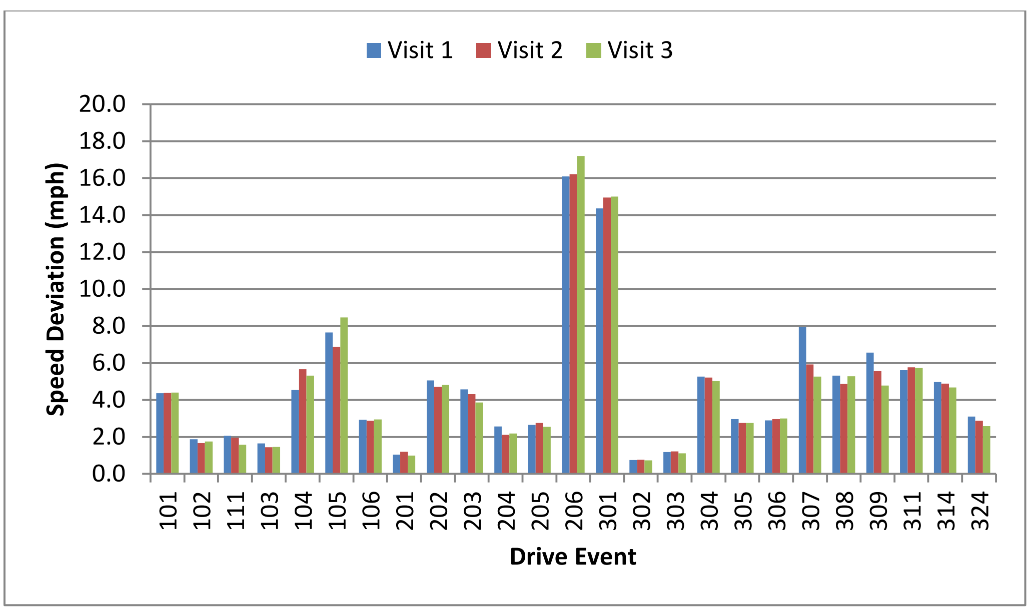


Figure U3. Speed deviation by visit number across scenario events.

APPENDIX V: DROWSINESS ACROSS ROADWAY CONDITIONS

V.1 Missing Data

Due to simulator restarts and subjects' welfare, there were instances in which data could not be collected for the entire drive. Tables V1 to V9 show which measures had missing data. No efforts were made to replace the missing data.

V.2 Descriptive Statistics

Tables V1 to V9 report the lane deviation, average speed measures, and speed deviation measures, and lane deviation measures by time of day condition, age group, and gender. Because subjects' performance and impairment may fluctuate across events, impairment at the event level may be difficult to interpret. To determine whether impairment was present across the entire drive, composite scores of lane deviation, average speed, and speed deviation were also examined. The composite scores were the *t*-scores ($M = 50$, $SD = 10$) of the standardized average of the *z*-scores of the measures across the events.

Table V1

Lane Deviation by Time of Day Condition Across Events

	Condition											
	Day			Early Night			Late Night			Total		
Event	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*
101	1.23	72	.61	1.06	72	0.55	1.11	72	0.55	1.13	216	0.57
102	.75	72	.18	0.72	72	0.15	0.79	72	0.19	0.75	216	0.18
111	.68	36	.25	0.61	60	0.19	0.65	48	0.19	0.64	144	0.21
103	.48	72	.16	0.42	72	0.14	0.47	72	0.19	0.46	216	0.17
104	.64	72	.27	0.54	72	0.27	0.63	72	0.32	0.60	216	0.29
105	1.07	72	.26	1.03	72	0.28	1.05	72	0.23	1.05	216	0.26
106	.83	72	.16	0.83	72	0.17	0.85	72	0.16	0.84	216	0.16
201	.58	72	.23	0.56	72	0.23	0.54	72	0.22	0.56	216	0.23
202	**1.21**	**72**	**.29**	**1.14**	**72**	**0.30**	**1.27**	**72**	**0.32**	**1.21**	**216**	**0.31**
203	1.44	72	.21	1.44	72	0.21	1.50	72	0.23	1.46	216	0.22
204	**1.49**	**72**	**.25**	**1.45**	**72**	**0.25**	**1.55**	**72**	**0.23**	**1.50**	**216**	**0.25**
205	**.95**	**72**	**.21**	**0.88**	**72**	**0.20**	**0.95**	**72**	**0.22**	**0.93**	**216**	**0.21**
206	.93	72	.27	0.92	72	0.27	0.90	72	0.27	0.92	216	0.27
301	1.09	72	.50	1.11	72	0.47	1.06	72	0.48	1.08	216	0.48
302	**.32**	**72**	**.22**	**0.33**	**72**	**0.23**	**0.43**	**72**	**0.25**	**0.36**	**216**	**0.24**
303	.63	72	.24	0.67	72	0.27	0.71	72	0.30	0.67	216	0.27
304	1.08	72	.21	1.08	72	0.22	1.13	72	0.27	1.10	216	0.24
305	**1.28**	**72**	**.45**	**1.39**	**72**	**0.42**	**1.48**	**72**	**0.47**	**1.39**	**216**	**0.45**
306	**.82**	**72**	**.21**	**0.78**	**72**	**0.17**	**0.88**	**72**	**0.20**	**0.82**	**216**	**0.20**

Table V1 (continued)

Lane Deviation by Time of Day Condition Across Events

	Condition									Total		
	Day			Early Night			Late Night					
Event	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*
307	1.81	71	.45	1.90	72	0.58	1.71	72	0.44	1.81	215	0.50
308	.96	48	.20	0.96	47	0.20	1.01	48	0.26	0.98	143	0.22
309	.94	48	.52	0.86	48	0.47	0.95	48	0.59	0.92	144	0.52
311	**.83**	**72**	**.26**	**0.80**	**72**	**0.22**	**0.95**	**72**	**0.26**	**0.86**	**216**	**0.26**
314	1.01	71	.18	1.01	68	0.20	1.06	72	0.25	1.03	211	0.22
324	.90	71	.38	1.01	68	0.36	0.99	72	0.40	0.97	211	0.38
Composite	**49.74**	**72**	**9.38**	**47.79**	**72**	**8.87**	**52.41**	**72**	**11.14**	**50.00**	**216**	**10.00**

Note. BAC differences shown in bold are statistically significant at $p < .05$.

Table V2

Lane Deviation by Age Group Across Events

	Age Group									Total		
	21-34			38-51			55-68					
Event	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*
101	1.05	72	0.55	1.19	72	0.56	1.16	72	0.60	1.13	216	0.57
102	0.74	72	0.19	0.76	72	0.20	0.76	72	0.14	0.75	216	0.18
111	0.59	48	0.17	0.67	48	0.23	0.66	48	0.21	0.64	144	0.21
103	**0.48**	**72**	**0.14**	**0.48**	**72**	**0.21**	**0.42**	**72**	**0.14**	**0.46**	**216**	**0.17**
104	0.62	72	0.29	0.60	72	0.31	0.59	72	0.27	0.60	216	0.29
105	1.05	72	0.26	1.09	72	0.20	1.01	72	0.29	1.05	216	0.26
106	0.86	72	0.16	0.84	72	0.19	0.82	72	0.15	0.84	216	0.16
201	0.53	72	0.23	0.59	72	0.21	0.57	72	0.24	0.56	216	0.23
202	**1.15**	**72**	**0.30**	**1.34**	**72**	**0.32**	**1.14**	**72**	**0.26**	**1.21**	**216**	**0.31**
203	**1.36**	**72**	**0.19**	**1.47**	**72**	**0.19**	**1.55**	**72**	**0.23**	**1.46**	**216**	**0.22**
204	**1.47**	**72**	**0.27**	**1.47**	**72**	**0.22**	**1.56**	**72**	**0.24**	**1.50**	**216**	**0.25**
205	**0.96**	**72**	**0.20**	**0.95**	**72**	**0.23**	**0.87**	**72**	**0.19**	**0.93**	**216**	**0.21**
206	0.94	72	0.23	0.94	72	0.30	0.88	72	0.27	0.92	216	0.27
301	**1.02**	**72**	**0.46**	**1.01**	**72**	**0.43**	**1.21**	**72**	**0.53**	**1.08**	**216**	**0.48**
302	0.35	72	0.25	0.36	72	0.24	0.37	72	0.23	0.36	216	0.24
303	0.69	72	0.29	0.66	72	0.26	0.67	72	0.27	0.67	216	0.27
304	1.06	72	0.23	1.13	72	0.29	1.11	72	0.17	1.10	216	0.24

Table V2 (continued)

Lane Deviation by Age Group Across Events

	Age Group									Total		
	21-34			38-51			55-68					
Event	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*
305	1.41	72	0.47	1.40	72	0.43	1.34	72	0.46	1.39	216	0.45
306	**0.81**	**72**	**0.21**	**0.78**	**72**	**0.18**	**0.89**	**72**	**0.19**	**0.82**	**216**	**0.20**
307	1.77	72	0.47	1.75	71	0.51	1.90	72	0.51	1.81	215	0.50
308	**1.07**	**47**	**0.24**	**0.96**	**48**	**0.22**	**0.91**	**48**	**0.18**	**0.98**	**143**	**0.22**
309	0.89	48	0.56	0.95	48	0.58	0.90	48	0.43	0.92	144	0.52
311	**0.95**	**72**	**0.27**	**0.85**	**72**	**0.26**	**0.78**	**72**	**0.20**	**0.86**	**216**	**0.26**
314	1.00	70	0.21	1.05	71	0.27	1.03	70	0.14	1.03	211	0.22
324	**0.98**	**70**	**0.34**	**1.04**	**71**	**0.43**	**0.87**	**70**	**0.35**	**0.97**	**211**	**0.38**
Composite	49.28	72	9.57	51.10	72	12.63	49.62	72	7.06	50.00	216	10.00

Note. BAC differences shown in bold are statistically significant at $p < .05$.

Table V3

Lane Deviation by Gender Across Events

	Gender								
	Female			Male			Total		
Event	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*
101	1.20	108	0.60	1.06	108	0.54	1.13	216	0.57
102	**0.78**	**108**	**0.17**	**0.73**	**108**	**0.18**	**0.75**	**216**	**0.18**
111	0.66	72	0.22	0.62	72	0.19	0.64	144	0.21
103	**0.48**	**108**	**0.19**	**0.43**	**108**	**0.14**	**0.46**	**216**	**0.17**
104	0.63	108	0.32	0.58	108	0.26	0.60	216	0.29
105	**1.11**	**108**	**0.23**	**0.99**	**108**	**0.27**	**1.05**	**216**	**0.26**
106	**0.88**	**108**	**0.16**	**0.79**	**108**	**0.15**	**0.84**	**216**	**0.16**
201	0.57	108	0.24	0.55	108	0.22	0.56	216	0.23
202	**1.15**	**108**	**0.31**	**1.27**	**108**	**0.30**	**1.21**	**216**	**0.31**
203	**1.42**	**108**	**0.21**	**1.50**	**108**	**0.21**	**1.46**	**216**	**0.22**
204	1.51	108	0.27	1.49	108	0.22	1.50	216	0.25
205	0.93	108	0.24	0.93	108	0.19	0.93	216	0.21
206	0.92	108	0.26	0.92	108	0.28	0.92	216	0.27
301	1.09	108	0.47	1.07	108	0.49	1.08	216	0.48
302	**0.40**	**108**	**0.26**	**0.32**	**108**	**0.21**	**0.36**	**216**	**0.24**
303	0.69	108	0.29	0.65	108	0.25	0.67	216	0.27
304	**1.06**	**108**	**0.23**	**1.13**	**108**	**0.23**	**1.10**	**216**	**0.24**
305	**1.31**	**108**	**0.46**	**1.46**	**108**	**0.44**	**1.39**	**216**	**0.45**
306	0.84	108	0.21	0.81	108	0.18	0.82	216	0.20
307	1.81	107	0.44	1.80	108	0.56	1.81	215	0.50
308	**1.01**	**71**	**0.23**	**0.94**	**72**	**0.21**	**0.98**	**143**	**0.22**
309	0.94	72	0.52	0.89	72	0.53	0.92	144	0.52
311	0.88	108	0.27	0.84	108	0.23	0.86	216	0.26
314	1.00	105	0.21	1.05	106	0.22	1.03	211	0.22
324	0.96	105	0.40	0.97	106	0.37	0.97	211	0.38
Composite	50.90	108	10.59	49.10	108	9.33	50.00	216	10.00

Note. BAC differences shown in bold are statistically significant at $p < .05$.

Table V4

Average Speed by Time of Day Condition Across Events

	Condition											
	Day			Early Night			Late Night			Total		
Event	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*
101	20.21	72	2.54	19.68	72	2.48	19.51	72	2.44	19.80	216	2.50
102	26.56	72	2.93	25.47	72	2.88	26.17	72	2.83	26.07	216	2.90
111	**26.60**	**36**	**4.07**	**24.74**	**60**	**2.71**	**24.97**	**48**	**2.84**	**25.28**	**144**	**3.21**
103	25.51	72	2.86	24.59	72	3.04	25.07	72	2.80	25.06	216	2.91
104	23.82	72	3.91	22.56	72	4.57	22.72	72	4.21	23.03	216	4.26
105	**17.08**	**72**	**3.05**	**18.55**	**72**	**3.73**	**17.51**	**72**	**3.65**	**17.71**	**216**	**3.53**
106	33.17	72	2.69	32.48	72	2.38	33.00	72	2.57	32.88	216	2.55
201	43.09	72	4.39	41.70	72	5.02	42.02	72	4.67	42.27	216	4.71
202	**47.71**	**72**	**5.98**	**44.70**	**72**	**6.27**	**46.39**	**72**	**6.67**	**46.27**	**216**	**6.40**
203	62.75	72	6.17	61.21	72	5.66	62.72	72	5.77	62.23	216	5.89
204	62.38	72	6.52	61.28	72	6.30	62.56	72	6.06	62.07	216	6.29
205	66.12	72	4.88	64.32	72	5.50	64.76	72	5.26	65.07	216	5.25
206	34.05	72	6.54	31.94	72	4.98	32.97	72	5.19	32.99	216	5.65
301	37.10	72	3.58	36.65	72	3.50	36.92	72	3.81	36.89	216	3.62
302	54.44	72	3.39	53.75	72	3.84	54.33	72	4.03	54.17	216	3.76
303	53.67	72	3.10	53.13	72	4.24	53.45	72	4.97	53.42	216	4.16
304	50.58	72	3.70	49.29	72	4.12	49.67	72	3.99	49.85	216	3.96
305	44.40	72	6.57	42.55	72	7.20	43.77	72	7.45	43.57	216	7.09
306	42.18	72	6.76	40.30	72	7.54	40.86	72	7.80	41.11	216	7.39
307	32.63	71	10.24	30.41	72	9.98	32.01	72	8.61	31.68	215	9.63
308	41.56	48	6.73	40.53	47	7.17	42.58	48	7.51	41.56	143	7.14
309	43.72	48	7.63	41.62	48	8.53	44.14	48	8.67	43.16	144	8.31
311	55.46	72	2.99	54.71	72	3.61	55.97	72	3.75	55.38	216	3.49
314	51.16	71	3.58	49.84	68	4.18	50.34	72	3.97	50.45	211	3.94
324	44.22	71	5.14	42.85	68	4.96	43.40	72	4.96	43.50	211	5.03
Composite	51.81	72	9.50	48.16	72	10.04	50.03	72	10.24	50.00	216	10.00

Note. BAC differences shown in bold are statistically significant at $p < .05$.

Table V5

Average Speed by Age Group Across Events

	Age Group											
	21-34			38-51			55-68			Total		
Event	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*
101	19.66	72	2.01	20.17	72	2.65	19.57	72	2.75	19.80	216	2.50
102	**27.24**	**72**	**2.49**	**25.66**	**72**	**3.24**	**25.29**	**72**	**2.57**	**26.07**	**216**	**2.90**
111	**26.39**	**48**	**2.13**	**25.02**	**48**	**3.74**	**24.43**	**48**	**3.29**	**25.28**	**144**	**3.21**
103	**26.59**	**72**	**2.50**	**24.62**	**72**	**2.97**	**23.97**	**72**	**2.62**	**25.06**	**216**	**2.91**
104	**24.54**	**72**	**4.73**	**22.67**	**72**	**3.79**	**21.88**	**72**	**3.79**	**23.03**	**216**	**4.26**
105	18.34	72	3.57	17.65	72	3.50	17.14	72	3.45	17.71	216	3.53
106	**33.78**	**72**	**2.31**	**32.81**	**72**	**2.51**	**32.06**	**72**	**2.57**	**32.88**	**216**	**2.55**
201	**44.08**	**72**	**4.16**	**42.87**	**72**	**4.27**	**39.86**	**72**	**4.71**	**42.27**	**216**	**4.71**
202	**49.72**	**72**	**6.09**	**46.48**	**72**	**6.21**	**42.60**	**72**	**4.77**	**46.27**	**216**	**6.40**
203	**65.84**	**72**	**4.46**	**63.27**	**72**	**4.57**	**57.58**	**72**	**5.27**	**62.23**	**216**	**5.89**
204	**65.63**	**72**	**4.47**	**62.84**	**72**	**5.60**	**57.75**	**72**	**6.01**	**62.07**	**216**	**6.29**
205	**67.80**	**72**	**3.65**	**65.72**	**72**	**4.55**	**61.69**	**72**	**5.47**	**65.07**	**216**	**5.25**
206	**36.15**	**72**	**5.76**	**33.45**	**72**	**5.60**	**29.36**	**72**	**2.92**	**32.99**	**216**	**5.65**
301	**36.19**	**72**	**3.30**	**38.10**	**72**	**3.44**	**36.38**	**72**	**3.83**	**36.89**	**216**	**3.62**
302	**55.26**	**72**	**3.03**	**54.11**	**72**	**3.81**	**53.16**	**72**	**4.10**	**54.17**	**216**	**3.76**
303	**55.08**	**72**	**3.53**	**53.13**	**72**	**4.17**	**52.05**	**72**	**4.22**	**53.42**	**216**	**4.16**
304	**52.17**	**72**	**3.53**	**49.94**	**72**	**3.70**	**47.43**	**72**	**3.16**	**49.85**	**216**	**3.96**
305	**47.79**	**72**	**5.86**	**43.65**	**72**	**6.88**	**39.28**	**72**	**5.83**	**43.57**	**216**	**7.09**
306	**43.05**	**72**	**7.21**	**41.82**	**72**	**6.41**	**38.46**	**72**	**7.80**	**41.11**	**216**	**7.39**
307	**35.02**	**72**	**8.81**	**33.07**	**71**	**9.35**	**26.97**	**72**	**8.95**	**31.68**	**215**	**9.63**
308	**43.84**	**47**	**6.68**	**41.99**	**48**	**6.44**	**38.92**	**48**	**7.51**	**41.56**	**143**	**7.14**
309	**47.22**	**48**	**7.53**	**42.68**	**48**	**7.58**	**39.58**	**48**	**8.10**	**43.16**	**144**	**8.31**
311	**57.08**	**72**	**4.32**	**55.26**	**72**	**2.21**	**53.80**	**72**	**2.80**	**55.38**	**216**	**3.49**
314	**52.72**	**70**	**3.57**	**50.58**	**71**	**3.61**	**48.06**	**70**	**3.19**	**50.45**	**211**	**3.94**
324	**46.77**	**70**	**4.79**	**43.05**	**71**	**4.34**	**40.68**	**70**	**3.97**	**43.50**	**211**	**5.03**
Composite	**55.99**	**72**	**8.45**	**50.48**	**72**	**9.28**	**43.53**	**72**	**8.13**	**50.00**	**216**	**10.00**

Note. BAC differences shown in bold are statistically significant at $p < .05$.

Table V6

Average Speed by Gender Across Events

	Gender								
	Female			Male			Total		
Event	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*
101	19.74	108	2.52	19.86	108	2.48	19.80	216	2.50
102	26.25	108	2.77	25.88	108	3.03	26.07	216	2.90
111	25.56	72	3.35	24.99	72	3.06	25.28	144	3.21
103	25.28	108	2.96	24.83	108	2.87	25.06	216	2.91
104	23.45	108	4.47	22.61	108	4.00	23.03	216	4.26
105	17.66	108	3.54	17.77	108	3.53	17.71	216	3.53
106	32.98	108	2.47	32.79	108	2.64	32.88	216	2.55
201	**41.18**	**108**	**4.67**	**43.37**	**108**	**4.52**	**42.27**	**216**	**4.71**
202	**43.96**	**108**	**5.72**	**48.57**	**108**	**6.24**	**46.27**	**216**	**6.40**
203	**60.66**	**108**	**6.05**	**63.79**	**108**	**5.29**	**62.23**	**216**	**5.89**
204	**61.17**	**108**	**6.50**	**62.98**	**108**	**5.97**	**62.07**	**216**	**6.29**
205	**63.95**	**108**	**5.62**	**66.18**	**108**	**4.62**	**65.07**	**216**	**5.25**
206	**31.74**	**108**	**5.02**	**34.24**	**108**	**5.99**	**32.99**	**216**	**5.65**
301	**36.34**	**108**	**3.47**	**37.44**	**108**	**3.70**	**36.89**	**216**	**3.62**
302	**53.54**	**108**	**4.22**	**54.81**	**108**	**3.13**	**54.17**	**216**	**3.76**
303	**52.43**	**108**	**4.76**	**54.41**	**108**	**3.19**	**53.42**	**216**	**4.16**
304	**48.59**	**108**	**3.86**	**51.10**	**108**	**3.67**	**49.85**	**216**	**3.96**
305	**41.76**	**108**	**7.17**	**45.38**	**108**	**6.57**	**43.57**	**216**	**7.09**
306	**39.99**	**108**	**7.16**	**42.23**	**108**	**7.48**	**41.11**	**216**	**7.39**
307	**29.85**	**107**	**9.44**	**33.50**	**108**	**9.51**	**31.68**	**215**	**9.63**
308	40.48	71	6.23	42.63	72	7.83	41.56	143	7.14
309	42.31	72	8.21	44.01	72	8.38	43.16	144	8.31
311	55.18	108	3.61	55.58	108	3.37	55.38	216	3.49
314	**49.15**	**105**	**3.80**	**51.75**	**106**	**3.64**	**50.45**	**211**	**3.94**
324	**42.18**	**105**	**4.93**	**44.80**	**106**	**4.80**	**43.50**	**211**	**5.03**
Composite	**47.91**	**108**	**9.82**	**52.09**	**108**	**9.78**	**50.00**	**216**	**10.00**

Note. BAC differences shown in bold are statistically significant at $p < .05$.

Table V7

Speed Deviation by Time of Day Condition Across Events

	Condition											
	Day			Early Night			Late Night			Total		
Event	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*
101	4.68	72	1.39	4.20	72	1.40	4.28	72	1.42	4.39	216	1.41
102	1.75	72	0.73	1.77	72	0.74	1.78	72	0.69	1.77	216	0.72
111	1.94	36	0.67	1.94	60	0.63	1.92	48	0.66	1.94	144	0.64
103	1.48	72	0.56	1.61	72	0.74	1.47	72	0.80	1.52	216	0.70
104	4.80	72	3.53	5.13	72	3.69	5.60	72	3.33	5.18	216	3.52
105	**8.32**	**72**	**1.35**	**7.03**	**72**	**1.14**	**7.65**	**72**	**1.37**	**7.67**	**216**	**1.39**
106	2.96	72	0.71	2.85	72	0.66	2.95	72	0.72	2.92	216	0.69
201	0.98	72	0.50	1.15	72	0.93	1.12	72	1.08	1.08	216	0.87
202	4.82	72	2.14	4.92	72	2.11	4.84	72	2.13	4.86	216	2.12
203	4.03	72	1.92	4.53	72	1.62	4.19	72	1.69	4.25	216	1.75
204	2.46	72	1.45	2.33	72	1.31	2.09	72	1.06	2.29	216	1.28
205	2.56	72	1.28	2.61	72	1.01	2.80	72	1.23	2.66	216	1.18
206	16.84	72	3.20	16.10	72	2.99	16.57	72	3.13	16.50	216	3.11
301	14.83	72	2.14	14.42	72	1.80	15.07	72	2.04	14.78	216	2.01
302	0.72	72	0.37	0.73	72	0.42	0.81	72	0.48	0.75	216	0.43
303	1.00	72	0.59	1.21	72	0.79	1.29	72	1.30	1.17	216	0.95
304	5.01	72	1.26	5.23	72	1.34	5.26	72	1.03	5.17	216	1.22
305	2.81	72	1.59	2.78	72	1.40	2.88	72	1.60	2.82	216	1.52
306	2.87	72	1.26	2.94	72	1.06	3.07	72	1.10	2.96	216	1.14
307	**6.78**	**71**	**3.86**	**7.05**	**72**	**3.64**	**5.33**	**72**	**3.49**	**6.39**	**215**	**3.73**
308	5.29	48	1.84	5.05	47	1.70	5.14	48	1.47	5.16	143	1.67
309	5.66	48	2.68	6.19	48	3.22	5.06	48	3.46	5.64	144	3.15
311	5.58	72	1.31	5.62	72	1.35	5.92	72	1.44	5.71	216	1.37
314	4.66	71	1.25	4.96	68	1.27	4.93	72	1.04	4.85	211	1.19
324	2.94	71	0.92	2.91	68	0.90	2.71	72	0.80	2.85	211	0.88
Composite	50.03	72	10.28	49.66	72	10.62	50.32	72	9.17	50.00	216	10.00

Note. BAC differences shown in bold are statistically significant at $p < .05$.

Table V8

Speed Deviation by Age Group Across Events

	Age Group									Total		
	21-34			38-51			55-68					
Event	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*
101	4.44	72	1.28	4.57	72	1.49	4.14	72	1.44	4.39	216	1.41
102	**1.55**	**72**	**0.63**	**1.88**	**72**	**0.78**	**1.88**	**72**	**0.69**	**1.77**	**216**	**0.72**
111	**1.74**	**48**	**0.56**	**2.02**	**48**	**0.59**	**2.05**	**48**	**0.74**	**1.94**	**144**	**0.64**
103	1.42	72	0.72	1.54	72	0.78	1.61	72	0.59	1.52	216	0.70
104	5.02	72	3.53	5.19	72	3.51	5.32	72	3.55	5.18	216	3.52
105	**8.25**	**72**	**1.37**	**7.44**	**72**	**1.35**	**7.31**	**72**	**1.28**	**7.67**	**216**	**1.39**
106	2.85	72	0.75	2.97	72	0.63	2.94	72	0.70	2.92	216	0.69
201	1.08	72	0.91	0.98	72	0.61	1.18	72	1.04	1.08	216	0.87
202	5.05	72	1.93	5.03	72	1.90	4.49	72	2.46	4.86	216	2.12
203	**3.77**	**72**	**1.80**	**4.01**	**72**	**1.22**	**4.98**	**72**	**1.92**	**4.25**	**216**	**1.75**
204	2.21	72	1.15	2.21	72	1.29	2.46	72	1.40	2.29	216	1.28
205	**2.48**	**72**	**1.11**	**2.56**	**72**	**0.96**	**2.93**	**72**	**1.38**	**2.66**	**216**	**1.18**
206	**18.01**	**72**	**2.54**	**17.00**	**72**	**3.26**	**14.50**	**72**	**2.37**	**16.50**	**216**	**3.11**
301	**15.37**	**72**	**1.91**	**14.73**	**72**	**2.00**	**14.22**	**72**	**1.96**	**14.78**	**216**	**2.01**
302	0.74	72	0.45	0.81	72	0.46	0.70	72	0.37	0.75	216	0.43
303	**0.97**	**72**	**0.63**	**1.13**	**72**	**0.76**	**1.40**	**72**	**1.28**	**1.17**	**216**	**0.95**
304	**4.80**	**72**	**1.35**	**5.16**	**72**	**1.16**	**5.54**	**72**	**1.02**	**5.17**	**216**	**1.22**
305	2.62	72	1.27	2.68	72	1.47	3.17	72	1.74	2.82	216	1.52
306	2.81	72	1.07	2.99	72	0.98	3.08	72	1.34	2.96	216	1.14
307	**5.48**	**72**	**3.48**	**6.08**	**71**	**3.49**	**7.59**	**72**	**3.91**	**6.39**	**215**	**3.73**
308	5.18	47	1.94	4.93	48	1.33	5.38	48	1.69	5.16	143	1.67
309	**4.16**	**48**	**2.17**	**6.47**	**48**	**3.21**	**6.27**	**48**	**3.44**	**5.64**	**144**	**3.15**
311	**6.60**	**72**	**1.63**	**5.40**	**72**	**0.84**	**5.11**	**72**	**1.04**	**5.71**	**216**	**1.37**
314	**4.56**	**70**	**1.27**	**4.80**	**71**	**1.19**	**5.19**	**70**	**1.04**	**4.85**	**211**	**1.19**
324	2.94	70	0.76	2.83	71	0.86	2.79	70	0.99	2.85	211	0.88
Composite	48.94	72	10.67	49.86	72	7.90	51.20	72	11.13	50.00	216	10.00

Note. BAC differences shown in bold are statistically significant at $p < .05$.

Table V9

Speed Deviation by Gender Across Events

	Gender								
	Female			Male			Total		
Event	*M*	*N*	*SD*	*M*	*N*	*SD*	*M*	*N*	*SD*
101	4.37	108	1.50	4.40	108	1.33	4.39	216	1.41
102	1.81	108	0.72	1.73	108	0.72	1.77	216	0.72
111	1.97	72	0.73	1.90	72	0.55	1.94	144	0.64
103	**1.63**	**108**	**0.78**	**1.41**	**108**	**0.60**	**1.52**	**216**	**0.70**
104	4.83	108	3.53	5.53	108	3.49	5.18	216	3.52
105	7.68	108	1.40	7.65	108	1.39	7.67	216	1.39
106	2.85	108	0.74	2.99	108	0.64	2.92	216	0.69
201	**1.24**	**108**	**1.11**	**0.92**	**108**	**0.50**	**1.08**	**216**	**0.87**
202	**4.51**	**108**	**1.80**	**5.21**	**108**	**2.35**	**4.86**	**216**	**2.12**
203	**4.67**	**108**	**1.89**	**3.83**	**108**	**1.49**	**4.25**	**216**	**1.75**
204	2.41	108	1.12	2.17	108	1.42	2.29	216	1.28
205	**2.94**	**108**	**1.36**	**2.38**	**108**	**0.87**	**2.66**	**216**	**1.18**
206	**15.43**	**108**	**2.99**	**17.58**	**108**	**2.86**	**16.50**	**216**	**3.11**
301	14.68	108	2.19	14.87	108	1.81	14.78	216	2.01
302	0.73	108	0.40	0.78	108	0.45	0.75	216	0.43
303	1.28	108	1.17	1.05	108	0.64	1.17	216	0.95
304	**5.44**	**108**	**1.21**	**4.90**	**108**	**1.16**	**5.17**	**216**	**1.22**
305	2.97	108	1.62	2.67	108	1.42	2.82	216	1.52
306	**3.26**	**108**	**1.08**	**2.66**	**108**	**1.12**	**2.96**	**216**	**1.14**
307	6.87	107	4.10	5.91	108	3.27	6.39	215	3.73
308	**5.44**	**71**	**1.70**	**4.89**	**72**	**1.60**	**5.16**	**143**	**1.67**
309	5.64	72	3.09	5.63	72	3.23	5.64	144	3.15
311	**5.90**	**108**	**1.44**	**5.51**	**108**	**1.28**	**5.71**	**216**	**1.37**
314	**5.16**	**105**	**1.15**	**4.54**	**106**	**1.15**	**4.85**	**211**	**1.19**
324	2.81	105	0.94	2.90	106	0.81	2.85	211	0.88
Composite	**51.97**	**108**	**10.62**	**48.03**	**108**	**8.97**	**50.00**	**216**	**10.00**

Note. BAC differences shown in bold are statistically significant at $p < .05$.

APPENDIX W: DROWSY LANE DEPARTURES GROUNDTRUTH DATA

A ground truth dataset was established for the evaluation of real-time drowsiness algorithms by matching drowsiness-related lane departures with verifiably alert periods on the same location of the roadway in the daytime drive, both within and between subjects. Truly drowsy data points were identified by manually reviewing the video for lane departures from all drives for signs of drowsiness in the driver. Raters were blind to the experimental condition and inter-rater reliability scores of .69 and .72 were observed using the intra-class correlation coefficient (ICC). The rating system, called Observer Rating of Drowsiness (ORD) is assessed based on the 60 seconds of video prior to each lane departure. The ORD scale from Wierwille and Ellsworth (1994) is continuous between 0 and 100, but Figure W1 shows an adapted ORD scale that has five levels with anchors.

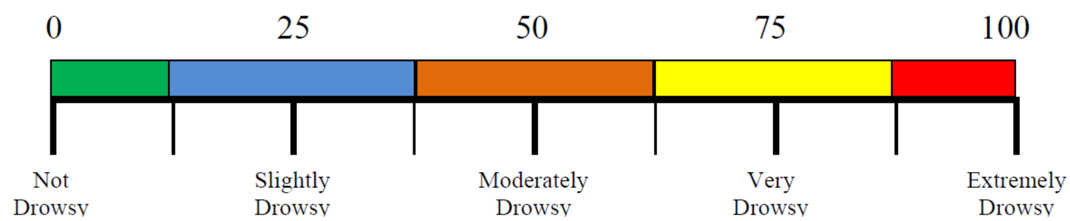


Figure W1. Discrete observer rating of drowsiness scale used to identify truly alert and truly drowsy data

The truly alert data points were selected to match the truly drowsy data. The truly drowsy points were projected onto the daytime drive of the same driver using the distance in the event as a matching variable. Truly drowsy points were also projected into the daytime drives of other drivers to obtain additional truly alert data points.

Whereas multiple people reviewed the video to verify the truly drowsy data points, the truly awake points were not reviewed. To ensure that these points represent alert drivers, only a subset of drivers were used that were verified as being alert during their daytime drives. Scores from the Stanford Sleepiness Scale (SSS), Retrospective Sleepiness Scale (RSS), and Psychomotor Vigilance Test (PVT) were used to identify these verifiably alert subjects. This subset is graphically represented in Figure W2 and Figure W3, first considering SSS and RSS, and then the PVT.

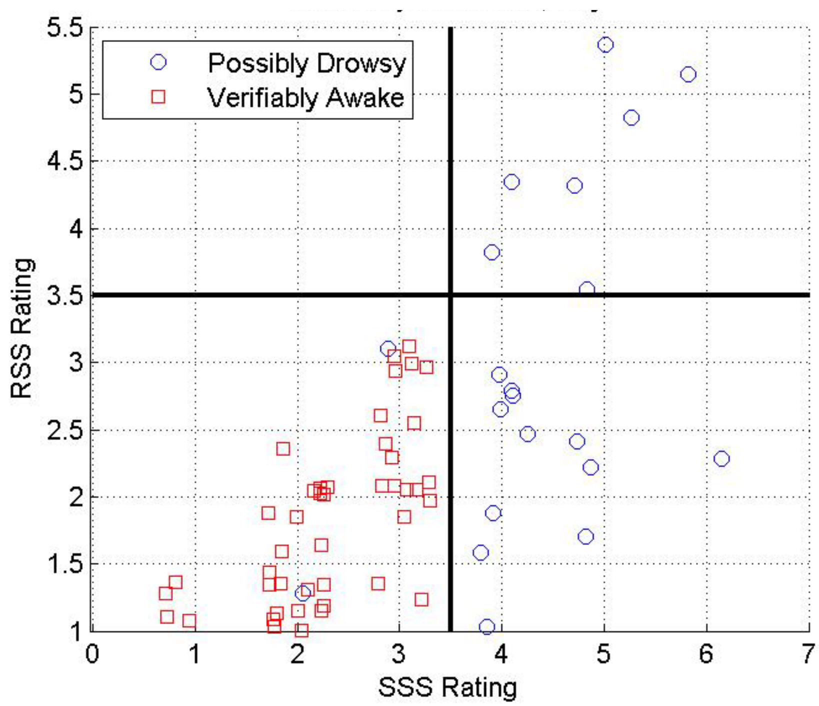


Figure W2. SSS and RSS ratings used to identify verifiably awake drivers

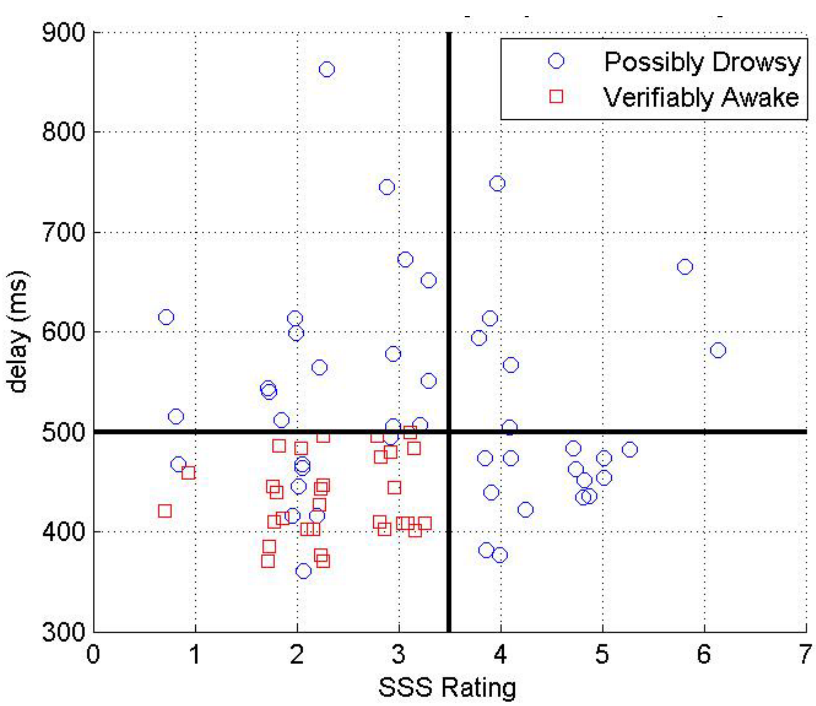


Figure W3. PVT scores to identify alert drivers using 90th percentile PVT delay, graphed against SSS rating

Applying the filters represented in Figure W2 and Figure W3 resulted in a subset of 28 verifiably alert drivers to define the truly alert events. From this set, the histogram of ORD ratings of lane departures is presented for each condition in the figure below (Figure W4). The distributions show that there are practically no differences between the number of lane departures with ratings of 1 and 2 between the day and lane night conditions. However, there are observably more lane departures with ratings of 3 and greater in the late night condition than in either the early night or daytime conditions. Based on these observations, an ORD rating of greater than two was used to select truly drowsy (TD) data points.

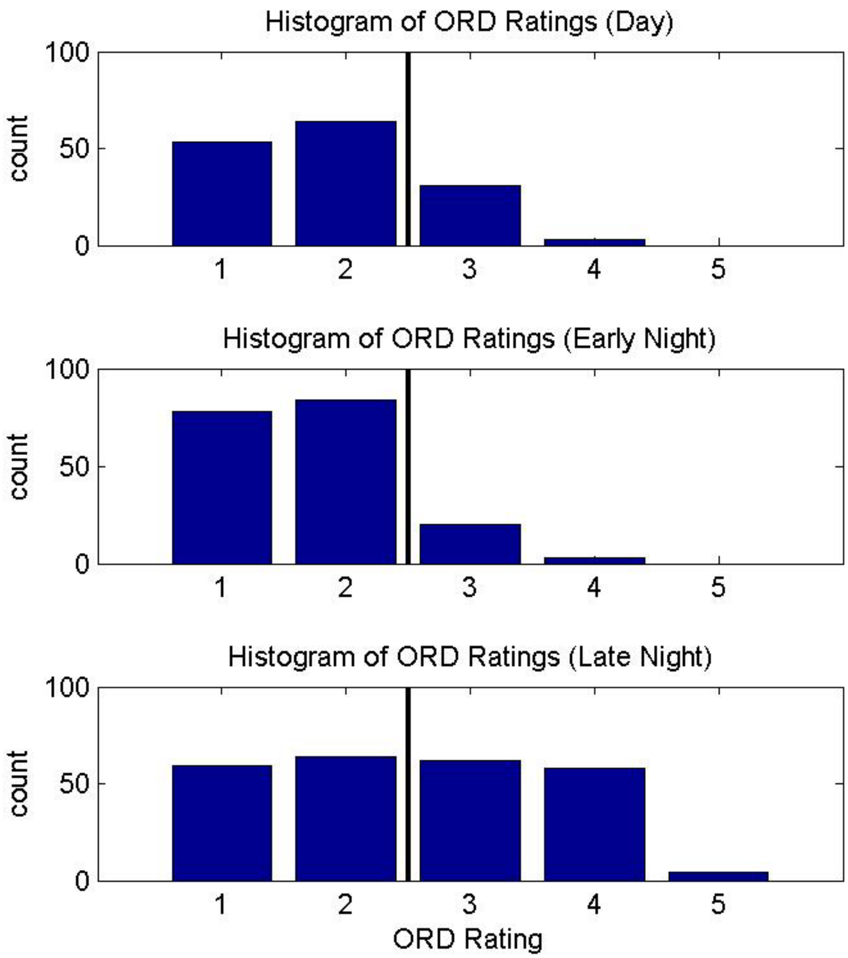


Figure W4. Histograms of ORD ratings to define verifiably drowsy and alert drivers

Since most of the real-time measures were smoothed using a 60 second moving average, a minimum separation of 60 seconds was enforced between adjacent truly alert or truly drowsy points. If two points are closer than this, they were suspected of being dependent and one was removed. After selecting the verifiably awake subjects, assigning the truly drowsy points, and projecting truly alert points into the daytime drives, a total of 162 truly drowsy lane departures were defined. A total of 80 truly alert points were matched to the truly drowsy points within subject; and 336 truly alert points were matched to the same location in the drive using data from other alert drivers' daytime drives. The final ratio of truly alert to truly drowsy data points was 2.57:1.

W.1 References

Wierwille, W. W., Ellsworth, L. A., Wreggit, S. S., Fairbanks, R.J., & Kim, C. L. (1994). Research on vehicle-based driver status/performance monitoring: development, validation, and refinement of algorithms for detection of driver drowsiness. (Report No. DOT HS 808 247). Washington, DC: National Highway Traffic Safety Administration Final Report.

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