The relationship of measures of eye behavior and driving performance under the influence of alcohol

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Abstract

Objective: The persistence of alcohol-involved crashes is a significant and persistent challenge to traffic safety that requires new strategies to combat the annual loss of life. This study examined the extent to which a modern vision-based driver monitoring system (DMS) could be used to detect driver-based measures of alcohol impairment.

Method: Thirty-six participants completed the study protocol. This baseline-controlled within-subject study involved testing on the decline at four sequential breath alcohol concentrations (BrACs) of 0.100, 0.085, 0.070, and 0.055 g/210L on a quarter-cab driving simulator with an integrated DMS. Visual measures from the DMS were used to predict alcohol impairment and driving performance as measured by standard deviation of lateral position (SDLP).

Results: In models predicting alcohol level (> 0.00, ≥ 0.05, and ≥ 0.08), two variables were significantly associated with the odds that a driver was above a given threshold: median eye opening (OR = 0.47, 0.62, and 0.68) and median percentage of time focused on the road center (OR = 1.05, 1.07, and 1.04). There were no other consistent predictors across the three models. Two models predicting driving performance (SDLP) included a general model (adjusted R^2 = 0.36) and an individualized model accounting for individual differences (adjusted R^2 = 0.56). In the general model, standard deviation of eye opening, median eye opening, median percentage of time focused on the road center, standard deviation of percentage of time focused on the road center, and standard deviation of horizontal gaze predicted SDLP. In the individualized model, median eye opening, standard deviation of eye opening, and median pupil diameter predicted SDLP.

Conclusion: Visual measures were used to predict alcohol-impaired drivers, but the summary measures alone lack the sensitivity and specificity to be used to identify them without including additional measures or context to the prediction. Models that accounted for individual differences between drivers were superior compared with those that did not account for these differences. Of the visual measures considered, decreasing median eye opening was particularly sensitive to alcohol-impaired driving. Increasing glance toward the forward roadway was predictive of increased levels of alcohol, especially when trying to predict alcohol above the legal limit of 0.08% blood alcohol concentration.

Keywords: alcohol; driving impairment; driver monitoring system; eye behavior

1. Introduction

Fatalities associated with motor vehicle crashes remain a significant source of preventable loss of life. In 2023, there were an estimated 40,990 fatalities associated with motor vehicle crashes (National Center for Statistics and Analysis, 2024b). In 2022, 13,524 of the 42,514 fatalities were from crashes where at least one of the drivers had a blood alcohol concentration (BAC) of 0.08 g/dL or higher and 67% of those had at least one driver above 0.15 g/dL (National Center for Statistics and Analysis, 2024a). From 2013 to 2019, the alcohol-impaired fatality rate ranged from 0.31 to 0.35 per 100 million vehicle miles traveled but increased to 0.43 and 0.42 in 2021 and 2022 (National Center for Statistics and Analysis, 2024b). The persistence of alcohol-involved crashes is a significant and persistent challenge to traffic safety that requires new strategies to combat the annual loss of life.

Mothers Against Drunk Driving (MADD) has been advocating for strategies to reduce alcohol-impaired driving since 1980. The organization has continued to advocate for technological improvements to eliminate drunk driving, which includes in-vehicle technology to prevent impaired driving (MADD, 2006). One of the outputs of this effort was a collaboration between the National Highway Traffic Safety Administration (NHTSA) and the automotive industry to advance technology to detect and prevent impaired driving; this ultimately became the Driver Alcohol Detection System for Safety (DADSS) that aims to prevent alcohol-impaired driving by detecting the BAC of the driver prior to driving. These systems, which are currently under development and testing, have to balance sensitivity and specificity to maximize detection of drivers over the legal limit while minimizing false positive classifications (Allen et al., 2023). Given this, there will likely be false negative instances where individuals over the legal limit are not captured by the DADSS, which necessitates other methods to detect alcohol-impaired drivers. In response to congressional action (Infrastructure Investment and Jobs Act, 2021), NHTSA issued an advanced notice of proposed rulemaking (ANPRM) in January 2024, beginning a formal rulemaking for a technological solution for impaired driving (NHTSA, 2024). NHTSA expanded the definition of impairment to include distraction and fatigue and notes heavily in the ANPRM the promise of driver monitoring systems (DMSs) as a potential solution for all these types of impairment.

DMSs have been used to detect impaired driving associated with both drowsiness and distraction and can work either through vehicle or camera-based sensors to infer driver state (Lee et al., 2013). Research has shown the ability of DMSs to use a variety of sensor data to detect both states as well as to differentiate between distraction and drowsiness (Brown et al., 2014; Gaspar et al., 2017; Gjoreski et al., 2020; McDonald et al., 2018; Mühlbacher-Karrer et al., 2017; Schwarz et al., 2016; Schwarz et al., 2019; Sigari et al., 2014). Industry has continued to work to deploy these technologies in an effort to improve traffic safety (Chacon-Murguia & Prieto-Resendiz, 2015) and, more recently, to assess driver state in partial driving automation (Schwarz et al., 2023; Seppelt & Lee, 2019).

Although DMSs have been used to detect distraction and drowsiness, there has been little research on the use of these systems to detect alcohol impairment. Some research has looked at how vehicle-based sensors can be used to detect alcohol-impaired driving (e.g., Lee et al., 2011), but broader based systems including video-based DMSs are rare at this point (Prendez et al., 2024). Prior efforts with research-grade eye trackers tried to identify which drivers are under the influence of alcohol. However, technological changes and differences in sensing technology have produced different measures that might be applicable to detecting which drivers are under the influence of alcohol. The prior research on detecting alcohol-impaired driving has focused on vehicle-based measures more so than driver-based measures.

Research using eye-tracking technology has shown differences associated with alcohol consumption in visual function while driving, specifically changes in the distribution of fixations such as a decrease in scanning away from the forward roadway and longer fixation times (Maurage et al., 2020; Shiferaw et al., 2019). Some results also show differences in pupillary reaction to light stimulation with increasing BAC (Amodio et al., 2018) and increases in pupil size associated with low levels of BAC (Castro et al., 2014). Blink frequency also has been reported to be associated with increased BAC levels (De Blasiis et al., 2020), and decreased eye openings also have been shown to be associated with the sedating effects of alcohol. While the capacity to detect these effects using research-grade eye-tracking technology is well documented, the extent to which they are replicable using an automotive-grade DMS, which is required to operate under a broader range of conditions and without calibration to individual users, has yet to be examined.

In this study, we examined the extent to which a modern, automotive-grade, vision-based DMS could be used to detect driver-based measures of alcohol impairment to identify drivers under the influence of alcohol. Specifically, we examined

- the relationship between alcohol concentration and vision-based measures and driving performance,
- the relationship between vision-based measures and driving performance, and
- the vision-based measures that best predict driving with alcohol in the system and driving performance.

2. Methods

The University of Iowa Institutional Review Board (IRB) approved the protocol and all corresponding participant-facing documents. Procedures included recruitment, eligibility screening via an online questionnaire, a screening visit that began with informed consent procedures and included training on study tasks, and a single alcohol-dosing visit.

2.1 Study design

This study was baseline controlled and used a within-subjects design with four levels of alcohol concentration. The order of presentation was fixed with baseline (0.000 BrAC) followed by 0.100, 0.085, 0.070, and 0.055 g/210L BrAC. The other within-subject factor was driving event: transition to dark (lighted to unlit roadways), dark (unlit) with curves, gravel, and long straightaway. Each event was comprised of rural nighttime driving. These events were in fixed order, but there were three different counterbalanced driving environments that varied the location of curves during the drive to minimize familiarity with the overall driving route.

2.2 Apparatus

2.2.1 miniSim™

The miniSim™ Research Driving Simulator is a PC-based research driving simulator (Figure 1) with powerful scenario editing and data acquisition capabilities. It is based on over a decade of

research and driving simulation experience. The University of Iowa Driving Safety Research Institute (DSRI) miniSim used in this study has been shown to be sensitive to the effects of alcohol on driving (Kay et al., 2013). The simulator includes a quarter cab with three 48-inch, high-definition (1080p), active LED-backlit LCD displays that provide a forward field of view of 141.4° horizontal × 27.5° vertical at a 48-inch viewing distance. The simulator also includes a realistic instrument cluster interface. The simulator includes a real vehicle seat, steering wheel, and pedals with an active steering loader with a DC motor/microprocessor control. The sound system includes a 2.1-channel sound system with a vibration transducer under the seat and an audio amplifier with external controls. A 22-inch LCD display provides the operators with a graphical user interface to start and stop the simulation and choose scenarios. Data are sampled at a rate of 60 Hz.

Figure 1. DSRI quarter-cab miniSim driving simulator with a nighttime scenario (top) and participant view (bottom).

2.2.2 Driver monitoring system

We integrated the automotive-grade DMS from Seeing Machines Ltd (Canberra, Australia) into the miniSim. This DMS was mounted securely to the simulator cab and configured similarly to a production vehicle. The DMS uses near-infrared lighting and an automotive-grade camera focused on the driver's face to capture ocular parameters that can be used to estimate driver state (see Figure 2). The system processes camera images to extract eye and face data such as head pose, gaze direction, and eye closure. The DMS stores data locally and shares its internal frame number with the data acquisition system to facilitate integration of the ocular and driving data for subsequent analysis.

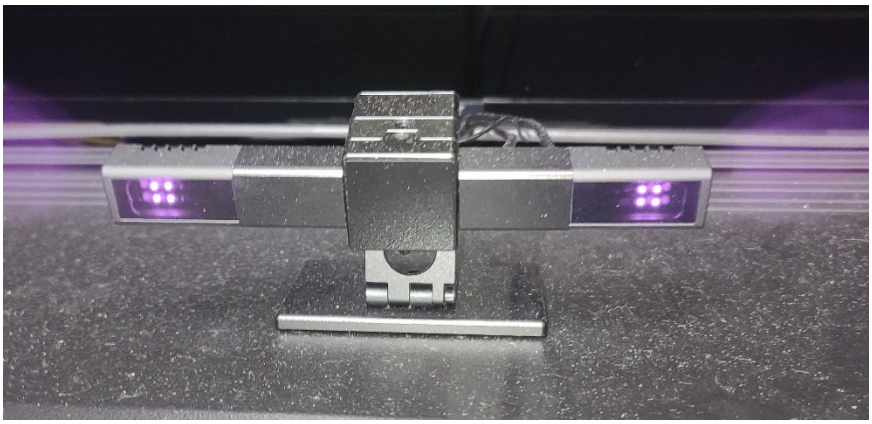

Figure 2. Seeing Machines' DMS camera and infrared light pods.

2.2.3 Breathalyzer

This study used an Alco-Sensor FST (Intoximeters, Inc., St. Louis, MO) breath alcohol testing instrument (Figure 3) to measure participants' breath alcohol concentration (BrAC). This handheld sensor uses a fuel cell to determine BrAC level. The system meets NHTSA's model specifications for evidential breath testing devices and is designed to measure BrAC levels from 0.000 to 0.440 g/210L with drift of less than 0.005 over several months. The device was checked weekly for calibration and recalibrated using an approved dry gas standard as needed.

Figure *3*. Alco-Sensor FST device displaying a reading of .000 BrAC.

2.2.4 Computerized tasks

This study involved cognitive testing using the NASA PVT+ and DRUID applications on a 9th generation iPad running iPadOS 12.1. These tasks were not analyzed as part of this effort.

2.3 Participants

Enrollment, defined as signing the informed consent document, occurred as the first procedure at the screening visit. A total of 44 individuals enrolled. Of these 44 individuals, 38 attended a dosing visit. Of the 38 participants who attended dosing, one was lost due to protocol challenges, and one was lost due to an adverse event resulting in too much missing data. This resulted in 36 participants who completed the study protocol. The demographic characteristics of this sample are described in Table 1.

Table 1. Sample demographic characteristics.

Variable	**Distribution**
Age	21–65 years (mean = 30.9, *SD* = 10.8)
Sex	Male =50%, Female = 50%
Hispanic	Yes = 4 (11.1%) No = 32 (88.9%)
Race	Asian/Asian American = 6 (16.7%) Black/African American = 3 (8.3%) White = 23 (63.9%) More than one race = 2 (5.6%) Prefer not to answer = 2 (5.6%)
Skin tone—Fitzpatrick scale (Fitzpatrick, 1988)	Type 1 = 0 (0%) Type 2 = 20 (55.6%) Type 3 = 8 (22.2%) Type 4 = 4 (11.1%) Type 5 = 3 (8.3%) Type 6 = 1 (2.8%)

Recruitment occurred through the DSRI Registry (n = 7,000+) via an email sent to individuals who met the age criteria and through word of mouth. Prospective participants completed an online eligibility questionnaire via REDCap to determine initial eligibility that involved a variety of yes/no and multiple-choice questions, as well as places for comments if the individual wished to include additional information.

If a person met the initial eligibility requirements, a researcher contacted them to schedule their screening appointment. They were asked to come to the DSRI facility located in the University of Iowa Research Park in Coralville, Iowa, for an in-person enrollment and screening visit where informed consent was obtained prior to a more rigorous screening process. Once enrolled, participants completed the following screening procedures: 12-panel urinalysis drug screen, pregnancy screen (if female), brief physical examination of vital signs (heart rate, blood pressure, temperature, oxygen saturation), brief medical history, and psychiatric exam. After successful completion of the physical, medical, and psychiatric screening, participants completed a demographic questionnaire. Participants then completed a screening drive in the miniSim that lasted approximately 7 min. Following the drive, participants completed a wellness questionnaire to determine individual risk for simulator sickness; participants were excluded from further participation in the study if they demonstrated elevated risk.

All participants received compensation for taking part in a study visit. Payment schedules went as follows: $25 for screening, $180 for the dosing visit, and $70 for transportation expenses if they attended the dosing visit. If a participant was unable to complete the study, they were paid for any past visits and at a rate of $10 per half hour of participation in the current visit.

2.4 Measures

The measures shown in Table 2 were collected for analysis during the drive for each of the driving events, and summary statistics of driving performance and visual measures were computed within each driving event. Median values for the eye-based measures were selected to minimize the impact of transient changes in eye behavior that could skew the central tendency of those measures.

Table 2. Measures used in the analyses.

Variable	Definition	Units
Breath alcohol concentration (BrAC)	The concentration of alcohol in the breath as measured at a given time point	g/210L
Standard deviation of lateral position (SDLP)	The variability of lane position relative to the average lane position	cm
Blink frequency	The average number of blinks per minute	1/min
Eye opening	The distance between the eyelids. Median and standard deviation are calculated for each driving event.	mm
Pupil diameter	For both the left and right eye, the measured size of the pupil. Median and standard deviation are calculated for each driving event.	mm
Percentage road center (PRC 17, PRC 60)	For both a 17-s and 60-s window, the percentage of time that the driver's gaze is directed to the center of the road. Median and standard deviation are calculated for each event.	%
Gaze direction	For both the horizontal and vertical component, the eccentricity of the gaze from straight ahead. Mean and standard deviation are calculated for each event.	Degrees

2.5 Experimental procedures

On arrival, researchers first conducted a brief confirmation of continued eligibility and completed a brief review of health history and substance use since the screening visit. Participants provided a breath alcohol content measurement to ensure sobriety and a urine sample for drug and pregnancy screening. Researchers next completed baseline measures for the following procedures:

vitals (blood pressure, heart rate, respiratory rate, pulse oximetry, and temperature), DMS setup and simulator drive, computerized tasks, and questionnaires.

After baseline procedures, researchers prepared the alcohol dose. Researchers used the Sahlgrenska formula that takes participant height, weight, age, sex, and drinking profile (light, moderate, or heavy drinker) into account to calculate alcohol doses. The amount of alcohol needed for the alcohol dose was calculated to produce a peak BrAC of 0.115 to allow for testing BrAC on the decline near the first target BrAC of 0.100. The drink consisted of 1 part alcohol to 1.5 parts orange juice (or a preapproved substitute of cranberry juice in one instance). A single drink was prepared and then split into three smaller drinks.

Participants were served one of the three equal-sized drinks every 10 min and instructed to pace the drink evenly over the 10-min drinking period. The total drinking period was 30 min. The participant then rested to allow their BrAC to rise to peak. The first 10 min of this resting period had no other procedures. After 10 min, BrAC was measured every 5 to 10 min until the target BrAC was reached. At about 20 min into the resting period, researchers took participant vitals. Once the first target BrAC was reached, participants resumed procedures. The same block of procedures occurred for each target BrAC (0.100 ± 0.010, 0.085 ± 0.010, 0.070 ± 0.010, and 0.055 ± 0.010). Participants completed BrAC measurements every 5 to 10 min until at the BrAC target, then completed a study drive followed by a post-drive BrAC measurement, computerized tasks, and subject questionnaire. After the final block, researchers measured BrAC until the discharge target of 0.030 or lower was reached. As the BrAC approached 0.030, researchers obtained discharge vitals and had participants complete an agreement stating they would not transport themselves home and indicating the mode of transport home (sober acquaintance, rideshare, or taxi). At any point post-dose, if BrAC was declining too quickly, researchers could administer a booster alcohol dose. The booster-dosing procedure involved a single, smaller drink calculated in the same way as the main drink but to the appropriate BrAC target and administered over a 10-min period.

Prior to each study drive, researchers asked the participant if they felt safe to drive on real roadways. All study drives were approximately 25 min in length, were simulated as nighttime, and contained rural curves and straights with stretches both with and without traffic.

2.6 Statistical analysis

Statistical analysis of the collected data was conducted using SAS Enterprise Guide, Version 8.3. The analysis was performed in four parts.

The first part of the analysis provided descriptive statistics for participant demographic characteristics and breath alcohol concentrations. The second part focused on the relationship between individual predictor measures and the observed BrAC levels. To assess this relationship, the SAS General Linear Models Select Procedure was used to examine how each predictor measure was influenced by alcohol dosing, with dose condition, pre-drive BrAC, post-drive BrAC, the interaction between pre- and post-drive BrAC, driving events, and participant identifier as potential model variables. The third part focused on the correlation between the predictor measures and driving performance as measured by standard deviation of lateral position (SDLP) and utilized the SAS Correlation Procedure. The fourth part of the analysis focused on predicting impaired driving.

The first set of models focused on predicting alcohol presence and utilized the SAS Logistic Procedure. The second model approach focused on predicting observed driving performance as measured by SDLP and utilized the SAS General Linear Models Select Procedure. Both approaches included predictor measures that had shown a significant relationship to one of the alcohol measures from the prior analysis. Significance level was set at a p value of 0.05 for all tests. For all reported results, values were rounded rather than truncated.

3. Results

3.1 Breath alcohol concentrations

An analysis of the BrAC levels prior to the drive confirmed the efficacy of the experimental procedure, as shown in Figure 4. The mean BrAC levels for the four dosed conditions were 0.102, 0.087, 0.073, and 0.060 (see Table 3). As can be noted from the distributions, there was overlap between the lower limit and upper limits of adjacent BrAC conditions.

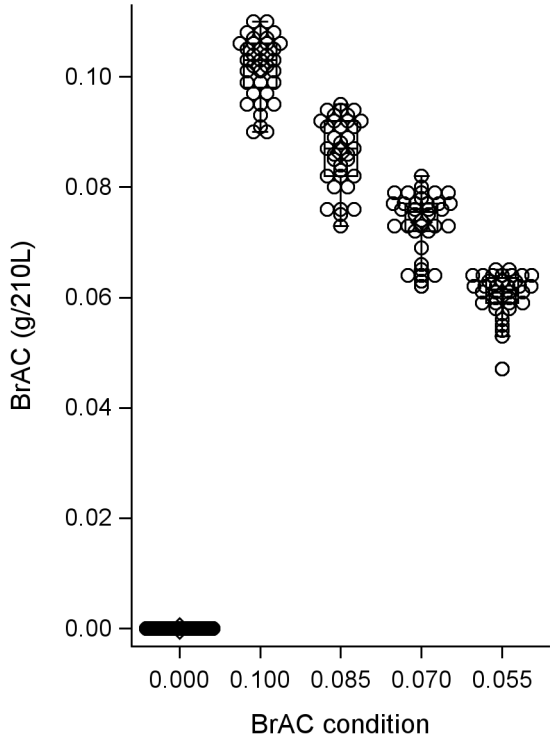

Figure 4. Distribution of pre-drive BrAC levels by condition.

Table 3. BrAC descriptive statistics by condition.

Target BrAC	Mean	Minimum	Maximum	Standard deviation
0.000	0.000	0.000	0.000	0.000
0.100	0.102	0.090	0.110	0.006
0.085	0.087	0.073	0.095	0.006
0.070	0.073	0.062	0.082	0.006
0.055	0.060	0.047	0.065	0.004

Note. BrAC = breath alcohol concentration.

3.2 Relationship to breath alcohol concentrations

To assess the extent to which different predictors were related to measures of recent alcohol use, we examined whether any of the measures of alcohol use were related to changes in the predictor measure and, if so, whether the measure was more related to the categorical dose condition or had some linear relationship with BrAC before or after the drive. Table 4 shows where one of the alcohol measures had a significant predictive relationship to a predictive measure. Given the nonlinear effects introduced by the interactive BrAC effect, the effects where the interactive effect was present or the main effects were less straightforward are illustrated in Table 5 and assume the mean pre- and post-drive BrAC for each condition.

Table 4. Generalized linear model outputs for measures that are significantly influenced by alcohol use.

Dependent (predictive) measure	Intercept	Dose condition		BrAC		
				Pre-drive	Post-drive	Pre- × post-drive interaction
SDLP	29.98				325.64	−2181.86
Blink frequency	18.4				66.5	−1104.6
Median eye opening	10.03	0.100	0.56			−130.42
		0.085	0.07			
		0.070	−0.13			
		0.055	−0.06			
Std dev eye opening	1.49	0.100	0.10			
		0.085	0.32			
		0.070	0.40			
		0.055	0.35			
Median pupil diameter (left eye)	4.74	0.100	−0.06			
		0.085	−0.28			
		0.070	−0.31			
		0.055	−0.19			
Std dev pupil diameter (left eye)	0.85	0.100	0.10			
		0.085	0.22			
		0.070	0.24			
		0.055	0.24			
Median pupil diameter (right eye)	4.50	0.100	0.86	−9.34		
		0.085	0.50			
		0.070	0.38			
		0.055	0.34			
Std dev pupil diameter (right eye)	0.95	0.100	0.13			
		0.085	0.21			
		0.070	0.24			
		0.055	0.22			
Median PRC 17	84.2			−85.3		1155.3
Median PRC 60	83.5			−85.6		1162.6
Std dev PRC 60	7.88					−85.0
Std dev horizontal gaze	0.116				−0.188	

Note. BrAC = breath alcohol concentration; SDLP = standard deviation of lateral position; PRC 17 and PRC 60 = percentage road center variable for a 17-s window and a 60-s window, respectively (Table 2). Std dev = standard deviation. SDLP = standard deviation of lateral position.

As expected, SDLP was related to recent alcohol use. Post-drive BrAC combined with an interactive effect between pre- and post-drive BrAC provided the best prediction. Across all conditions, SDLP increased relative to baseline with average predicted increases ranging from 9.5 to 11.3 cm and the peak SDLP increase observed at the 0.070 BrAC condition.

Blink frequency showed a similar pattern as SDLP. Blink frequency increased with increasing post-drive BrAC values but was reduced by an interaction between pre- and post-drive BrAC levels. The largest decrease in blink frequency is predicted for the 0.100 BrAC with four fewer blinks per min. By the 0.055 BrAC, the decrease had largely dissipated.

Median eye opening was predicted by the dosing condition adjusted by an interaction between pre- and post-drive BrAC levels. The net change accounting for both effects is a decrease in average eye opening of approximately 0.6 mm at the 0.100 and 0.055 BrAC levels and 0.9 mm at the 0.085 and 0.700 BrAC levels.

Standard deviation of eye opening also was related to dosing condition. In all dosing conditions, the standard deviation of eye opening was greater than baseline with the smallest increase (0.10 mm) for the 0.100 BrAC condition and the largest increases for the 0.085 to 0.055 BrAC conditions (range 0.32 to 0.40 mm).

Decreases in median diameters were observed for both eyes for all dosing conditions. The smallest decreases were for the 0.100 BrAC condition for both the left (−0.06 mm) and right (−0.10 mm) eyes. Larger decreases were observed for both eyes at lower BrAC levels ranging from 0.19 to 0.62 mm.

Consistent with median pupil diameter, standard deviation of pupil diameter for both the right and left eye were related to dosing condition. Increases in variability in pupil diameters were observed for both eyes across all dosing conditions. The smallest increases were observed for the 0.100 BrAC conditions (0.10 and 0.13 mm) with larger increases associated with the 0.085 to 0.055 BrAC conditions (ranging from 0.21 to 0.24 mm).

Gaze focus on the forward roadway was associated with pre-drive BrAC and the interactive effect between pre- and post-drive BrAC. For both PRC 17 and PRC 60, this resulted in an increase in gaze focus on the forward roadway at the 0.100 and 0.085 BrAC conditions and a decrease at the 0.070 and 0.055 BrAC conditions.

Table 5. Predicted values for measures with a significant interactive effect or complex effect.

Dose condition (BrAC)	BrAC		SDLP (cm)	Blink frequency (1/min)	Average eye opening (mm)	Pupil diameter		PRC 17 (%)	PRC 60 (%)	PRC 60 std dev (%)
	Pre-drive	Post-drive				Left	Right			
0.100	0.102	0.091	39.5	14.2	8.9	4.7	4.4	83.8	85.7	7.1
0.085	0.086	0.080	41.0	16.1	8.6	4.4	4.1	82.4	84.3	7.3
0.070	0.073	0.068	41.3	17.4	8.6	4.4	3.9	81.4	83.2	7.5
0.055	0.060	0.055	40.7	18.4	8.9	4.5	3.9	80.6	82.4	7.6
0.000	0.000	0.000	30.0	18.4	9.5	4.7	4.5	81.9	83.6	7.9

Note. BrAC = breath alcohol concentration. SDLP = standard deviation of lateral position. PRC 17 and PRC 60 = percentage road center variable for a 17-s window and a 60-s window, respectively (Table 2). Std dev = standard deviation.

3.3 Correlation to driving performance

While the prior analysis related changes in alcohol levels (dose condition) to variation in measures of potential interest for predicting alcohol-impaired driving, this analysis relates predictor measures to observed driving performance as measured by SDLP (see Table 6). Of the measures considered, only blink frequency was not significantly correlated with SDLP. SDLP was positively correlated with standard deviation of the following measures: eye opening, pupil diameter, percentage of time focused on road center over a 60-s window, and horizontal gaze. SDLP was negatively correlated with median eye opening, pupil diameter, and median percentage of time focused on the road center over 17-s and 60-s windows.

Table 6. Correlations between predictor measures and driving performance.

Dependent measure	Pearson correlation	*p*
Blink frequency	−0.060	0.1116
Median eye opening	−0.407	<.0001
Std dev eye opening	0.464	<.0001
Median pupil diameter (left eye)	−0.132	<.0001
Std dev pupil diameter (left eye)	0.405	<.0001
Median pupil diameter (right eye)	−0.143	<.0001
Std dev pupil diameter (right eye)	0.415	<.0001
Median PRC 17	−0.496	<.0001
Median PRC 60	−0.516	<.0001
Std dev PRC 60	0.336	<.0001
Std dev horizontal gaze	0.091	0.0164

Note. Std dev = standard deviation; PRC 17 and PRC 60 = percentage road center variable for a 17-s window and a 60-s window, respectively (Table 2).

3.4 Predicting impaired driving

Building on the measures associated with alcohol-impaired driving performance, those measures that had significant correlations with driving performance were further analyzed to determine factors that predict whether a driver was under the influence of any alcohol, alcohol above 0.050 BrAC, or alcohol above 0.080 BrAC. Predictors of degraded driving performance (i.e., increased SDLP) were also analyzed.

Table 7 presents the odds ratios for each of the three logistic regression models. For predicting the presence of any alcohol, increases in variability in eye opening and median PRC 17 and decreases in median eye opening and variability in horizontal gaze increase the likelihood that the individual has a positive BrAC. Increases in variability in left pupil diameter and median PRC 17 and decreases in median eye opening and left pupil diameter increase the likelihood that the individual has alcohol above the 0.050 BrAC threshold. For predicting that an individual is above the 0.080 BrAC threshold, increases in variability in right pupil diameter and median PRC 17 and decreases in median eye opening increase the likelihood that the individual has alcohol above this level.

Table 7. Logistic regression odds ratios and 95% confidence intervals for models to predict alcohol presences above 0.000, 0.050, or 0.080 BrAC.

Effect	Alcohol level		
	>0.000	>0.050	>0.080
Median eye opening	0.47 [0.38, 0.58]	0.62 [0.51, 0.77]	0.68 [0.57, 0.80]
Std dev eye opening	4.48 [2.78, 7.21]		
Median pupil diameter (left eye)		0.68 [0.50, 0.92]	
Std dev pupil diameter (left eye)		7.17 [3.58, 14.39]	
Median pupil diameter (right eye)			1.34 [1.03, 1.75]
Std dev pupil diameter (right eye)			
Median PRC 17	1.05 [1.01, 1.09]	1.07 [1.04, 1.10]	1.04 [1.02, 1.06]
Median PRC 60			
Std dev PRC 60			
Std dev horizontal gaze	0.01 [0.00, 0.78]		

Note. Std dev = standard deviation. PRC 17 and PRC 60 = percentage road center variable for a 17-s window and a 60-s window, respectively (Table 2).

Two models, summarized in Table 8, were considered for predicting driving performance as measured by SDLP. The first model focused on only the predictor variables and the second model accounted for individual differences between participants and difference in driving context by adding the participant and event IDs. The general model had an adjusted R^2 of 0.36, and the individualized model had an adjusted R^2 of 0.56. The general model predicted increased SDLP when there were increases in variability in eye opening, median PRC 60, and variability in PRC 60 and decreases in median eye opening and variability in horizontal gaze. For the individualized model, increases in variability in eye opening and decreases in median eye opening and median pupil diameter (left eye) were predicted to increase SDLP.

Table 8. Generalized linear models for predicting driving performance.

Parameter	Estimate general model	Estimate accounting for event and participant
Intercept	69.97	98.68
Median eye opening	−2.92	−3.94
Std dev eye opening	9.11	7.81
Median pupil diameter (left eye)		−7.10
Std dev pupil diameter (left eye)		
Median pupil diameter (right eye)		
Std dev pupil diameter (right eye)		
Median PRC 17		
Median PRC 60	0.30	
Std dev PRC 60	0.78	
Std dev horizontal gaze	−43.22	

Note. Std dev = standard deviation. PRC 17 and PRC 60 = percentage road center variable for a 17-s window and a 60-s window, respectively (Table 2).

4. Discussion

The results present an interesting perspective on the types of general measures that can be collected from DMSs that may help predict alcohol-impaired driving. Although the measures examined were not all inclusive, they were measures that were easily derived with data from an automotive-grade DMS. To assess how well different measures can capture impaired driving, we consider the three objectives.

First, there were significant relationships between the vision-based measures and driving performance and different measures of alcohol intoxication. One key distinction when looking at this relationship is that some measures had a more linear relationship while others were best explained by considering the rough level of alcohol use (as defined by the dosing condition). Measures related to the eyes (i.e., eye opening and pupil diameter) were better explained by considering the rough level of alcohol in the body rather than a specific BrAC, although both median eye opening and median right eye pupil diameter were adjusted to account for a dose response relationship. This broadly may indicate that there is a higher order effect that is better modeled with categorical values rather than a linear function. Other measures including SDLP, blink frequency, and gaze were better explained by considering the actual BrAC, although the choice of pre- or post-drive BrAC was not consistent

across analyses. The significance of the interaction between pre- and post-drive BrAC for most of these measures also reflects a nonlinear relationship that may reflect the effect of the BrAC decline during the drive or a higher-order nonlinear relationship for some of the measures.

Some of the measures, such as measures related to vertical gaze and median horizontal gaze, were not related to alcohol level. We can conclude that the measures identified for consideration in predicting impaired drivers are indeed influenced by alcohol use. We were able to confirm that decreases in blink frequency and eye opening can be observed following alcohol use. Contrary to expectations for low-level BrACs, we observed decreased pupil sizes at the alcohol levels evaluated. Additionally, the focus to the forward roadway was more complex than expected. Variability in horizontal gaze did decrease with increasing BrAC levels. However, percentage of time spent focused on the forward roadway was less at the 0.055 and 0.070 BrAC levels but increased at higher BrAC levels. Considering the observed relationships, these measures are good candidates for identifying alcohol-impaired drivers.

For the vision-based measures that were significantly influenced by alcohol, we next considered which of those measures were related to observed driving performance. The only measure related to alcohol use that was not significantly related to SDLP was blink frequency. Despite the strong relationship with measured BrAC, the changes in blink frequency did not correspond to observed changes in performance. The other measures that had been related to alcohol level all showed strong correlations to changes in driving performance. Linking changes in observed visual behavior to changes in driving rather than just association with alcohol use was important to providing a solid foundation for acceptance of any vision-based detection approach. As a result, blink frequency was not further considered in the predictive models but all other variables were retained.

Finally, we considered the ability to use the vision-based measures derived from a DMS to identify individuals that were alcohol-impaired. Two efforts were undertaken that would link these measures to meaningful alcohol cutoffs and to observed driving behavior. When predicting whether the driver had a positive BrAC level or was above a 0.050 or 0.080 g/210L threshold, decreasing median eye opening and increasing median time focused on the road center significantly increased the odds that a driver was above the given alcohol threshold. There were no other consistent predictors

across the three models. When looking at the quality of the models, the model quality decreased as the alcohol threshold increased. The "any alcohol" threshold model had a Somers' D value of 0.52, whereas the 0.050 and 0.080 BrAC models had values of 0.45 and 0.26, respectively, which indicates decreasing model quality with increasing threshold. It should be noted that we cannot rule out a confound between lower BrACs and time on task given the study design. When considering prediction of worse driving performance as measured by SDLP, both models incorporated eye opening metrics; the general model was augmented with measures associated with gaze focus, whereas the more individualized model relied on pupil diameter to predict driving performance. The individualized model produced a more accurate prediction of driving performance that indicated changes in pupil diameter better account for changes in performance when individual differences in driving are considered. All models considered, regardless of whether they were predicting alcohol levels or driving performance, still failed to account for a significant proportion of the variability.

There are several limitations to this research that must be considered. Although the design of the study produced a more natural pattern of studying alcohol-impaired driving on the descending arm, it does produce longer time on task at lower BrAC levels that could produce increased levels of drowsiness and may confound the results. Also, this effort focused only on the vision-based DMS measures and not on vehicle-based measures such as steering and throttle inputs. The addition of these measures may improve the quality of the prediction models. Additionally, this analysis focused on summary measures of the measures rather than time-series data that may provide more nuanced changes in visual performance that could improve prediction quality. Other measures such as fixations and saccades, as well as specific focus on objects in the world, could also be added for a time-series type analysis.

Based on these findings, we can conclude that visual measures can be used to predict alcohol-impaired drivers, but the summary measures alone lack the sensitivity and specificity to be used to identify them without including additional measures or context to the prediction. It also can be concluded that models that account for individual differences between drivers are superior to those that act in a more general manner. We also can conclude that of the visual measures considered, decreasing median eye opening is particularly sensitive to alcohol-impaired driving but care must be

given that it is not specific to only higher levels of alcohol. For example, drowsiness has been shown to increase blink frequency and decrease eye opening (Kolus, 2024). When predicting alcohol impairment, increasing glance toward the forward roadway, particularly over a 17-s window, can be predictive of increased levels of alcohol, especially when trying to predict alcohol above the legal limit of 0.08 BAC. These results point to the need to also consider the driver states (e.g., drowsiness, distracted) against which a system is trying to differentiate.

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6. References

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