Identifying Effectiveness of Engineering Traffic Control Devices for Wrong-Way Driving from the Driver Behaviors Perspective

By

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Abstract

This dissertation aims to identify the effectiveness of engineering traffic control devices for wrong-way driving (WWD) from a driver behavior perspective, which contains two tasks: i) WWD fatal crash analysis, and ii) driving simulator study design and analysis.

For the WWD fatal crash analysis, the study aims to conduct a comprehensive analysis of WWD fatal crashes on divided highways using 17 years (2004–2020) of WWD fatal crash data which were extracted from the National Highway Traffic Safety Administration (NHTSA) Fatality Analysis Reporting System (FARS) database. The FARS database has the distinct advantage of providing WWD fatal crashes nationwide with more than 140 variables that record crash, vehicle, driver, passenger, and pedestrian information, whereas previous studies were mostly based on the limited WWD crash data collected from several states. The analysis included: i) updating the trends for WWD fatal crashes up to 2020; ii) analyzing the distribution of WWD fatal crashes among states, genders, and ages; and iii) examining the WWD fatal crash risk factors using binary logistic regression and multiple correspondence analysis (MCA). The results revealed that i) an average of 302 WWD fatal crashes happened each year, and the number of WWD fatal crashes has not been declining over the years; ii) over 60% of WWD fatal crashes are alcohol involved; and iii) young driver, male driver, alcohol-impaired driver, and nighttime conditions are predominate in the WW fatal crashes. The research results help readers understand the national trend of WWD fatal crashes and the risk actors that cause WWD fatal crashes, which may support the decision-making for FHWA, state DOTs, and local governments in the future. Most importantly, these results, especially the contributing factors, will be considered as the base of the scenario development and lab testing design for the driving simulator study.

For the driving simulator study, the main purpose is to evaluate the effectiveness of the proposed traffic control devices (TCD(s)) to prevent WWD for highly intoxicated drivers by analyzing drivers' behavioral data collected from the driving simulator and eye-tracking device. The driving simulator study provides a unique opportunity to study drivers' behaviors when they face different kinds of wrong-way-related TCD(s), which can not be achieved through traditional field data collection and crash data analysis. 30 male participants with an average age of 25 were recruited for the driving simulator study. The non-alcohol session and real-alcohol session were given to the participants in counterbalanced order. For each session, participants were required to complete three scenarios that contains the proposed TCD(s) in counterbalanced order. The driving simulator data and eye-tracking video data were collected for analysis purposes, which encompasses more than 1,500 minutes of video and more than 5,506,580 data points at 0.16-s intervals, respectively. First, the general information such as drivers' information and actual BrAC level was summarized for the study. Then the comparison of the forward driving scene between normal and alcohol-impaired conditions was analyzed based on visualization and Chi-square results. Finally, the effectiveness of TCD(s) was evaluated by three criteria: i) the number of WWD events; ii) fixation duration; and iii) brake response distance. The research results provided detailed information regarding how drivers react facing different TCD(s) based on those three criteria, which can be utilized by transportation agencies for TCD selection and to better design off-ramps and prevent WWD events.

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This dissertation is a milestone that remarks the end of a long and memorable journey as a student at Auburn University, and the new stage of my life as an employee in society. I am not able to complete it without the dedicated support I have received from so many people.

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List of Abbreviations

ANOVA	Analysis of Variance
AOI	Area of Interest
BrAC	Breath Alcohol Concentration
Caltrans	California Department of Transportation
CAMUTCD	California Manual on Uniform Traffic Control Devices
CFX	Central Florida Expressway Authority
DNE	Do Not Enter
DOT	Department of Transportation
DRS	Directional Rumble Strips
DUI	Driving Under the Influence
FARS	Fatality Analysis Reporting System
FHWA	Federal Highway Administration
IDOT	Illinois Department of Transportation
ISAT	Interactive Scenario Authoring Tool
IRB	Institutional Review Board
ITS	Intelligent Transportation System
LED	Light-Emitting Diode
MCA	Multiple Correspondence Analysis
MUTCD	Manual on Uniform Traffic Control Devices
NADS	National Advanced Driving Simulator

NHTSA	National Highway Traffic Safety Administration
NTSB	National Transportation Safety Board
NTTA	North Texas Tollway Authority
OR	Odds Ratio
RRFB	Rectangular Rapid Flashing Beacon
RRPM	Red Retroreflective Raised Pavement
RPM	Raised Pavement Marker
RW	Right-Way
TCD	Traffic Control Device
TMC	Traffic Management Center
TMT	Tile Mosaic Tool
TOI	Time of Interest
USDOT	United States Department of Transportation
WSDOT	Washington State Department of Transportation
WW	Wrong-way
WWD	Wrong-way Driving

Chapter 1 Introduction

1.1 Background

Wrong-way driving (WWD) crashes happen when a driver drives in the opposite direction of traffic flow inadvertently or deliberately. Crashes related to driving the wrong way (WW) on freeways have challenged transportation officials as far back as a half-century (*Hulbert and Beers, 1966*) and have received increased attention in recent years. According to Federal Highway Administration (FHWA), in the United States, wrong-way driving (WWD) crashes result in 300 to 400 people killed each year on average, representing approximately one percent of the total number of traffic-related fatalities that occur annually (*FHWA, 2017*). Although it can be regarded as a small percentage overall, WWD crashes are not as prevalent as other types of roadway crashes since WWD crashes involve head-on or opposite-direction sideswipe crashes at high speeds. A past study found that the WWD fatality rate, which was calculated as the number of fatalities per WWD crash, was 27 times greater than other crash types on interstate highways (*Vaswani, 1973*). Morena and Leix (*2012*) also found that WWD crashes had 12 times higher fatality rates than all other crash types. Additionally, according to an overview of WWD crashes in the United States (*Baratian-Ghorghi et al., 2014*), WWD crashes have not declined over the years compared with the overall trends of fatal traffic crashes.

Though WWD crashes are rare and random, past research consistently indicated that a disproportionate number of these crashes were related to alcohol. Copelan reported that impaired drivers on California freeways accounted for almost 60 percent of all WWD crashes and nearly 77 percent of fatal WWD crashes from 1983 to 1987 (*Copelan, 1989*). A Washington State Department of Transportation (DOT) study found that 50 percent of the 30 WWD crashes in the

I-82 Yakima-to-Tri-Cities corridor study were alcohol- or drug-related (*Moler, 2002*). Researchers in Indiana determined that out of 77 WWD crashes in the 1970 to 1972 time period, 42 involved driving under the influence (DUI) (*Scifres and Loutzenheise, 1974*). Based on a study (*Zhou et al., 2016*) investigating contributing factors for WWD on high-speed divided highways, a driver whose condition is DUI is almost four times more likely to have WWD crashes than normal drivers.

Based on the current fact of WWD crashes, there are many strategies and treatments that agencies can consider for implementation that are designed to address wrong-way maneuvers, ranging from geometric design elements to conventional traffic control devices (TCDs) to various Intelligent Transportation Systems (ITS) based solutions. In addition, newly emerged TCDs such as directional rumble strips and LaneAlert 2X pavement systems are entering the marketplace, which provides new solutions for WWD prevention. However, due to the lack of data, the effectiveness of those engineering traffic control devices has not been fully evaluated, particularly for those highly intoxicated WW drivers. Although several studies can be found for WWD related countermeasure evaluation, most of them tried to evaluate them from the engineering side rather than from driver behaviors perspectives. Therefore, there is a need for research that seeks to evaluate WWD-related TCDs from a driver behavior perspective. The findings of such a research study are likely to support the formation of conclusions regarding the effect of the current WWD TCDs on overall roadway safety.

1.2 Study Objectives

The ultimate goal of this study is to identify the effectiveness of engineering traffic control devices for WWD from a driver behavior perspective. The following steps were used to achieve the goal:

- Analyzed the WWD crash trends, distributions, and contributing factors (individual and group) for the current years.
- Identified the engineering countermeasures that have the potential for deterring WWD movements, especially for severely intoxicated WW drivers.
- Developed driving simulator scenarios on selected engineering countermeasures.
- Recruited participants and conducted lab testing for the driving simulator study.
- Interpreted the results and provide suggestions regarding the effectiveness of TCDs, especially for severely intoxicated drivers.

1.3 Research Outline

The succeeding chapters of this dissertation are structured in the described format and order:

- Chapter 2 provides a concise overview of WWD, particularly regarding WWD statistics, contributing factors, countermeasures, the effectiveness of countermeasures, and the current driving simulator-based studies.
- Chapter 3 discusses current WWD crash facts and methodologies used for data analysis, including trends, distributions, and contributing factors (individual and group).
- Chapter 4 presents a detailed description of the driving simulator study, including participant recruitment, driving simulator scenario development, lab experiment design, procedures, and future work regarding proposed data collection and statistical analysis methods.
- Chapter 5 introduces the data collection process for driving simulator data and eye-tracking data, as well as the data analysis methods.

- Chapter 6 summarizes the results of the driving simulator study based on general information, the difference between the forward driving scene, and the effectiveness of TCD(s).
- Chapter 7 concludes the key findings from the driving simulator study and points out the needs of future studies.

Chapter 2 Literature Review

2.1 Wrong-Way Driving Statistics

Few past studies, to the best knowledge, have examined the national trend of WWD crashes. In 2012, the National Transportation Safety Board (NTSB) conducted a study to identify WWD fatal crash trends on divided highways by using five years' (2004–2009) data extracted from the National Highway Traffic Safety Administration (NHTSA) Fatality Analysis Reporting System (FARS) database (*NTSB, 2012*). The results showed that approximately 360 people died annually in 260 WWD fatal crashes. In 2014, Baratian–Ghorghi et al. updated WWD fatal crash trends using the FARS database from 2004 to 2011 (Baratian-Ghorghi et al., 2014). It was found that an average of 269 fatal WWD crashes happened each year, which caused 359 fatalities annually.

2.2 Contributing Factors

Over the past few decades, a number of reports and papers have explored contributing factors to WWD crashes (**Table 2.1**). According to **Table 2.1**, the majority of studies used descriptive statistics to describe the trends and characteristics of WWD crashes (*Copelan, 1989; NTSB, 2012; Zhou et al., 2017a; Zhou et al., 2017b; Kittelson & Associates, 2015; Finley et al., 2014; Savolainen et al., 2018; Zhou et al., 2012; Braam, 2006*). Although the results of descriptive statistics are easy to understand, they are not sufficient to illustrate the impact of the contributing factors to WWD crashes. Kemel conducted a comprehensive analysis of WWD crashes on divided roads in France using a logistic regression model. The obtained results revealed that nighttime conditions, non-freeway roads, older drivers, impaired drivers, passenger cars, and older vehicles are factors that contribute to WWD crashes (*Kemel, 2015*). By considering the rareness of the WWD crashes, Pour-Rouholamin *et al.* (*Pour- Rouholamin and*

Zhou, 2016a) applied Firth's penalized-likelihood logistic regression, which revealed that driver age, time of day, driver residency, and driver condition could best describe the characteristics of WWD crashes.

In another study, Fitzsimmons *et al.* (*2019*) employed an ordinary logistic model, using 11 years (2005–2015) of crash data to characterize WWD crashes that occurred on a Kansas divided highway. The authors identified factors such as driving under the influence (DUI), lighting conditions, driver age, and the usage of the safety equipment as the contributing factors to WWD crashes. Taking advantage of the random-parameters ordered probit model, Jalayer *et al.* (Jalayer et al., 2018) revealed that driver age, driver condition, roadway surface condition, and lighting condition are significantly associated with the injury severity of the WWD crash. Pour-Rouholamin and Zhou also found similar results using the ordered logit model, generalized ordered logit model, and partial proportional odds model (*Pour-Rouholamin and Zhou, 2016b*). In another study, Das *et al.* (*Das et al., 2018*) used the Eclat algorithm to analyze WWD crashes in Louisiana. The results showed that head-on collisions, male drivers, and off-peak hour are over-represented in fatal WWD crashes.

Ponnaluri *et al.* (*2016*) conducted a study in Florida to explore significant factors associated with WWD crashes and fatalities. Results of the survey questionnaire and binomial logistic regression model revealed that driver age, driver condition, lighting condition, facility type, license state, driver seatbelt use, and the number of vehicles involved in the crash are significantly related to fatal WWD crashes. Lathrop *et al.* (*Lathrop and Nolte, 2009*) analyzed WWD fatal crashes in New Mexico between 1990 and 2004. In order to differentiate WWD fatal crashes and non-WWD fatal crashes on freeways, Fisher's exact test was used for categorical variables, along with the Wilcoxon rank-sum test for continuous variables. The results indicated that darkness, intoxicated drivers, older drivers, male drivers, non-Hispanic, and Native Americans are more likely to be involved in WWD fatal crashes.

Table 2.1 A SUMMARY OF WWD CRASH CONTRIBUTING FACTORS

Federal and State Reports				
State	**Method**	**Study Year**	**Roadway Type**	**Contributing Factors**
Nationwide *(NTSB, 2012)*	Descriptive statistics	2004–2009	Entrance/exit ramps and controlled-access highways	Drunk driver, driving while intoxicated or impaired, older driver (70 or more), driver license statuses, 6:00 p.m.–6:00 a.m.
AL (*Zhou et al., 2017a; Zhou et al., 2017b*)	Haddon matrices, logistic regression model	2009–2013	Freeway	25–34 years old, older driver, male driver, DUI driver, passenger car, corner radius more than 80 ft
	Haddon matrices, logistic regression model	2009–2013	Divided highway	Older driver, male driver, DUI driver, passenger car, darkness
FL (*Kittelson & Associates, 2015*)	Descriptive statistics	2009–2013	Freeway	Month (January through April, June, and July) weekend, head-on crash, impaired drivers, darkness, younger drivers
TX (*Finely et al., 2014*)	Descriptive statistics	2007–2011	Freeway	7:00 p.m.–12:00 p.m., younger driver (16–24 years), male driver, impaired driver
IA (*Savolainen et al., 2018*)	Descriptive statistics	2008–2017	All roadways	Interstate highway, urban area, dark condition, younger driver, older driver, male driver, impaired driver, driving alone
IL (*Zhou et al., 2012*)	Causal tables, Haddon matrix, significant test	2004–2009	Freeway	Alcohol impairment, driver age group, driver gender, driver physical condition, driver skills/experience/knowledge, time of day, interchange type, area type
NC (*Braam, 2006*)	Descriptive statistics	2000–2005	Freeway	Younger driver, older driver, alcohol involvement, interstate route, rural area, midnight–5:59 a.m., month (February and June), two-quadrant parclo interchange, full diamond interchanges
CA (*Copelan, 1989*)	Descriptive statistics	1983–1987	Freeway	Darkness, intoxicated driver, time of the day, urban area, interchanges with short sight distance, interchange types, ramps types, five-legged intersections near the exit ramp
Journal Article				

Author	**Method**	**Study Year**	**Roadway Type**	**Contributing Factors**
Kemel (*2015*)	Logistic regression model	2008–2012	Divided road	Nighttime hours, non-freeway roads, older drivers, impaired drivers, older vehicles, passenger cars
Pour-Rouholamin *and Zhou* (*2016a*)	Firth's penalized-likelihood logistic regression	2009–2013	Interstate highway	Driver age, time of day, driver condition, and driver residency
Fitzsimmons *et al.* (*2019*)	Ordinary logistic model	2005–2015	Divided highway	DUI driver, lighting condition, 55 years and older, use old safety equipment
Jalayer *et al.* (*2018*)	Random-parameters ordered probit model	2009–2013 for AL; 2004–2013 for IL	Controlled-access highway	Driver age, driver condition, roadway surface condition, lighting condition
Pour-Rouholamin and Zhou (*2016b*)	Ordered logit, generalized ordered logit, partial proportional odds	2009–2013 for AL; 2004–2013 for IL	Controlled-access highway	Driver age, condition, seatbelt use, time of day, airbag deployment, type of setting, surface condition, lighting condition, type of crash
Das *et al.* (*2018*)	Data mining (“Eclat”) algorithm	2010–2014	All road types	Head-on collision, male drivers, off-peak hours
Ponnaluri (*2016*)	A binomial logistic regression model	2003–2010	Freeway and arterial	Driver age, driver condition, lighting condition, driver seatbelt use, license state, facility type, number of vehicles involved in the crash
Lathrop *et al.* (*2009*)	Chi-square, Fisher’s extract test, Wilcoxon rank-sum tests, *t*-tests	1990–2004	Interstate highway	Darkness, intoxicated drivers, older drivers, male drivers, passenger cars, November, non-Hispanic and Native Americans

2.3 Countermeasures for Wrong-Way Driving

2.3.1 Current countermeasures implemented to deter wrong-way driving

Practitioners and researchers have proposed, developed, and tested countermeasures focused on reducing the number and severity of WWD crashes. The Manual on Uniform Traffic Control Devices (MUTCD) provides states and agencies with the basic standards regarding deterring the WW. According to the MUTCD, "DO NOT ENTER" (DNE) and "WRONG WAY" (WW) signs are recommended for multi-lane roadways (*MUTCD, 2009*). The standard DNE sign is square (36-inch × 36-inch) with white background, a solid red central disc with white lettering, and a board horizontal white line. It is used in locations where traffic is prohibited from entering a restricted roadway. The standard WW sign is a rectangle (42-inch × 30-inch) with a red background, white border, and white lettering. As a supplement to the DNE sign, it is implemented on the exit ramp or the one-way roadway that does not physically discourage or prevent wrong-way entry. In order to control WW movements at ramp terminals, as shown in **Figure 2.1**, at least ONE WAY sign for each direction, at least one DNE sign, and at least one WW sign are required to be placed by MUTCD (*MUTCD, 2009*). Additionally, the double solid yellow lines used as a center line for two-lane paved crossroads and lane used arrows are recommended to be placed by MUTCD. The additional ONE WAY signs, WW signs, and wrong-way arrow pavement markings may be used to supplement the signs and pavement markings (*MUTCD, 2009).*

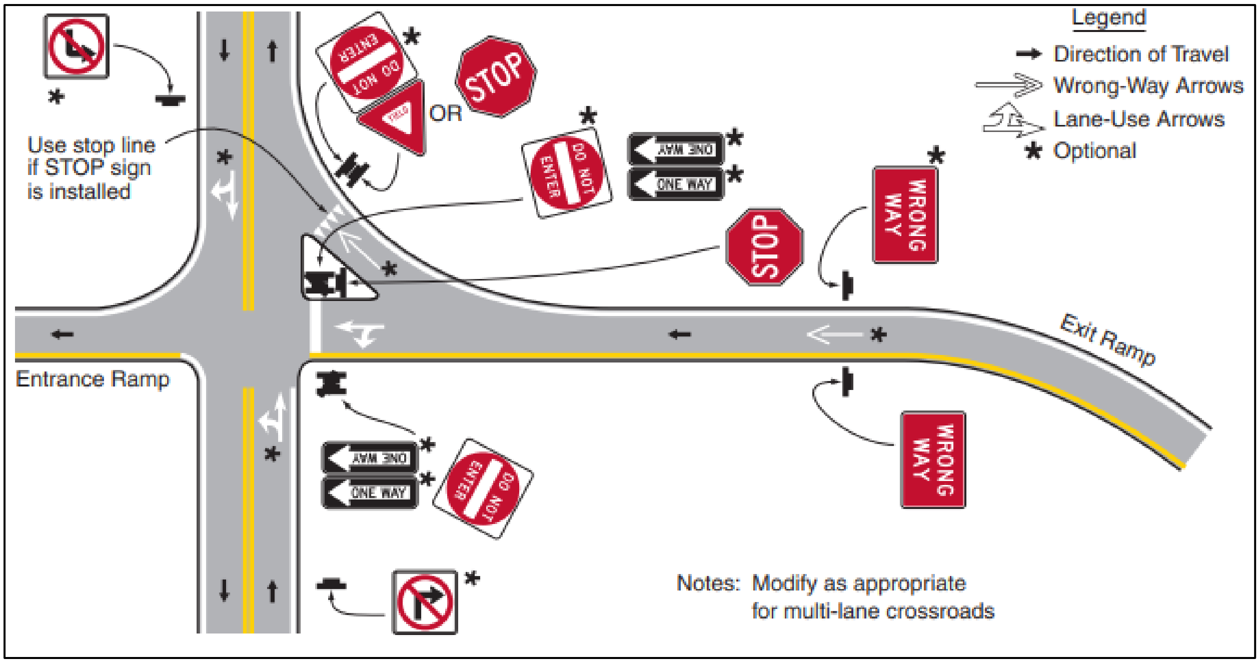


Figure 2.1. MUTCD's Example of Application of Regulatory Signing and Pavement at an Exit Ramp Termination to Deter Wrong-Way Entry

Table 2.2 lists the existing WWD guidelines developed by each state; except for the MUTCD, which is commonly adopted for each state, 11 states have developed additional guidelines regarding countermeasures implementation for deterring WWD.

Table 2.2 Existing State WWD Guidelines

Year	State	Primary Content
2014	Illinois	1. Provided guidelines for signs (DNE sign, WW sign, ONE WAY sign, KEEP RIGHT sign, and turn prohibition sign), pavement markings (in-lane arrows, longitudinal lines, stop lines, and enhanced delineation), and traffic signals 2. Provided design guidelines of the geometric element (exit/entrance ramps, frontage road, raised median, channelizing island, corner radius, and sight distance) 3. Provide design guidelines by using advanced technologies 4. Provide guidelines on enforcement and education (*Zhou and Pouholamin, 2014*)
2015	Florida	The standard for signing and pavement marking at exit ramp intersections are described as follows: 1. Include MUTCD "optional" signs: (second DNE sign, second WW sign, ONE WAY sign) 2. Include NO RIGHT TURN and NO LEFT TURN signs 3. Use 3.5 x 2.5 ft. WRONG WAY signs with 4 ft. mounted height. Apply the retroreflective strip on sign supports 4. Include two to four dotted guideline striping for left turns 5. Include retroreflective yellow paint on-ramp median nose where applicable 6. Include a straight arrow and route Interstate shield pavement marking in left-turn lanes 7. Include a straight arrow and ONLY pavement message (*FDOT, 2015; FDOT, 2019*)

2015	Arizona	1. Use DNE sign, and WW sign assemble on the same post 2. Use large-sized signs: DNE 48 x 48 in., WW 48 x 36 in. 3. The minimum mounting height is 3 ft. 4. Strips of red retroreflective sheeting may optionally be placed on the signpost (*ADOT, 2015*)
2015	Connecticut	The following guidelines were used to improve the static signing and pavement markings at the interchange ramps: 1. Mount larger-sized signs at exit ramps (48-in. DNE signs, 42 x 24 in. WW signs) 2. Low-mounted WW and DNE signs (5 ft., consideration of snow) 3. Applied red reflective delineator strips on the signpost 4. 24-in. wide stop bar applied 5. As for the locations with an adjacent on/off ramps: (a) Applied the pavement marking extension lines at signalized locations (b) Double yellow centerline between the ramps (*Athey Creek Consultants, 2016*)
2015	Wisconsin	The basic requirements should follow MUTCD, additionally: 1. The following strategies may be used at freeway ramp locations that have exhibited problems with WW drivers entering the freeway: (a) Larger-sized the DNE and WW signs (b) Stop bar and type-4 pavement arrows (c) Dotted pavement markings line extensions through the intersection 2. The following strategies are optional and shall only be used at side-by-side ramp locations that exhibit problems with WW drivers entering the freeway: (a) Additional WW sign mounted below the DNE sign at 3-ft. mounting height (b) Reflective strips on WW and DNE signpost (c) A freeway entrance sign (d) Dynamic (flashing) WW signs (*WisDOT, 2015*)
2016	Ohio	Ohio DOT created a drawing of partial cloverleaf interchanges and diamond interchanges with single-lane exits to improve signs and pavement markings at ramps. These drawings became statewide standards in 2016: 1. Two WW signs assembled on the same post with a low-mounted height (3 ft.) 2. Red reflective tape shall be added to the STOP sign, DNE sign, and WW sign 3. Include pavement marking extension line to guide drivers onto the right way 4. Include dual-directional route marker signs at the end of ramps 5. Include a yellow-painted island between the entrance and exit ramp 6. Additional signs followed MUTCD minimum requirements The DNE sign may be angled 45 degrees toward the left turning vehicle (*Ohio DOT, 2016*)
2017	Michigan	1. For freeway ramps, the mounting height of DNE and WW signs shall be 4 ft. 2. Red reflective sheeting shall apply to the signposts. WW and DNE signs should be turned around 20 degrees from the crossroad to face the protentional WW drivers (*Michigan DOT, 2011*)
2017	North Carolina	1. List tools used on signs to deter WWD (low mounting height, reflective strips, dynamic signs, larger-sized signs, turn prohibition signs, etc.) 2. List tools used on markings to deter WWD (WW pavement marking arrows, lane extensions, stop line, delineate median, etc.) 3. List tools used on geometric design to deter WWD (channelizing island, median, corner radius, median barrier, roundabout, lighting) (UNC Highway Safety Research Center, 2017)
2018	Oregon	1. Additional guidance regarding low mounted installations for WW entrance signing on the interstate freeways 2. The standard for low-mounted installations (*Oregon DOT, 2018*)

2019	California	1. The DNE (R5-1) sign and WW (R5-1a) sign shall be used at the exit end of a one-way road or ramp to inform motorists that an entrance thereto is prohibited. 2. At intersections where the left-turn lane treatment results in channelized offset left-turn lanes (e.g., a parallel or tapered left-turn lane between two medians), the size of the DNE (R5-1) sign or WW (R5-1a) sign, if used, should be of the next higher roadway classification, to reduce the potential for WW maneuvers by road users turning left from a stop-controlled, intersecting minor roadway. 3. Where there are no parked cars, pedestrian activity, or other obstructions such as snow or vegetation, and if an engineering study indicates that a lower mounting height would address WW movements on freeway or expressway exit ramps, a DNE sign(s) and/or a WW sign(s) that is located along the exit ramp facing a road user who is traveling in the wrong direction may be installed at a minimum mounting height of 3 ft., measured vertically from the bottom of the sign to the elevation of the near edge of the pavement. 4. A stop beacon shall be used only to supplement a STOP sign, DNE sign, or WW sign (*Caltrans, 2019*).
2019	Washington	Three categories of countermeasures to discourage WWD: 1. Signing and Delineation DNE and WW signs, ONE WAY signs, turn restriction signs, red-backed raised pavements markers (RPMs), directional pavement arrows, yellow edge line on left and white edge line on the right side of exit ramps, pavement marking extension lines. 2. Intelligent Transportation Systems (ITS) 3. Geometric Design Separate on-and off-ramp terminals, reduced off-ramp terminal throat width, increased on-ramp throat width, intersection balance, visibility, angular corners on the left of off-ramps terminals (*WSDOT, 2019*).

According to **Table 2.2**, common guidelines for additional WW-related countermeasures are summarized below:

Signage

- *Size:* Oversized signs (DNE sign, WW sign, or both) are required to be implemented on the roadside to ensure better visibility. The 48 x 48-in. DNE signs were commonly included in guidelines for those 11 state DOTs. However, there is no uniform size for the WW sign.
- *Mounting height:* Low-mounted signs (DNE sign, WW sign, or both) were recommended by 10 out of 11 state DOTs. The height of the sign may be different from state to state, which varies from 3 to 5 ft. For example, the 5 ft. DNE sign and WW sign were contained in Connecticut DOT’s (CTDOT) guidelines due to the snow accumulation in winter (*Athey Creek Consultants, 2016*).

- *Retroreflective tape:* Six (6) out of 11 state DOTs recommended applying the retroreflective tape on the signpost. Four states set this guideline as standard, while two states regarded it as optional. However, there is no uniform requirement on retroreflective material among 11 states.
- *Assembled sign:* Three state DOTs included the assembled sign in their guideline; however, different states will assemble different signs on the same post. For example, the ADOT put DNE sign and WW sign on the same post (*ADOT, 2015*), whereas the Ohio DOT assembled two WW signs on the same post (*Ohio DOT, 2016*).

Except for those common features appearing in the state guidelines, other features such as sign angles, dynamic signs, or additional signs were also mentioned by several states.

Pavement Markings

- *Pavement marking extension line:* Six out of 11 state DOTs were encouraged to apply pavement marking extension lines between ramps and crossroads to guide drivers in the right direction. However, there are no uniform requirements on the line type, the number of lines, or applied conditions among the six states. For example, the FDOT required two (2) or four (4) dotted guidelines striping at the intersections between exit ramps and crossroads (*FDOT, 2015; FDOT, 2019*). However, in Connecticut, the extension line is only applied at the signalized intersections with adjacent on and exit ramps (*Athey Creek Consultants, 2016*).
- *Lane use arrows:* Several states applied the lane use arrows on the ramps. However, different states had different requirements for lane use arrows.
- *Route shield signs:* Except for those common features that appeared in the state guidelines, other features such as route shield signs and stop bars were also

recommended by several states. However, there is no guideline on the application of route shield signs

2.3.2 Evaluation of WWD countermeasure

Although many agencies applied different kinds of WWD countermeasures, the evaluation of WWD countermeasures can be difficult due to the randomness of WWD crashes and the lack of before-and-after data. The survey studies conducted by Pour-Rouholamin and Zhou gave an overview of the effectiveness and level of acceptance for over ten engineering countermeasures, including WW-related signage, pavement markings, geometric modification, and ITS technologies (*Pour-Rouholamin et al., 2014*). According to the ENTERPRISE Transportation Pooled Fund TPF5 Study (*Athey Creek Consultants, 2016*), the purposes of these countermeasures can be grouped as preventative countermeasures and reactive countermeasures. The preventative countermeasures refer to the countermeasure which can prevent the vehicle from entering the WW. And the reactive countermeasures are those countermeasures that can warn WW drivers that they are going the WW.

Table 2.3 summarizes the evaluation results of the recently implemented traditional and advanced WWD countermeasures in these two categories.

Table 2.3 Evaluation Results of the Recently Implemented Traditional and Advanced WWD Countermeasures

<table>
<tr><td colspan="6">Preventative WWD Countermeasure</td></tr>
<tr><td>State</td><td>TCDs</td><td>Data</td><td>Evaluation Method</td><td>Effectiveness</td><td>Reference</td></tr>
<tr><td>CA</td><td>Lower-mounted Signs
Specific requirements for sign installation</td><td>WWD incident</td><td>Before-and-after study</td><td>90% reduction in WWD incident frequency</td><td>*Leduc, 2008*</td></tr>
<tr><td>GA</td><td>Countermeasure combo (trailblazers, low mounted WW signs, stop bar, yellow ceramic buttons</td><td>WWD incident</td><td>Before-and-after study</td><td>97% reduction in WWD incident frequency</td><td>*Campbell and Middlebrooks, 1988*</td></tr>
<tr><td>TX</td><td>Directional arrows</td><td>WWD incident</td><td>Before-and-after study</td><td>90% reduction in WWD incident frequency</td><td>*Chrysler and Schrock, 2005*</td></tr>
<tr><td>TX</td><td>Sign and Pavement marking improvement (repainting, striping additions, and WW sign on signal mast arms)</td><td>WWD incident</td><td>Before-and-after study</td><td>The number of WWD incidents decreased significantly after improvements</td><td>*Ouyang, 2013*</td></tr>
<tr><td>FL</td><td>Newly-develop signing and pavement marking (S&PM) standards</td><td>Survey data</td><td>survey</td><td>Very positive effectiveness on arterials</td><td>*Lin et al., 2018*</td></tr>
<tr><td>AL</td><td>Pavement markings improvement (repainting, striping additions, and stop bar)</td><td>WWD incident</td><td>Before-and-after study</td><td>63% reduction in the number of WWD incidents</td><td>*Chang et al., 2019*</td></tr>
<tr><td colspan="6">Reactive WWD Countermeasure</td></tr>
<tr><td>State</td><td>TCDs</td><td>Data</td><td>Evaluation Method</td><td>Effectiveness</td><td>Reference</td></tr>
<tr><td>AL</td><td>WW sign combined with WW arrow</td><td>WWD incident</td><td>Before-and-after study</td><td>More than 90% come back rate for WWD incidents</td><td>*Chang et al., 2019*</td></tr>
</table>

AL	Directional rumble strips	WWD incident	Field data	Improve self-correction rates and reduce WWD incidents while offering good visual attentiveness and applicability	*Yang et al., 2018*
FL	Rectangular flashing beacon (RFB) WW Sign	911 calls and citation	Before-and-after study	48.5% reduction in 911 calls, 52.9% reduction WWD citations, and 44.1% reduction in combined WWD 911 calls and citations	*Al-Deek et al., 2019*
		WWD incident	Before-and-after study	77% reduction in WWD incident frequency	*Lin et al., 2017*
FL	LED WW sign	WWD incident WWD crash Survey data	Field testing Crash/incident data analyzing survey driving simulator	14% reduction in WWD incident frequency	*Lin et al., 2018*
	Detection-triggered LED lights around WW signs			Effective for mitigating WWD	
	Detection-triggered blank-out signs that flash “WW”			Effective for mitigating WWD	
	Wigwag flashing beacons			Effective for mitigating WWD	
	Delineator along exit -ramps			The least effective countermeasures	
FL	Red Rectangular Rapid Flash Beacons (RRFBs)	WWD incident	Before-and-after study	60% – 85% self-correction rates	*Ozkul and Lin, 2017*

HI	Red Retroreflective Raised Pavement Markings (RRPMs)	WWD incident	Field observation/Before-and-after study	RRPM helped drivers realize when they were going in the wrong direction. Replacing supplemental RRPMs with supplemental arrows always improved the rates of self-correct responses	*Miles et al., 2014*

The evaluation methods conducted by different agencies mainly focused on before-and-after studies of WWD crashes or incidents, driving simulation, surveys, field tests, and investigation of agency records. For the preventative WWD countermeasures, five states have made the improvement or enhancement of traditional "DO NOT ENTER" (DNE) or WW signs and pavement markings for deterring WWD incidents, which showed a significant reduction in WWD incidents up to 97% (Leduc, 2008; Lin et al., 2018; Ouyang, 2013; Chang et al., 2019; Campbell and Middlebrooks, 1988). In addition, the LED border for DNE and WW signs and directional arrows on exit ramps were proved to be effective in deterring WWD incidents (Lin et al., 2018). Last, the raised/vertical longitudinal channelizing devices and geometric modifications for exit-ramp terminals can prevent WWD incidents (Ouyang, 2013).

As for reactive WWD countermeasures, transportation agencies tended to apply more advanced countermeasures, such as RFBs, which was found to reduce WWD incident, 911 calls, WWD citations, as well as the combined 911 calls and citations efficiently (Kayes et al., 2019; Al-Deek et al., 2019 & Lin et al., 2018). Other reactive WWD countermeasures like red RRFBs, wigwag flashing beacons, LED WW signs, detection-triggered blank-out signs that flash "WW" and detection-triggered LED lights around WW signs have been proved to be significantly effective for improving self-correction rates. The IIRPM is not as effective as other kinds of advanced countermeasures (Lin et al., 2018), which can be considered a supplemental countermeasure. The traditional reactive countermeasures such as a WW sign combined with a WW arrow and directional rumble strips (DRS) can also effectively reduce WWD incidents (Chang et al., 2019). Compared with the WWD countermeasures mentioned above, the delineators along exit ramps were considered the least-effective countermeasures (Lin et al., 2018).

2.4 Current Driving Simulator-Based Studies

Within the last decade, vehicle driving simulators have been accepted and adopted to conduct transportation research. Although only a few simulator studies were conducted to evaluate traffic control devices to prevent WWD, especially for drunk drivers, simulators have been widely used to evaluate drivers' reactions to the various roadway and roadside treatments. For instance, Yan et al. used a driving simulator to measure the effect of a "SIGNAL AHEAD" pavement marking countermeasure with a varied speed limit, treatment type, and yellow phase onset distance. T-tests, logistic models, and Chi-square tests were used to analyze the data. The results show that there is not a significant difference between intersections with and without the pavement markings. The pavement markings reduced the uncertainty region from 17 meters to 10 meters for the 30 mph intersections and from 31 meters to 16 meters for the 45 mph intersections, and the countermeasure reduced the number of red-light running incidents by 65%. Based on the results, a field study of pavement marking was developed (*Yan and Guo,* 2007). In another study, the effectiveness of steady burn warning lights was evaluated through driving simulator experiments and field tests. The simulator scenarios were created to mimic a work zone that had drums with and without steady burn warning lights. A comparison of the number of crashes within the experiment showed that the sites with warning lights had significantly more crashes than those without (*McAvoy, et al., 2006*).

A report by Robinson et al. discussed a driving simulator study as part of the evaluation pf a complex at-grade rail crossing project in Ottawa, Canada. This scenario mimicked the at-grade rail crossing with a 32-degree skew angle, the widening of the roadway, an at-grade rail crossing, and a transitway extension at a 30-meter offset from the rail crossing. The simulator measured the velocity, stopping accuracy, the probability of drivers stopping when the light changes and they are in the dilemma zone, the maneuver type used when a truck was stalled beyond the crossing, along with eye movements using a sophisticated eye-tracking camera. Forty-eight participants of varying ages completed the study. Overall, the results helped with the final development and optimization of the placement of the guidance and warning signs and signals (*Robinson et al., 2007*).

A study by Abbas et al. investigated driver perception of the use of a dynamic all-red interval extension in urban and suburban settings. Other factors considered include the presence of cross traffic, the extension being on the major or minor street, and the red-light runner being followed closely by another vehicle. The results showed that the urban/suburban setting was the only significant factor, and in urban areas, drivers were less likely to notice an extension and perceive red-light running as more dangerous (*Abbas et al., 2006*).

In a study by Noyce and Knodler, a driving simulator was used to evaluate drivers' comprehension of flashing yellow arrows that were retrofitted to three section and five-section cluster signals. A total of fifty-six participants completed the study. Participants were presented with 12 intersections with different signal setups. The study found that there was not a significant difference in the driver's ability to comprehend the three-section signal, but the driver's comprehension was significantly lower for the inclusion of the flashing yellow arrow in the five-section cluster signal. Additionally, qualitative measures showed that 28% of drivers preferred the flashing yellow arrow in the middle section compared to 9% who preferred I in the bottom section (*Noyce and Knodler, 2014*).

2.5 Current Research Gap

The current literature review shows that the WWD crash trends are outdated and need to be updated to recent years. Additionally, most past studies and state reports contribute to crash-prone factor identification for WWD crashes based on descriptive statistics and regression models using limited WWD crash data from several states. The clusters of contributing factors associated with WWD fatal crashes on freeways across the nation haven't been identified.

As for the evaluation of traffic control devices, to the best of knowledge, few studies aim to evaluate the effectiveness WWD related countermeasures for intoxicated drivers. Past studies have already tested several countermeasures using the driving simulator. However, no driving simulator study had been conducted to test the WWD countermeasures with Caltrans specifications such as enlarged size and low mounting height. Considering several countermeasures that currently emerge and are adopted by Alabama and Caltrans, it is also necessary to evaluate the effectiveness of these countermeasures and figure out a potential combination that has better communication with the drunk drivers.

Chapter 3 Facts of WWD and Alcohol Related WWD Crashes

Considering the existing gaps found in the literature review, the WWD crash analysis was conducted to identify the current WWD crash trends and contributing factors. This chapter provides specifics regarding WWD fatal crash data collection and methods used for data analysis. Additionally, detailed analysis results are provided, which will aid in the laboratory testing design in the following chapter.

3.1 WWD Fatal Crashes Data Collection

The Fatality Analysis Reporting System (FARS) database is a nationwide database for fatal crashes maintained by the National Highway Traffic Safety Administration (NHTSA). Crashes that involve motor vehicles on a public traffic way and cause at least one death of a driver, occupants, or non-occupants within 30 days will be contained in the FARS data set (*FARS, 2019*). These crash data are first gathered on the state level from multiple sources such as police crash reports, vehicle records, and emergency medical service reports. After combining this information into the same format, the data are transferred from each state to NHTSA and fulfill the FARS database. The FARS database contains more than 140 FARS data variables that record crash, vehicle, driver, passenger, and pedestrian information based on police crash reports, state vehicle registration files, state driver licensing files, etc. (*NHTSA, 2021*). For the purpose of this study, the WWD-related data were extracted for a 17-year period (2004–2020) from the FARS database. The main procedures used to extract WWD fatal crashes followed a similar protocol as described in the study conducted by Baratian-Ghorghi *et al.* (*2014*). Since the FARS database updates frequently, variable names or classifications for the variable may change over the years. The main procedure still remains the same. In this study, a WWD fatal crash on freeways is defined by the following criteria:

1) Roadway Function Class
    a. Before 2014: Includes categories named Rural Principal Arterial Interstate, Rural Principal Arterial Other, Urban Principal Arterial Interstate, Urban Principal Arterial Other Freeways or Expressway, and Urban Principal Arterial.
    b. After 2014: So-called Road Function System: includes categories named Interstate, Principal Arterial Other Freeways and Expressways, and Principal Arterial.
2) Trafficway Description
    a. Before 2009: Includes categories named Divided Highway Median Strip (Without Traffic Barrier), Divided Highway Median Strip (With Traffic Barrier), One-Way Trafficway, and Entrance/Exit Ramp.
    b. After 2009: Includes categories named Two-Way Divided Unprotected Median, Two-Way Divided Positive Median Barrier, One-Way Trafficway, and Entrance/Exit Ramp.
3) Sequence of Events
    a. Before 2009: Excludes category named Cross Median/Centerline;
    b. After 2009: Excludes categories named Cross Median, and Cross Centerline.
4) Violations Charged: Inclusive categories named Driving Wrong Way on One-Way Road, and Driving on Left/Wrong Side of Road Generally.
5) Driver Related Factors: Inclusive categories named Driving Wrong Way on One-Way Trafficway and Driving on the Wrong Side of Road.

In addition, non-WWD fatal crashes were also extracted from the FARS data set for the purposes of comparison. This data set applied the same filtering criteria for the roadway type to be consistent with WWD fatal crash data sets. Information for the at-fault driver for each crash will be regarded as driver information for further analysis. Violation charged and driver-related factors determined driver fault or responsibility for the crash. Typically, the at-fault driver can be identified if one or more contributing factors or violations existed, whereas other drivers did not have any violations presented. This study follows the same ideas to identify the at-fault driver as described in one study conducted by the National Highway Traffic Safety Administration (NHTSA) (*NHTSA, 2009*).

The FARS dataset did not contain a specific variable to point out whether the fatal crash was alcohol-related. As a result, additional variable which aims to identify intoxicated driver was created based on other variables, such as alcohol test results, alcohol involvement, driver-related factors, and driver violation charged.

3.2 Methodology

3.2.1 Descriptive analysis

The descriptive analysis was conducted first in this study to update crash trends and distributions for WWD fatal crashes in recent years. The number of WWD fatal crashes and non-WWD fatal crashes are calculated for 17-year period (2004–2020). Additionally, the descriptive analysis of alcohol-related WWD fatal crashes regarding year, BrAC level, age, and gender are also conducted.

3.2.2 Statistical analysis

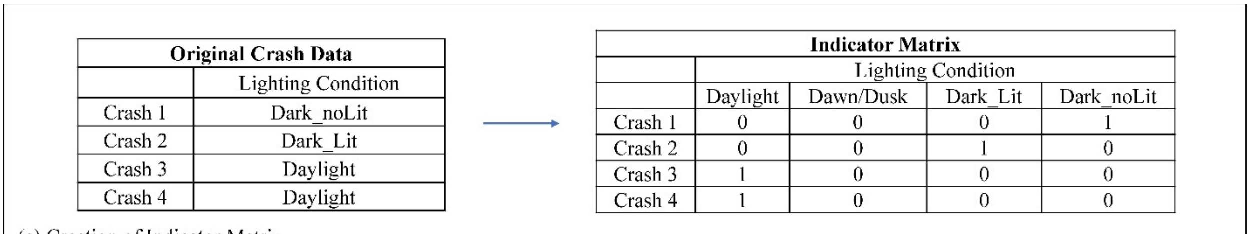
As a second step, the 17-year data set was analyzed using binomial logistic regression procedures contained in *Rstudio*. The binomial logistic regression model was used to determine if WWD fatal crashes differ from other types of fatal crashes; crash type (1 = WWD fatal crashes; 0 = other types of fatal crashes) was used as the dependent variables. To get meaningful results, 20 key variables were selected for further analysis based on the previous literature review. Most of these variables are categorical variables. Some continuous variables were regrouped and transformed into quantitative variables; for instance, driver age was divided into six categories: 24 or less years old; 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, and 65 or more years old. The crash data with missing values will be deleted from the data set. The final data set contains 4,203 fatal WWD crashes and 73,027 non-WWD fatal crashes over 17 years in the United States. Finally, the odds ratio was computed to identify how likely a certain variable would lead to a WWD fatal crash.

3.2.3 Multiple correspondence analysis (MCA)

MCA has been used to investigate the correlation between multiple variables and explore patterns among variables through enhanced exploratory data visualization. Unlike the regression methods, however, it can examine the association between a set of variables (potential contributing factors) and crash outcomes. The MCA method summarizes the relationship between individuals or variable categories and creates similar groups from the data set. Typically, the similarity is determined by distance. The longer the distance, the less similarity between two individual or variable categories. The goal of the MCA method is to map all variable categories of crash data on an X–Y plane through (i) matrix construction; and (ii) distance computation. The following part summarizes the basic principle of matrix construction and distance computation. More detailed concepts and computations of MCA can be found in various books and literature (*Baireddy, Zhou and Jalayer, 2018; Jalayer, Pour-Rouholamin, and Zhou, 2018; Das et al., 2018, Roux and Rouanet, 2010*).

Matrix Construction

The actual MCA computations are conducted on the matrix, which is derived from the basic table of the crash data set. The indicator matrix is the most classical and standard matrix that has been widely adopted in previous studies. In an indicator matrix **Z**, each row represents an individual *i*. As for the column, the indicator matrix (**Z)** expands the original Q variables to K categories with the binary coding of the categories. **Figure 3.1(a)** shows an example of the creation of the indicator matrix. However, due to the scale of the data set, the representation quality on a given dimension is poor, which means less data information was obtained in a particular plane (*Husson et al., 2017*). As a result, the Burt matrix can address this issue and enhance the quality of the analysis. The Burt matrix can be defined as $\mathbf{C}=\mathbf{Z}^{T}\mathbf{Z}$, and the process to create the Burt matrix is illustrated in **Figure 3.1(b)**. The Burt matrix is a square matrix of K×K dimensions and is efficient in terms of data storage (*Husson et al., 2017*). It should be noticed that the representation of categories by using the Burt matrix is similar to the indicator matrix categories, and the percent of data contained, so-called inertia, of each component is increased. Based on a previous study by Nenadić *et al.* (*Nenadić and Greenacre, 2007*), the MCA method based on the Burt matrix with an adjustment of inertia outperformed the indicator matrix due to the fact that the optimal scaling properties of MCA are conserved while raising the percentage of inertia and squared correlations.



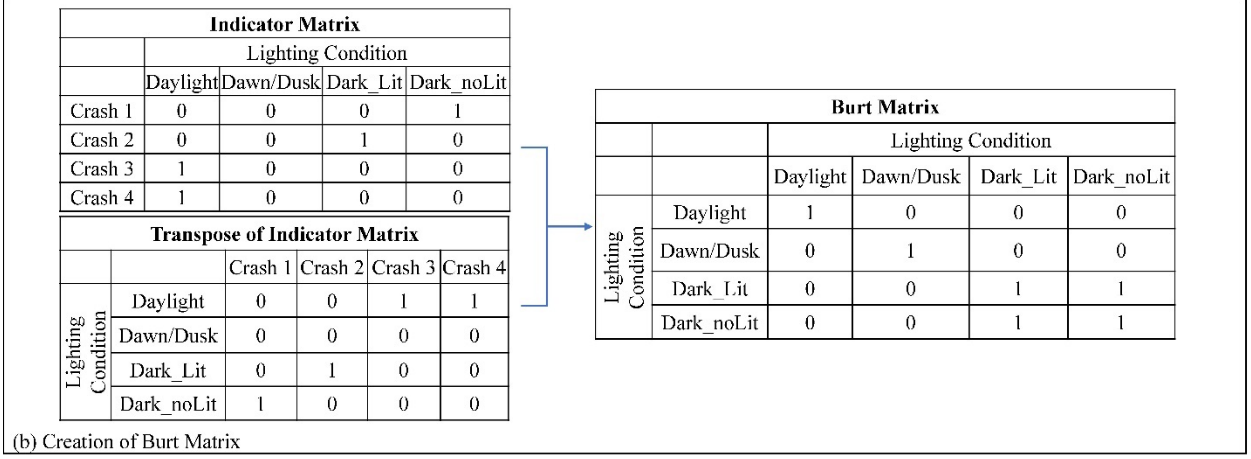
Original Crash Data

	Lighting Condition
Crash 1	Dark_noLit
Crash 2	Dark_Lit
Crash 3	Daylight
Crash 4	Daylight

Indicator Matrix

	Lighting Condition			
	Daylight	Dawn/Dusk	Dark_Lit	Dark_noLit
Crash 1	0	0	0	1
Crash 2	0	0	1	0
Crash 3	1	0	0	0
Crash 4	1	0	0	0

(a) Creation of Indicator Matrix



Indicator Matrix

	Lighting Condition			
	Daylight	Dawn/Dusk	Dark_Lit	Dark_noLit
Crash 1	0	0	0	1
Crash 2	0	0	1	0
Crash 3	1	0	0	0
Crash 4	1	0	0	0

Transpose of Indicator Matrix

		Crash 1	Crash 2	Crash 3	Crash 4
Lighting Condition	Daylight	0	0	1	1
	Dawn/Dusk	0	0	0	0
	Dark_Lit	0	1	0	0
	Dark_noLit	1	0	0	0

Burt Matrix

		Lighting Condition			
		Daylight	Dawn/Dusk	Dark_Lit	Dark_noLit
Lighting Condition	Daylight	1	0	0	0
	Dawn/Dusk	0	1	0	0
	Dark_Lit	0	0	1	1
	Dark_noLit	0	0	1	1

(b) Creation of Burt Matrix

Figure 3.1 Matrix construction

Distance Computation

After creating the Burt matrix, the distance computation can be performed. The basic idea for MCA is to discern the position of the profile points in the multidimensional space. The associations between profile points depend on the distance. Distances between profiles are measured using the chi-square distance (*Greenacre, 2007*). Typically, two points of clouds- individual clouds and category clouds- will be generated by MCA methods. The relative squared distance between individuals and categories can be computed as follows:

The distance between two individuals depends on the chosen categories. For example, if two individuals choose the same category for a variable, then the distance between two individuals will be zero. If two individuals *i* and $i^{'}$ choose different category *k* and *k'*, separately, for the variable *q*, then the part of the squared distance between two individuals due to a single variable can be computed by **Equation 1** (*Baireddy, Zhou and Jalayer, 2018; Jalayer, Pour-Rouholamin, and Zhou, 2018; Das et al., 2018, Roux and Rouanet, 2010*):

$$d_q^2\,(i, i') = \frac{1}{f_k} + \frac{1}{f_{k'}}\,, \tag{1}$$

where f_k and $f_{k'}$ are the relative frequencies of individuals who have chosen these two categories.

When considering all the variables in the data set, the squared distances between two individuals are calculated based on **Equation 2** (*Baireddy, Zhou and Jalayer, 2018; Jalayer, Pour-Rouholamin, and Zhou, 2018; Das et al., 2018, Roux and Rouanet, 2010*):

$$d^2(i, i') = \frac{1}{Q} \sum_{q \in Q} d_q^2\,(i, i')\,, \tag{2}$$

where Q is the number of the variables within the data set.

Geometrically, the distance between an individual point and their average points is called inertia, which is a measure of deviations of the individual to their average (*Greenacre, 2007*). If G denotes the mean point of the individual cloud and M^i is the point of individual i, the squared distance between M^i and G is calculated by **Equation 3** (*Baireddy, Zhou and Jalayer, 2018; Jalayer, Pour-Rouholamin, and Zhou, 2018; Das et al., 2018, Roux and Rouanet, 2010*):

$$(GM^i)^2 = (\frac{1}{Q} \sum_{k \in K_i} \frac{1}{f_k}) - 1, \tag{3}$$

where K_i is the category pattern for Q variables of individual i.

The distances between categories can be computed in a similar way. Suppose K denotes the number of categories in the data set, then the cloud of categories contains K points. If M^k denotes the point of category k then n_k is the number of individuals that select this category.

Consider that the number of individuals who have chosen both categories k and k' denotes as $n_{kk'}$, then the squared distance between M^k and $M^{k'}$ can be computed as **Equation 4** (*Baireddy, Zhou and Jalayer, 2018; Jalayer, Pour-Rouholamin, and Zhou, 2018; Das et al., 2018, Roux and Rouanet, 2010*):

$$(M^k M^{k'})^2 = \frac{n_k + n_{k'} - 2n_{kk'}}{n_k n_{k'}/n}\,, \tag{4}$$

Due to the structure of the Burt matrix, the total inertia for all dimensions will be overestimated. As a result, the percentage of inertia problems can be partly improved by using adjusted inertias, where the positions of each individual or categorical points will be rescaled to better estimate the results. If the inertia λs from a certain dimension satisfies the condition λs ≥ $1/\mathrm{Q}$, then the adjusted inertias should be applied based on **Equation 5** (*Greenacre and Blasius, 2006*):

$$\lambda_s^{adj} = (\frac{Q}{Q-1})^2 \left(\lambda_s - \frac{1}{Q}\right)^2 \tag{5}$$

In this study, the distances between categories were calculated and plotted in the principal dimensional space for identifying clusters of contributing factors. Typically, first two or three principal dimensional spaces will be used for further analysis since the first several dimensions contain most of the categorical information, which is determined by eigenvalues. Different variable categories have different correlations and contributions to different principal dimensional space. To generate more accurate and interpretable results in the selected dimensions, it is necessary to filter out the variable categories that have strong relationships and higher contributions with the selected dimensions. All selected variable categories will be displayed on the factor map with the selected dimensions. The category points that close to each other will generate clusters. The cluster indicates that the likelihood of the occurrence of the crashes will increase when these variable categories happen at the same time.

3.3 Results

3.3.1 Descriptive analysis results

Figure 3.2 shows two trend lines depicting changes in the number of WWD fatal crashes and the number of overall fatal crashes on divided highways. **Figure 3.3** indicates the trends of WWD fatalities and overall facilities caused by fatal crashes on divided highways. An average of 302 WWD fatal crashes happened each year, which caused an average of 409 people to die annually. In other words, the fatality rate (number of people killed per fatal crash) for WWD fatal crashes is 1.36, which is relatively higher than the overall fatality rates (calculated as 1.11) on divided highways. The results provide evidence that WWD crashes are more severe than other types of crashes, which is in accord with the previous literature (*Copelan, 1989; Vaswani, 1973; Cooner et al., 2004a; Cooner et al., 2004b; Simpson, 2013*).

Trends for fatal crashes show that the number of overall fatal crashes decreased from 2005 to 2009 but increased after 2011 to reach the same level as 2005 and reached the peak in 2020. Observing the trends for WWD fatal crashes, it is found that although the number of WWD fatal crashes follows the same trend as total fatal crashes, the overall WWD fatal crashes increased substantially from 2004 to 2020. In addition, no large variability is found when calculating WWD fatal crashes as a percentage of overall fatal crashes on divided highways over the year, with a high of 3.80% in 2020 and a low of 2.47% in 2005. The 17-year scope of this study shows that the number of WWD fatal crashes has not been declining over the years; in fact, the percentage of fatal crashes comprising WWD crashes has increased.

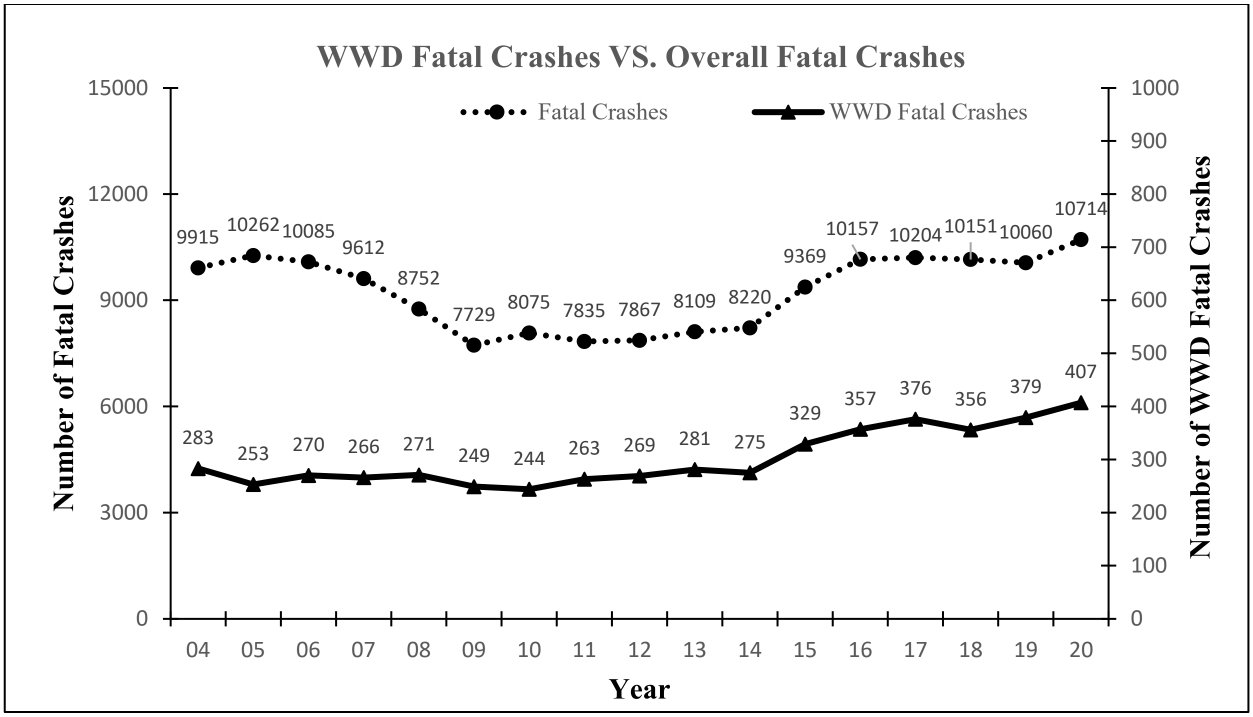


Figure 3.2 Trends for WWD Fatal Crashes and Overall Fatal Crash on Divided Highways

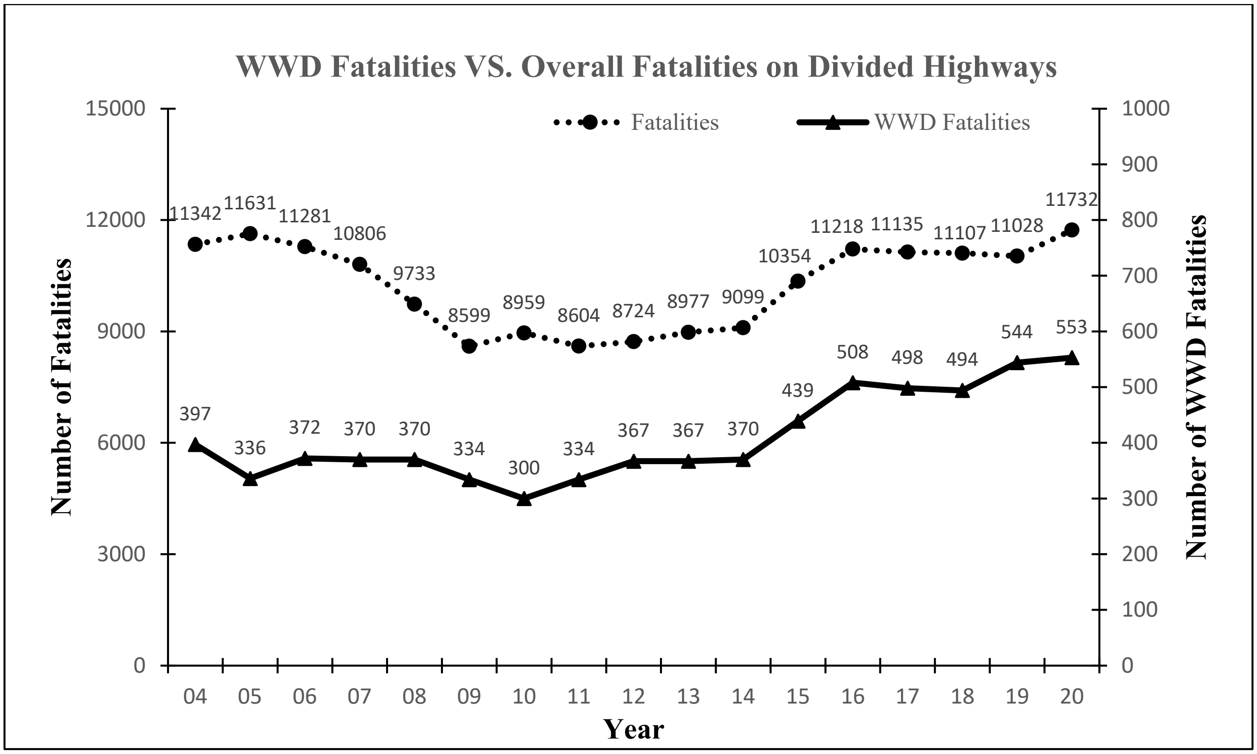


Figure 3.3 Trends for WWD Fatalities and Overall Fatalities on Divided Highways

Table 3.1 Distribution of Average WWD Fatal Crashes on Divided Highways for Each State (2004-2020)

State	Average Frequency	% of Total Fatalities	State	Average Frequency	% of Total Fatalities
TX	46	15%	AK	4	1%
CA	28	9%	MN	4	1%
FL	24	8%	IA	3	1%
MO	12	4%	MA	3	1%
GA	11	4%	KY	3	1%
PA	11	4%	WI	3	1%
TN	10	3%	KS	3	1%
IL	8	3%	UT	3	1%
AZ	8	3%	WV	3	1%
OH	8	3%	OR	2	1%
MS	7	2%	NM	2	1%
AL	7	2%	MT	1	1%
OK	7	2%	ID	1	0.4%
NY	7	2%	RI	1	0.4%
WA	6	2%	WY	1	0.3%
MI	6	2%	DE	1	0.3%
VA	6	2%	SD	1	0.3%
CO	6	2%	HI	1	0.2%
NJ	6	2%	ND	1	0.2%
NC	5	2%	ME	1	0.2%
MD	5	2%	NH	0	0%
LA	5	2%	NE	0	0%
NV	5	2%	VT	0	0%
SC	5	2%	AK	0	0%
IN	4	1%	DC	0	0%
CT	4	1%			

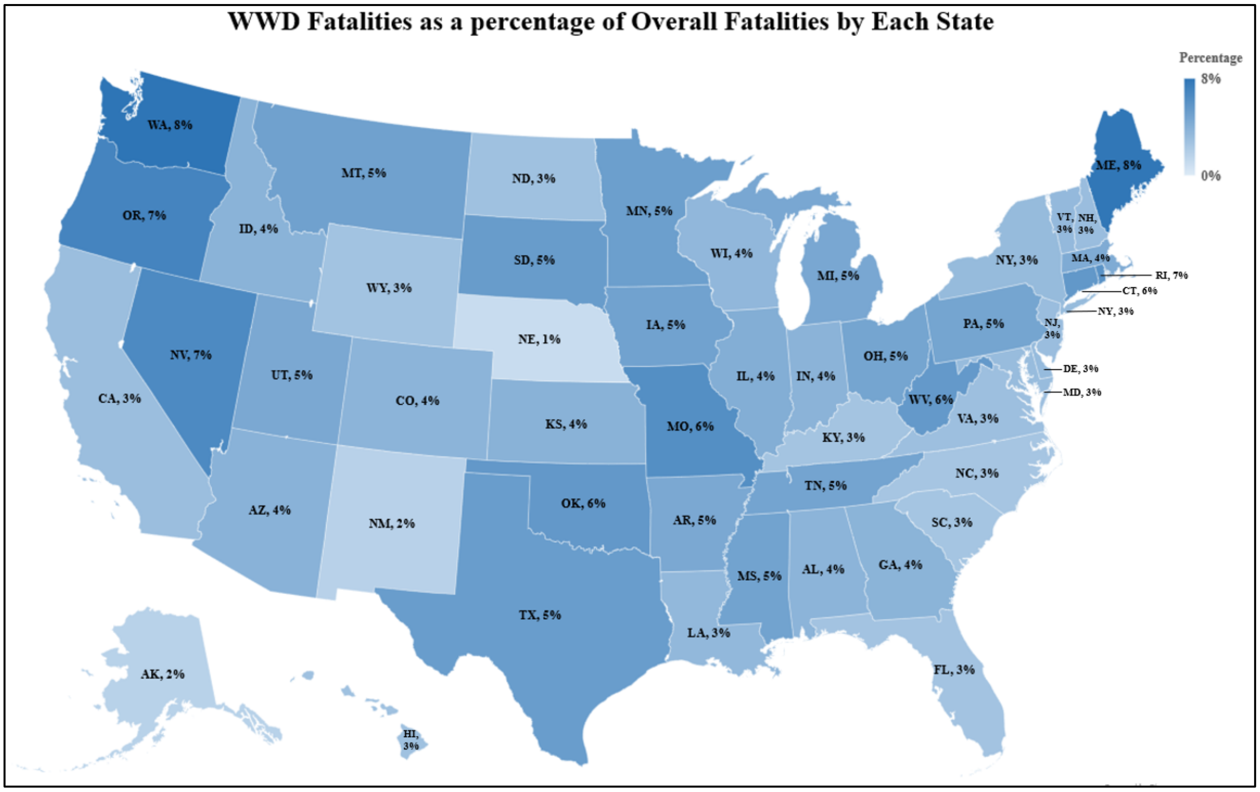


Figure 3.4 Heat Map of WWD Fatalities as a Percentage of Overall Fatalities by Each State

Table 3.1 lists the distribution of average WWD fatal crashes for each state during 17-year period. It can be found that WWD fatal crashes are not equally distributed across the nation. Texas, California, and Florida have the highest number of WWD fatal crashes, with an average of 46, 28, and 24 WWD fatal crashes per year, respectively. These results are consistent with the previous result summarized by Baratian–Ghorghi et al. (*2014*). **Figure 3.4** depicts WWD fatalities as a percentage of overall fatalities on divided highways for each state. According to the figure, the national average is about 4%. Overall, 17 states have a WWD fatality rate higher than the national average, 13 states are about the same as the national average, and 20 are lower than the national average.

As for alcohol-related WWD fatal crashes, **Table 3.2** and **Table 3.3** list the detailed distribution regarding year, age, and sex. A total of 3,172 WWD fatal crashes were found caused by DUI drivers during the 17-years period, which occupies 62% of total WWD fatal crashes. The results indicated that alcohol involvement is a factor that causes WWD fatal crashes, which may have stronger effects than expected. For those alcohol-related WWD fatal crashes, 77% of them (2,442) were found with recorded BrAC levels in the database. Among these WWD fatal crashes with recorded BrAC levels, 32% of them had BrAC levels less than 0.08. About 40% of them had BrAC levels below 0.12 across the nation. When considering drivers' age and gender, as shown in **Table 3.3**, 74% of the alcohol-related WWD fatal crashes are caused by male drivers, while only 26% are caused by female drivers. It should also be found that male drivers, especially those aged less than 45 years old, are predominated in alcohol-related WWD fatal crashes.

Table 3.2 Alcohol Involved WWD Fatal Crashes in 17-Years Period

Year	WWD Fatal Crashes	Alcohol Involved WWD Fatal Crashes	%
2004	283	158	56%
2005	253	152	60%
2006	270	157	58%
2007	266	170	64%
2008	271	157	58%
2009	249	152	61%
2010	244	154	63%
2011	263	174	66%
2012	269	169	63%
2013	281	191	68%
2014	275	190	69%
2015	329	197	60%
2016	357	221	62%
2017	376	222	59%
2018	356	220	62%
2019	379	240	62%
2020	407	248	61%
Average	302	187	62%

Table 3.3 Distribution of Alcohol-Related WWD Fatal Crashes by Age and Gender

	Alcohol-Related WWD Fatal Crashes													
	Male							Female						
Year	**24 or less**	**25-34**	**35-44**	**45-54**	**55-64**	**65 or over**	**NA**	**24 or less**	**25-34**	**35-44**	**45-54**	**55-64**	**65 or over**	**NA**
2004	27	21	35	17	10	8	1	14	7	8	7	0	1	0
2005	39	31	18	21	3	5	0	11	8	8	3	4	2	0
2006	31	37	23	16	6	5	0	11	16	7	5	0	0	0
2007	26	40	22	13	6	3	1	19	22	10	7	0	1	0
2008	24	45	27	12	8	7	0	11	6	9	6	1	1	0
2009	27	44	20	13	9	3	0	10	11	9	4	1	0	0
2010	24	40	23	17	5	3	0	13	17	6	8	4	2	0
2011	27	39	22	21	8	8	0	11	19	7	4	2	2	0
2012	28	35	28	16	10	4	0	20	13	6	4	2	1	0
2013	20	54	23	25	13	9	0	11	22	5	5	2	1	0
2014	24	51	29	14	12	7	0	15	18	6	8	4	2	0
2015	35	50	28	18	9	4	0	19	13	9	12	4	2	0
2016	36	60	28	16	11	11	0	13	24	10	5	6	1	0
2017	33	55	37	18	17	14	0	8	16	9	5	2	3	0
2018	39	57	23	20	15	10	0	13	21	9	8	3	1	0
2019	33	60	29	25	13	6	0	19	19	10	10	4	0	0
2020	42	56	38	23	9	10	0	21	20	11	6	2	2	0
Total	515 (22%)	775 (33%)	468 (20%)	305 (13%)	164 (7%)	117 (5%)	2 (0%)	239 (29%)	272 (33%)	140 (17%)	107 (13%)	41 (5%)	25 (3%)	0 (0%)
	2,347 (74%)							825 (26%)						
	3,172													

Table 3.4 Distribution and Odds Ratio for WWD Fatal Crashes

Variable	Categories	WWD Fatal	%	Other Fatal	%	OR	2.5% CI	97.5% CI
Passenger Status	No Passenger	2,877	87%	37,555	62%	Ref.		
	With Passenger*	430	13%	23,017	38%	0.43	0.38	0.49
Day of Week	Weekday	1,919	58%	39,978	66%	Ref.		
	Weekend*	1,389	42%	20,594	34%	1.10	1.00	1.22
Time of the Day	12:00–17:59	331	10%	17,566	29%	Ref.		
	0:00–5:59*	1,720	52%	14,537	24%	2.72	2.13	3.48
	6:00–11:59*	298	9%	12,720	21%	1.21	1.01	1.45
	18:00–23:59*	992	30%	15,749	26%	1.36	1.08	1.71
Work Zone Related	None work zone	3,209	97%	58,149	96%	Ref.		
	Work zone	99	3%	2,423	4%	0.94	0.71	1.23
Lighting Condition	Daylight	562	17%	30,892	51%	Ref.		
	Dark light*	1,025	31%	12,114	20%	3.04	2.42	3.83
	Dark no light*	1,621	49%	15,143	25%	3.20	2.57	3.98
	Dawn/dusk*	99	3%	2,423	4%	1.86	1.40	2.47
Rural/Urban	Rural	1,356	41%	24,835	41%	Ref.		
	Urban	1,952	59%	35,737	59%	1.06	0.95	1.18
Drunk Driver	No	1,191	36%	44,823	74%	Ref.		
	Yes*	2,117	64%	15,749	26%	2.98	2.66	3.33
Weather Condition	Clear	2,679	81%	50,275	83%	Ref.		
	Rain/snow/sleet/hail/Fog*	298	9%	6,057	10%	1.15	0.88	1.49
	Other*	331	10%	4,240	7%	1.61	1.35	1.91
Month	Apr–Jun	761	23%	15,749	26%	Ref.		
	Jan–Mar	827	25%	13,326	22%	1.12	0.97	1.29
	July–Sep*	794	24%	16,354	27%	1.15	1.00	1.32
	Oct–Dec	926	28%	15,143	25%	1.11	0.97	1.27
License State	Out-of-state	496	15%	10,903	18%	Ref.		
	In-state	2,812	85%	49,669	82%	0.99	0.86	1.14
Driver Age	45–54	397	12%	9,086	15%	Ref.		
	24 or less	662	20%	14,537	24%	0.85	0.72	1.02
	25–34*	893	27%	13,326	22%	1.14	0.96	1.36
	35–44	529	16%	9,692	16%	1.11	0.92	1.33
	55–64*	265	8%	6,663	11%	1.32	1.07	1.63
	65 or more*	562	17%	7,874	13%	3.65	3.03	4.40
Sex	Female	992	30%	15,749	26%	Ref.		
	Male*	2,316	70%	44,823	74%	0.80	0.72	0.89
License Status	Valid	2,646	80%	51,486	85%	Ref.		
	Not licensed*	232	7%	3,029	5%	1.38	1.12	1.70
	Suspended/revoked/expired/cancelled	430	13%	6,057	10%	1.11	0.96	1.30
Driver Injury Severity	No injury	99	3%	9,086	15%	Ref.		
	Injury*	860	26%	15,749	26%	2.35	1.82	3.03
	Fatal*	2,349	71%	35,132	58%	2.79	2.19	3.55

Previous Accident Record	No	2,779	84%	51,486	85%	Ref.		
	Yes	529	16%	9,086	15%	1.10	0.96	1.26
Roadway Alignment	Straight	2,746	83%	49,669	82%	Ref.		
	Curved	562	17%	10,903	18%	1.05	0.92	1.20
Roadway Profile	Level	2,448	74%	46,640	77%	Ref.		
	Grade	728	22%	12,720	21%	1.14	1.00	1.28
	Hillcrest*	132	4%	1,030	2%	2.27	1.67	3.09
	Sag*	33	1%	182	0%	3.64	1.47	9.05
Surface Condition	Dry	2,911	88%	51,486	85%	Ref.		
	Ice frost	5	0%	1211	2%	0.07	0.03	0.19
	Other	2	0%	183	0%	0.47	0.08	2.80
	Snow/slush	16	0%	423	1%	0.35	0.18	0.68
	Wet	364	11%	7,269	12%	0.70	0.56	0.88
Speed Limit	40 mph or less	132	4%	6,663	11%	Ref.		
	45–70 mph*	2,944	89%	50,275	83%	2.57	2.09	3.16
	75 mph or more*	232	7%	3,634	6%	5.68	4.22	7.65
Collision Type	Front to rear	33	1%	9,086	15%	Ref.		
	Angle*	198	6%	12,114	20%	11.77	7.76	17.85
	Front to front*	2,713	82%	2,538	4%	486.18	325.73	725.68
	Sideswipe*	132	4%	2,308	4%	24.94	16.19	38.42
	Other	232	7%	34,526	57%	2.88	1.90	4.35

Note:
* P-value < 0.5

3.3.2 Statistical analysis results

Table 3.4 presents the distribution of WWD fatal crashes and other types of fatal crashes for each variable as well as the odds ratios (ORs) computed after fitting the binary logistic regression model. This section discusseses only the statistically significant results at 95% confidence interval (*p*-value <0.05) in the regression model.

As for the temporal variables shown in the table, it can be found that driving during 0:00–5:59 (OR = 2.72), 6:00–11:59 (OR = 1.21), and 18:00–23:59 (OR = 1.36) increased the odds of experiencing WWD fatal crashes compared with driving during 12:00–17:59. This result is in accordance with the previous study conducted by Ponnaluri, which showed that the midnight to 6 a.m. period had the highest odds for WWD and WWD fatal crashes as referring to noon to 6 p.m. (*Ponnaluri, 2016*). Low visibility during late night and early morning increases the driver's burden to identify the right way. Additionally, late-night driving is usually combined with impaired or intoxicated driving, which increases the chance of having a WWD fatal crash. Similarly, results show that weekends have a higher likelihood (OR = 1.11) than weekdays to have WWD fatal crashes, which may also be because more people hang out and drink during the weekend (*Braxton, 2021*). In terms of month, the odds of a WWD fatal crashes during July to September is 1.15, referring to April to June.

When considering crash-related characteristics, the odds of a WWD fatal crash in dark no light was 3.20 times that of daylight conditions. The likelihood of a WWD fatal crash at dawn or dusk (OR = 1.86) and dark light conditions (OR = 3.04) were also increased compared with daylight conditions (OR = 0.5). In other words, driving at night without lighting will increase the occurrence of WWD fatal crashes due to the limitation of visibility. The results are consistent with most of the previous literature findings (Zhou et al., 2012; *Ponnaluri, 2016; Pour-*

Rouholamin and Zhou, 2016). A past study also indicated the importance of lighting conditions to reduce the injury severity of a crash occurring in dark conditions (*Anarkooli and Hosseinlou, 2016*). In terms of weather conditions, the odds of WWD fatal crashes increased during severe weather conditions (1.15 times for rain/snow/sleet/hail/fog and 1.61 times for other weather conditions) compared with clear weather. Previous literature also obtained similar results (*Ponnaluri, 2016*). Another study also revealed that the risk of fatal crashes would increase by 34% due to severe weather conditions such as rain, snow, and ice (*Stevens et al., 2019*). Regarding the roadway profile, the study results indicated that driving on a sag curve (OR = 3.64) or hillcrest (OR = 2.27) will increase the odds of a WWD fatal crash resulting from limited sight distance. WWD fatal crashes were more likely to result in front-to-front collisions, with a dramatically large OR of 486.18. Another type of collision that is related to WWD fatal crashes are the sideswipe collision (OR = 24.94) and angle collision (OR = 11.77).

It is also essential to analyze the effect of driver characteristics on WWD fatal crashes. When compared with no passenger presented in a vehicle, the presence of passengers in a vehicle had an OR of 0.43. The result suggested that the occurrence of a WWD fatal crash will decrease with the presence of passengers. The result is considered reasonable since the passenger can help a driver correct the fault and identify the right way, which is consistent with previous literature (*Savolainen et al., 2018*). Other studies suggested that the presence of adult passengers will reduce the driver's crash risk (*Lee and Abdel-Aty, 2008; Vollrath et al., 2002*). The binomial regression model revealed that DUI drivers had a higher OR (2.98) of being involved in the WWD fatal crashes. The distribution result for WWD fatal crashes also shows that DUI drivers are over-represented. When considering a driver's age, the results indicated that the odds of WWD fatal crashes increased by three times (OR = 3.65) when the driver was 65 years or more, in reference to 45–54 years old. Older drivers have also been identified as a contributing factor for WWD crashes in previous studies (*Fitzsimmons et al., 2019*; *Ponnaluri, 2016*). It is also found that the OR for 25–34 and 55–64 in reference to the 45–54 years old were 1.14 and 1.32, respectively. When thinking about the effectiveness of gender, the results show that male drivers are less likely to have WWD fatal crashes than female drivers, although male drivers occupy around 70% of drivers in both WWD fatal crashes and other types of fatal crashes. Similar results were obtained from the study conducted by the AAA Foundation (*Villavicencio et al., 2021*). However, opposite results are found in Ponnaluri (*Ponnaluri, 2016*), which showed that male drivers would increase the likelihood of WWD crashes. The difference is probably due to the different data sets used for analysis (national VS. Florida-specific). Finally, as for drivers' injury severity caused by a crash, it is found that crashes that caused driver death (OR = 2.79) or injury (OR = 2.35) are more likely to be WWD fatal crashes when compared with fatal crashes for drivers. The result seems reasonable when considering the severity of WWD fatal crashes.

3.3.3 MCA Results

The R *Version 3.05* statistical software was used to perform multivariate exploratory data analysis of 20 potential WWD contributing factors with 62 categories. Specifically, the R package "*ca*" was applied to perform MCA analysis, and the R package "*ggplot2"* was used to aid the result visualization (*Greenacre et al., 2020; Wickham, 2009*). In this study, the total dimensions generated by MCA is 20, which means the MCA depicts the data points in this dimensional space. Each dimension will carry out a different amount of categorical information, which can be explained by eigenvalues. The eigenvalues of a dimension can vary between 0 and 1. The larger the eigenvalue, the larger the total variance among the variables' contribution to that dimension. **Table 3.5** summarizes the eigenvalue and percentage of variance for the top 10 dimensions. **Figure 3.5** visualizes the percent of variance explained by the top 10 dimensions.

Table 3.5 Eigenvalue and Percentage of Variance for Top 10 Dimensions

Dimension	Eigenvalues	Variance%	Cumulative Variance%
1	0.008166	37.6	37.6
2	0.002566	11.8	49.4
3	0.001877	8.6	58.0
4	0.000707	3.3	61.3
5	0.000592	2.7	64.0
6	0.000306	1.4	65.4
7	0.000232	1.1	66.5
8	0.000111	0.5	67.0
9	9.40E-50	0.4	67.4
10	6.80E-50	0.3	67.7

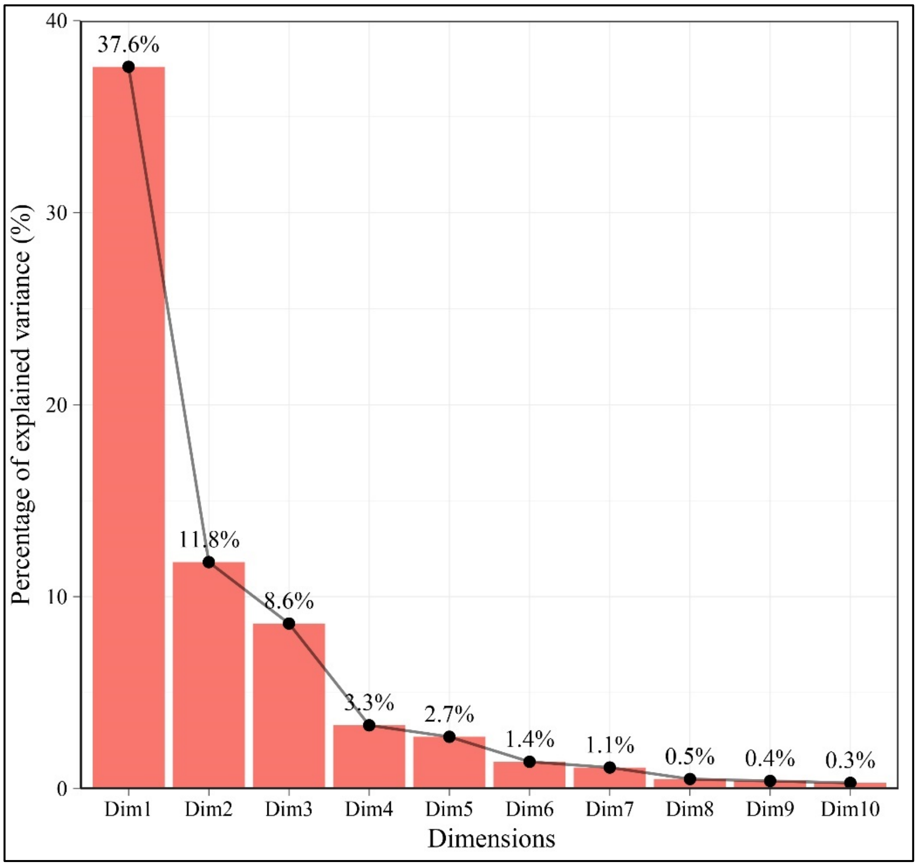


Figure 3.5 Percentage of variance explained by top 10 dimensions

According to **Table 3.5** and **Figure 3.5**, the eigenvalues decrease when the dimensions increase. The first two dimensions carry out 49.4% of the variance in the data set; further, none of the remaining dimensions explain more than 10% of the variance. The results indicate that the first two dimensions cover almost half of the data information, which means that it is proper to plot the first two dimensions for further illustration purposes. Compared with the previous studies conducted by Das *et al.* (*2018)* and Jalayer *et al. (Jalayer, Pour-Rouholamin, and Zhou, 2018*), which obtained 37.6% and 11.8% of the explained variance in the first two dimensions, respectively, the data variability explained by the first two dimensions in this study improves significantly. This is due to the usage of the Burt matrix with adjustment of inertias in MCA analysis. By doing this, the percent of the data contained for each component is increased, and the results will be more accurate. However, it is still necessary to consider the random nature of the crashes, which resulted in the heterogeneity of variables. **Figure 3.6** shows the correlation between variable categories and principal dimensions. The squared correlations between variable categories and the dimensions are used as coordinates. The squared correlation is a coefficient, which is varied between 0 and 1, with 0 being no relationship and 1 being a strong relationship between the variable categories and MCA dimensions. According to the figure, the categories that are most correlated with the first dimension are DUI drivers, non-DUI drivers, driver age (65 or more), time of the day (0:00–5:59 a.m.), and day of the week (weekday and weekend). Similarly, the categories that associate most with the second dimension are lighting conditions (dark no light), speed limit (65-70 mph, 45-50 mph), and area type (urban and rural).

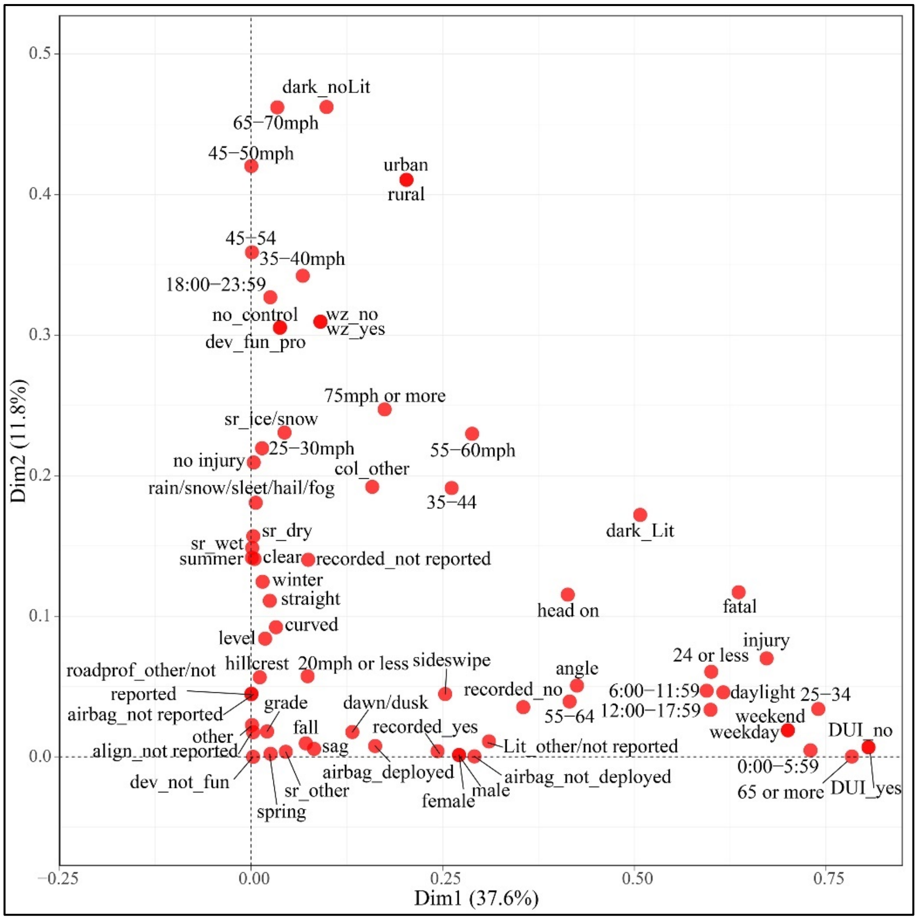


Figure 3.6 Correlation between variable categories and principal dimensions

The contributions of the variable categories (in %) for the first two dimensions are shown in descending order in **Figure 3.7**. The variable categories with the larger value contribute the most to the first two dimensions. Variable categories that have a higher contribution in the first two dimensions are important to explain the variability in the dataset (*Kassambara, 2017*). The figure illustrates that variable categories such as daylight, 12:00–17:59, 65 or more, rural, and DUI_no (non-DUI drivers) have higher contributions in the first two dimensions. However, categories, such as dev_not_fun (control device not function), spring season, sag (sag roadway profile), and wz_no (no work zone related) contributed less in the top two dimensions. Typically, those categories are less related and not well represented in the top two dimensions. In other words, positions of the corresponding points on the factor maps should be interpreted with caution.

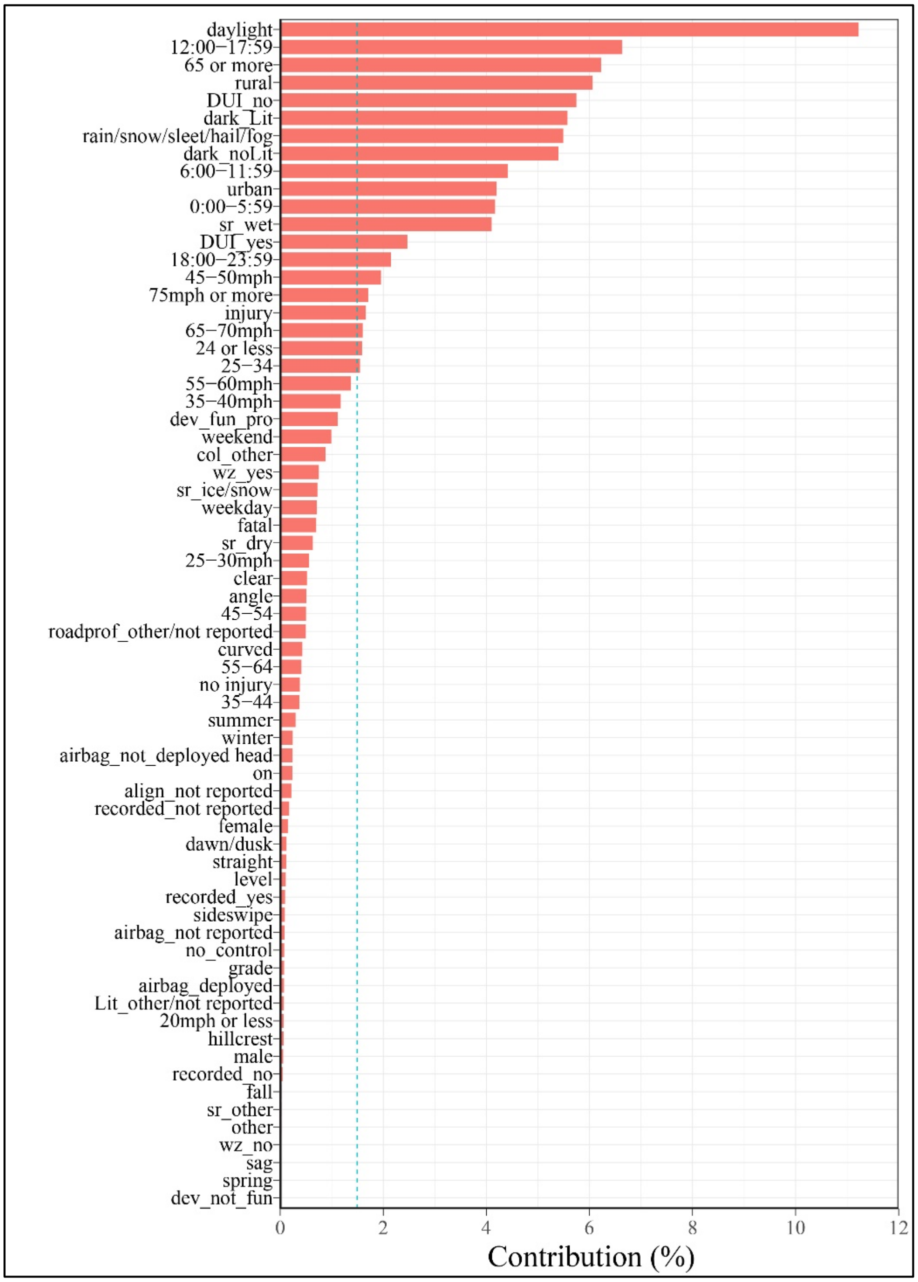


Figure 3.7 Categories contributions for the top two dimensions

In order to obtain a reliable result, the top 20 contributing categories in **Figure 3.7** were selected and depicted in the factor map. As shown in **Figure 3.8**, the proximity of the category points on the factor map enables the creation of point clouds. When the categories within each cloud act together, the risk of WWD fatal crashes will be increased.

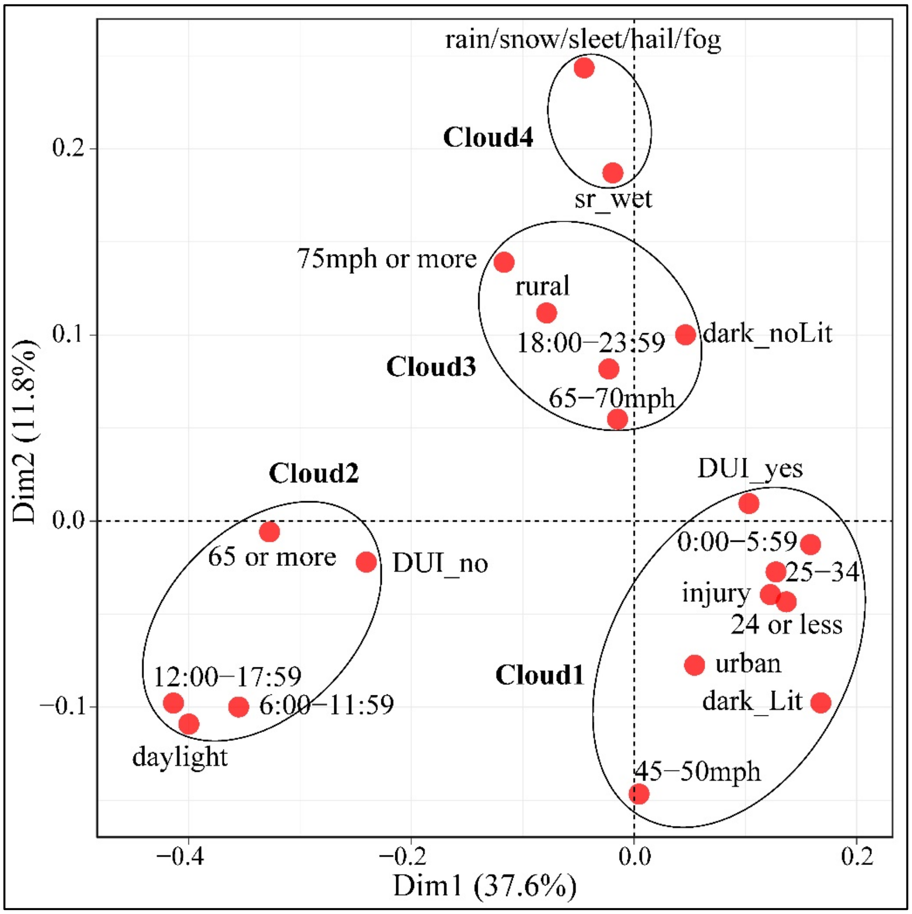


Figure 3.8 MCA plot of top 20 key categories

According to **Figure 3.8**, Cloud 1 contains categories: “DUI_yes,” “0:00-5:59,” “25-34,” “injury,” “24 or less,” “urban,” “dark_Lit,” and “45-50 mph.” This suggests that a large portion of WWD fatal crashes occurred when younger drivers drove after drinking alcohol during the midnight and early morning in an urban area, despite a relative lower speed limit and good street lighting. The results also indicated that WW drivers were more likely to sustain a severe injury in the crash. The key findings from Berkeley Safe Transportation Research and Education Center (SafeTREC) also mentioned that alcohol-impaired drivers who are younger than 35 years old are over-represented in fatal and severe injury crashes in 2016 (*SafeTREC, 2020*). This result is in accordance with most of the findings in the existing literature (*Zhou et al., 2012; Ponnaluri, 2016*).

Cloud 2 bunches the categories “DUI_no,” “65 or more,” “6:00–11:59,” “12:00–17:59,” and “daylight,” which indicates that WWD fatal crashes involving older drivers often occurred during the daytime in normal physical conditions. Jalayer *et al*. identified a similar cloud in a previous study (*Jalayer, Pour-Rouholamin, and Zhou, 2018*). Previous studies conducted by Pour-Rouholamin *et al.* also indicated that older drivers (65 or more) are nine times more likely involved in WWD crashes (*Pour-Rouholamin et al., 2016b*).

As for Cloud 3, categories, such as “dark_noLit,” “18:00-23:59,” “75 mph or more,” “65 -70 mph,” and “rural” can be observed to be clustered together. This can be interpreted as driving in rural areas with inadequate lighting and high-speed limit during 18:00-23.59 PM is associated with WWD fatal crashes. The higher speed usually results in a shorter reaction time for right-way drivers to react to WWD vehicles. Additionally, most of the freeway segments and intersections in rural areas do not have adequate lighting, resulting in poor visibility and a high likelihood of WWD fatal crashes. Lighting condition is not only related to WWD fatal crashes but also associated with all types of crashes. Past studies also highlighted the importance of deploying street lights at freeway interchange areas or near intersections (or access points) to reduce crash severity. For instance, one study showed that the injury severity of a crash occurring in dark conditions would highly increase (*Anarkooli and Hosseinlou, 2016*).

Similarly, categories “rain/snow/sleet/hail/fog” and “sr_wet” are plotted close to each other in Cloud 4. This is a clear indication of the relationship between WWD fatal crashes and adverse weather conditions. The adverse weather condition results in a wet road surface, which reduces the visibility of traffic signs and pavement markings. A similar trend was found by Ponnaluri (*Ponnaluri, 2016*), who showed that the chance of a WWD crash during rain and fog is twice compared with a clear condition. Another study also revealed that, with rain, snow, and ice, the risk of fatal crashes increases by 34% (*Stevens et al., 2019*).

3.4 Summary

This chapter introduces the current WWD fatal crash trends and distributions, alcohol-related WWD fatal crashes facts, and contributing factors. A 17-year period of FARS data were analyzed using descriptive analysis, binomial regression, and MCA analysis. The results revealed that the number of WWD fatal crashes did not decrease over the years. Additionally, drunk drivers, male drivers, young drivers, old drivers, and nighttime conditions predominated the WWD fatal crashes. The results in this chapter, especially the contributing factors, will be considered in the next chapter for the designation of the laboratory testing using the driving simulator.

Chapter 4 Driving Simulator Study

4.1 Driving Simulator-Based Study Introduction

A driving simulator based analysis was adopted in this dissertation to understand the effectiveness of TCDs for severely intoxicated WW drivers regarding driving behaviors. This chapter provides specifics regarding the laboratory devices overview, laboratory testing design, and procedure used to recruit and test participants. Additionally, detailed information regarding testing countermeasures and specific driving events is also provided.

4.2 Driving Simulator and Eye-tracking Device Overview

Driving simulators provide researchers the ability to examine driving behaviors in a controlled virtual environment. It provides a less expensive, less dangerous, and more repeatable alternative to field experiments. Considering the potential hazards for highly intoxicated drivers, the driving simulator is a great choice that enables the investigation of various aspects of driving behaviors. A National Advanced Driving Simulator (NADS) MiniSim^{TM} driving simulator and a Tobii Pro Glasses 2 wearable eye tracker were used in this research.

4.2.1 Driving simulator

The NADS MiniSim^{TM} driving simulator is a PC-based driving simulator in which both software and hardware have been developed by the NADS lab at the University of Iowa (*NADS, 2022*). It has an anodized aluminum chassis with carpet, dashboard, wheel, pedals, and driver controls that accurately mimic a real care from the driver's perspective, which facilitates a wide variety of research applications. As shown in **Figure 4.1**, the NADS MiniSim^{TM} driving simulator used in the lab consists of five displays with a different purposes. Three 50-inch TV monitors are installed on the triple floor standing monitor stand, giving driver a 180° horizontal and 50° vertical field of view of the simulated environment. Each display has a resolution of 1360×768 pixels and a refresh rate of 60Hz. The 12-inch display in front of the car seat is the virtual instrument cluster which can provide drivers information such as gear status and current speed. In addition, a 24-inch operator display is set aside aiming for the laboratory test operation for researchers. The instruments equipped on the aluminum chassis (except the car seat and display) contain a variety of functions similar to a standard roadway vehicle, which is illustrated in **Figure 4.2**. The 13-inch leather-wrapped steering wheel is implemented on the Fanatec ClubSport wheel base. Button box 1 can control mirrors, lights, and Aux buttons. Similarly, button box 2 contains the engine starter, gear selector, wipers, and hazards. The functional acceleration and brake pedal are also implemented on the chassis. Additionally, a soundbar, a speaker, and a transducer are equipped on the driving simulator to provide sounds and vibrations that mimic typical roadway noise to the participant during the simulation.

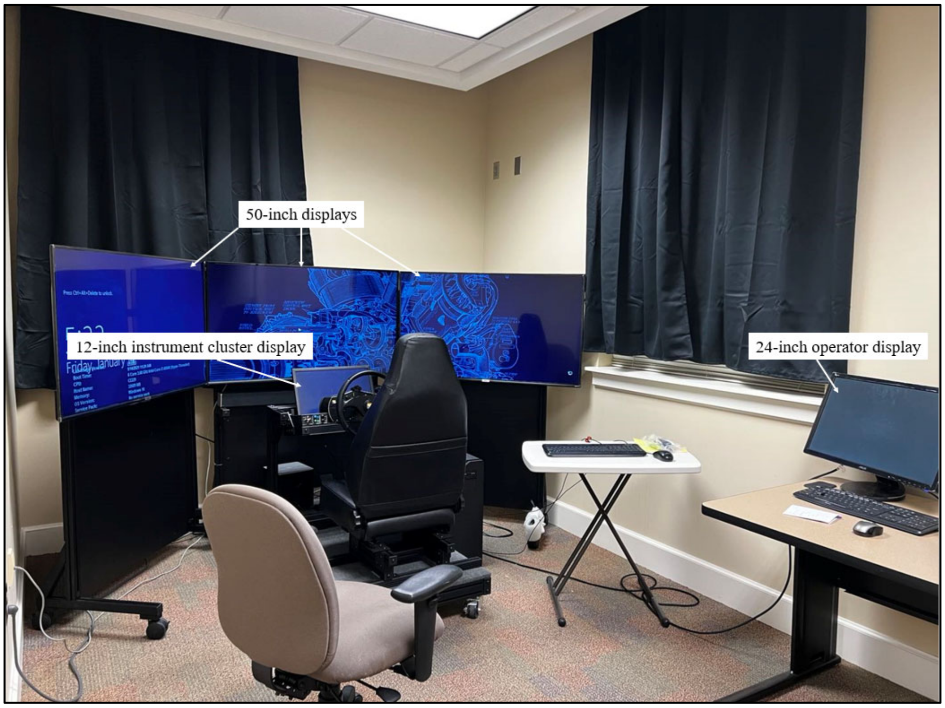


Figure 4.1 Driving Simulator Displays

Figure 4.2 Instruments Equipped on the Aluminum Chassis: (a) Steering wheel; (b) Button box 1; (c) Button box 2; (d) Fanatec CSL Elite Pedals (NADS, 2022)

4.2.2 Eye tracking device

The Tobii Pro Glasses 2 wearable eye tracker gives researchers deep and objective insights into human behavior by showing exactly what a person is looking at in real time. Understand how people interact with their environment, what catches their attention, drives their behavior, and influences decision making (*TobiiPro, 2022*). The system tracks corneal reflection and dark pupil using 50 Hz sampling rate. Tobii Pro Glasses 2 wearable eye tracker incorporates a head unit and recording unit, which is illustrated in **Figure 4.3**. The head unit is a highly sophisticated measuring device. The head unit contains a high-definition scene camera used to capture a full HD video of what is in front of the participant and a microphone that picks up sound from the participant and its surroundings. It also contains eye-tracking sensors to record eye orientation and IR illuminators to illuminate the eyes to support the eye-tracking sensors. The recording unit is a small computer that controls the head unit and connects with the head unit using a cable. It records and stores eye-tracking data, sounds, and scene camera video on a removable SD memory card. The recording unit carries a replaceable and rechargeable Li-ion battery that supplies power to both the recording unit and the head unit.

Figure 4.3 Tobii Pro Glasses 2 Wearable Eye Tracker

4.2.3 Breathalyzer

An Alco-Sensor IV handheld breath alcohol tester manufactured by Intoximeters, Inc. is also used in this thesis study to record participants' breath alcohol concentration (BrAC). As shown in **Figure 4.4**, The Alco-Sensor IV is an evidential grade handheld breath alcohol tester, providing a simple, accurate and economical method of determining a subject's BrAC with evidential grade accuracy. It is the most widely used breath testing instrument today, which meets the NHTSA model specifications for Evidential Breath Test Devices (*Intoximeters, 2022*). It utilizes an Intoximeters electrochemical fuel cell sensor which generates an electrical response. The LED display on the breathalyzer is used to show the BrAC results with a standard three-digit readout. Additionally, it is easy to operate with a mouthpiece powering the instrument "on" and "off."

Figure 4.4 Alco-Sensor IV Handheld Breath Testers

4.3 Experimental Design

4.3.1 Target BrAC Level

When evaluating relevant alcohol and driving simulation studies, the highest reported target BrAC researchers have dosed participants is a 0.10 BrAC (*Mets et al., 2011, Helland et al.,* *2016; Huizinga et al., 2019; Finley et al., 2014, 2017; Subramaniyam et al., 2018; Irwin et al., 2017*) with a maximum observed BrAC of 0.12. As for the laboratory-based alcohol administration studies, the highest reported target BrAC is 0.12, with a maximum observed BrAC of 0.15 (*Stock et al., 2014, 2016; Wolff et al., 2016; Chmielewski et al., 2018; Zink et al., 2019*). Based on previous literature and considering the fact that around 40% of fatal WWD crashes as a result of alcohol intoxication in the U.S. occur at a BrAC of 0.12, The target BrAC level used for this study is 0.12.

During the laboratory session, the amount of alcohol dose consumption was calculated based on the equation developed by the psychology department, which is highly related to body weight. In other words, the participant with a large body weight is anticipant to receive more doses. The alcohol dose is a mix of absolute alcohol and three parts carbonated lemon/lime flavored soda. Participants consumed each dose in 10 minutes and they would be expected to reach the target BrAC level 60 -70 minutes after consumption.

4.3.2 Recruiting and Screening Participants

Preceding the information of this study, approved protocol #21-061 MR 2102 was obtained through the Auburn University Institutional Review Board (IRB). Following the protocol's participant recruitment and screening procedures, this study recruited 30 participants, determined by an a priori test using G*Power (*Faul et al., 2007*). The sample size required for the planned within-subject means comparison requires at least 27 people to detect significance with a power of 0.8 and a medium effect size, which is commonly used in studies on the effects of alcohol intoxication on simulated driving (*Irwin et al., 2017*). Additionally, the medium effect size used for estimation is conservative since the alcohol doses used in the study would likely produce larger effects. As a result, the sample size of 30 should be more than sufficient to answer the research question.

As for 30 participants, male adult drivers at least 21 years of age were recruited into the study since males are more likely to engage in intoxicated WWD based on previous literature and previous chapters. The university students were recruited through an online research participation system operated by the Department of Psychological Sciences at Auburn University. Individuals from the community were recruited via local advertising. Female participants were excluded from the study due to the potential hazards of pregnancy or breastfeeding. Additionally, there is no upper limit on age-related inclusion criteria as data have indicated that older adults tend to be overrepresented in WWD crashes as well.

Considering the relatively high BrAC level used for the study, potential participants are required to fill out the screening materials to identify heavy social drinkers. In the screen materials, participants are required to self-report frequency, duration, and amount of alcohol use within the last month. Then the highest approximate BrAC can be calculated based on their weight and height. This method has been utilized in past alcohol-related laboratory studies (*Chmielewski et al., 2018*), which ensured that participants have been familiarized previously with the dose of alcohol administered in the laboratory session to reduce the risk of adverse events in laboratory testing as well as increase ecological validity of our study. Additionally, this study also excluded individuals who meet the criteria for alcohol use disorder or have previously sought treatment and/or are currently in treatment relating to substance use. The individual who reports a current or previous history of the treatment of alcohol use was also excluded from the study. The study decided to exclude individuals who report visual impairments, as well as any psychiatric and/or medical condition that the investigators deem could potentially interfere with the study procedure. Lastly, participants who self-report currently taking a medication that interacts adversely with alcohol were also be excluded from the study. All of these exclusion criteria are common practice in laboratory-based alcohol administration studies (*Van Dyke and Fillmore, 2014, 2017; Chmielewski et al., 2018*).

Individuals who meet the criteria for the three-session study and express an interest in participating were scheduled for a laboratory session at Auburn University. Participants could receive $200 for completing all study procedures.

4.3.3 Testing countermeasures

To fulfill the current research gap, the proposed countermeasures were: a standard WW sign, DNE sign, and WW sign on the same post, a WW sign with LED border, WW pavement arrow with retroreflective raised pavement markers (RPMs), LaneAlert 2X, and directional rumble strips. As shown in **Figure 4.5**.

Figure 4.5 Proposed Testing Countermeasures

The standard WW sign (**Figure 4.5(a)**) followed the specifications listed in the MUTCD. As illustrated in **Figure 4.5(b)**, the DNE sign and WW sign on the same post followed CAMUTED requirements, which are enlarged and low-mounted as 3ft. The WW sign with an LED border (**Figure 4.5 (c)**) had the same sign dimension as the traditional WW sign. Right LED lights are embedded on the sign border and will be triggered when WW vehicle is detected by loop detection and thermal camera.

4.3.4 Driving simulator scenario development

Two software, the Tile Mosaic Tool (TMT) and the Interactive Scenario Authoring Tool (ISAT) provided by NADS miniSim^{TM} were used for the driving simulator scenario development. The TMT used to assemble a road network from a library of 95 road/landscape segments called "tiles" and export a complete database to the ISAT. And the ISAT is designed for building scenarios on the assembled database. Since the existing library did not contain the desired tiles for the studies, three basic tiles were modified based on the existing tiles, as illustrated in **Figure 4.6**. The roadway tile (**Figure 4.6 (a)**) contains a rural roadway with 24ft wide. In order to avoid additional visual aids existing on the roadway, all the land markings were removed. The T-intersection tile (**Figure 4.6 (b)**) had a three-leg intersection at the center of the tile. Additionally, no land markings existed on the roadway for the same purpose. Lastly, the turn-around tile (**Figure 4.6 (c)**) contains a large round space that simulates the dead-end and allows the driver to turn around smoothly. The roadway network can be assembled using the three tiles described above. The roadway network developed for this study contains several T-intersections connected by a different number of straight roadway tiles. At the end of the intersection, a turn-around around area was provided to force WW drivers back to the right way.

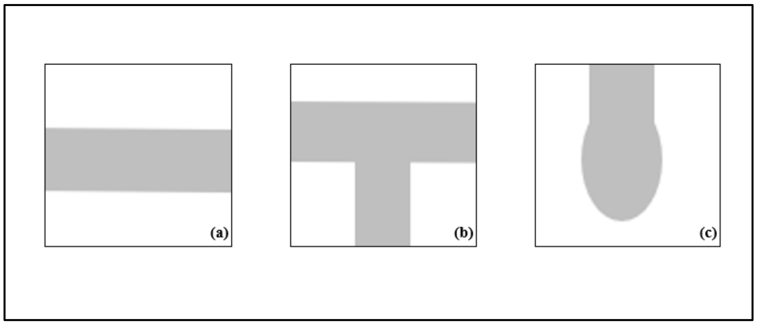
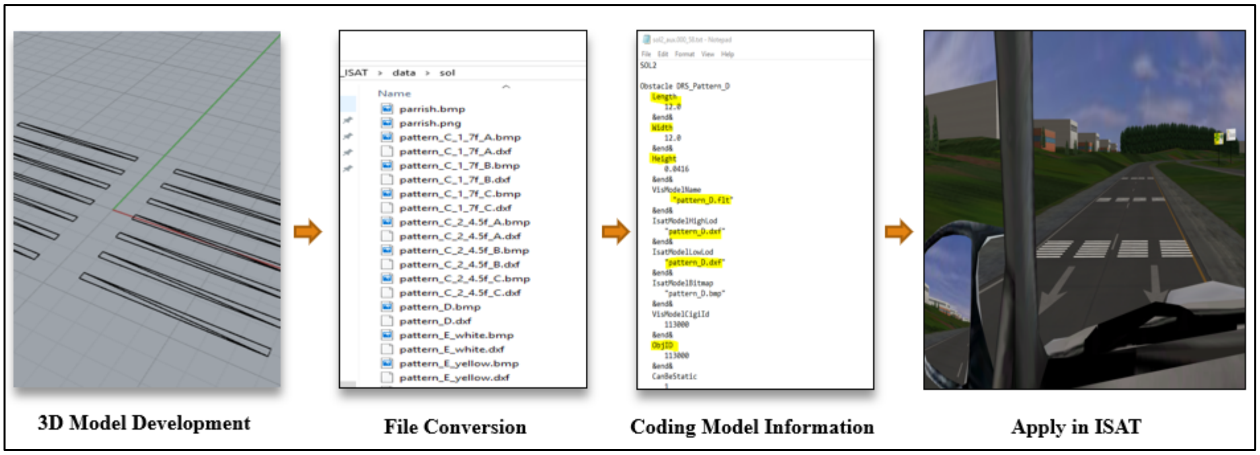


Figure 4.6 Three Basic Tiles Used for Scenario Development: (a) Roadway Tile; (b) T-Intersection Tile; (c) Turn-Around Tile

Besides the roadway network development, proposed countermeasures also need to be either modified or created. Some existing countermeasure models were modified to meet Caltrans' standards. DNE & WW signs in the driving simulator object library have smaller sizes and higher mounting heights than Caltrans' standards. The research team developed enlarged DNE and WW mounted on the same post and as installed in CA. For those countermeasures that did not exist in the ISAT library. The research team created 3D models for LaneAlert 2X, WW pavement arrows, and DRS. The 3D models were converted into the open flight file (.flt), the top view file (.dxf), and the ¾ view model file (.bmp) and then saved in the objects library with the texture image in the driving simulator. After coding the countermeasures (dimensions, color, texture, etc.) on the backend of the driving simulator, the three newly developed countermeasures work as planned in the driving simulator. The procedures for new countermeasure development are illustrated in **Figure 4.7**.



```
parrish.bmp
parrish.png
pattern_C_1_7f_A.bmp
pattern_C_1_7f_A.dxf
pattern_C_1_7f_B.bmp
pattern_C_1_7f_B.dxf
pattern_C_1_7f_C.bmp
pattern_C_1_7f_C.dxf
pattern_C_2_4.5f_A.bmp
pattern_C_2_4.5f_A.dxf
pattern_C_2_4.5f_B.bmp
pattern_C_2_4.5f_B.dxf
pattern_C_2_4.5f_C.bmp
pattern_C_2_4.5f_C.dxf
pattern_D.bmp
pattern_D.dxf
pattern_E_white.bmp
pattern_E_white.dxf
pattern_E_yellow.bmp
pattern_E_yellow.dxf
```

```
SOL2

Obstacle DRS_Pattern_D
  Length
    12.0
  &end&
  Width
    12.0
  &end&
  Height
    0.0416
  &end&
  VisModelName
      "pattern_D.flt"
  &end&
  IsatModelHighLod
     "pattern_D.dxf"
  &end&
  IsatModelLowLod
     "pattern_D.dxf"
  &end&
  IsatModelBitmap
     "pattern_D.bmp"
  &end&
  VisModelCigiId
    113000
  &end&
  ObjID
    113000
  &end&
  CanBeStatic
    1
```

Figure 4.7 Procedures for New Countermeasure Development

Since WWD usually happens during the nighttime condition, the nighttime condition was applied for the driving simulator scenario development. Four scenarios were developed for this study for different purposes. The training scenario aims to let participants be familiar with the driving simulator. The participant will not be informed regarding the experiment's purpose. In the training scenario, no proposed testing countermeasures were implemented on the road/roadside, and no other vehicles were presented on the roadway. Participants can see instructions pop out on the TV monitors to let the driver make left/right turns, speed up, slow down, and turn around, which can help the driver familiarize with the maneuvers that would be used in the testing session. The first testing scenario is aimed to evaluate the effectiveness of individual countermeasures. In this testing scenario, each proposed countermeasure was randomly placed at a random T-intersection and directly face the driver, as illustrated in **Figure 4.8**. There are several blank T-intersections on the roadway with no countermeasures implemented to avoid drivers' self-learning. Participants krpt facing different countermeasures and make a U-turn back if they pass through the proposed countermeasures to a dead-end at the beginning of the testing session. As shown in **Figure 4.9**, the second testing scenario aims to test whether the current countermeasure combinations followed by CAMUTCD will be more effective than the countermeasure combinations provided by MUTCD. This scenario had a similar roadway layout as the first one, but the testing countermeasures were different. The placement of the countermeasures was followed by the instructions on MUTCD and CAMUTCD. Each time when the participant entered the wrong way, they would encounter DNE and WW signs as placed on California's off-ramps. The third testing scenario aims to analyze the effectiveness of WW sign and pavement marking combinations. In this testing scenario (**Figure 4.10**), the driver encountered two combinations of WW signs and three types of pavement markings (wrong-way arrow with RRPM, LaneAlert 2X, and directional rumble strips). The wrong-way arrow with RRPM and laneAlert 2X followed the Caltrans implemented design, and directional rumble strips were used ALDOT study results. This testing scenario is used to examine the effectiveness of six different combinations in deterring WWD movements. A similar roadway layout was used for this scenario.

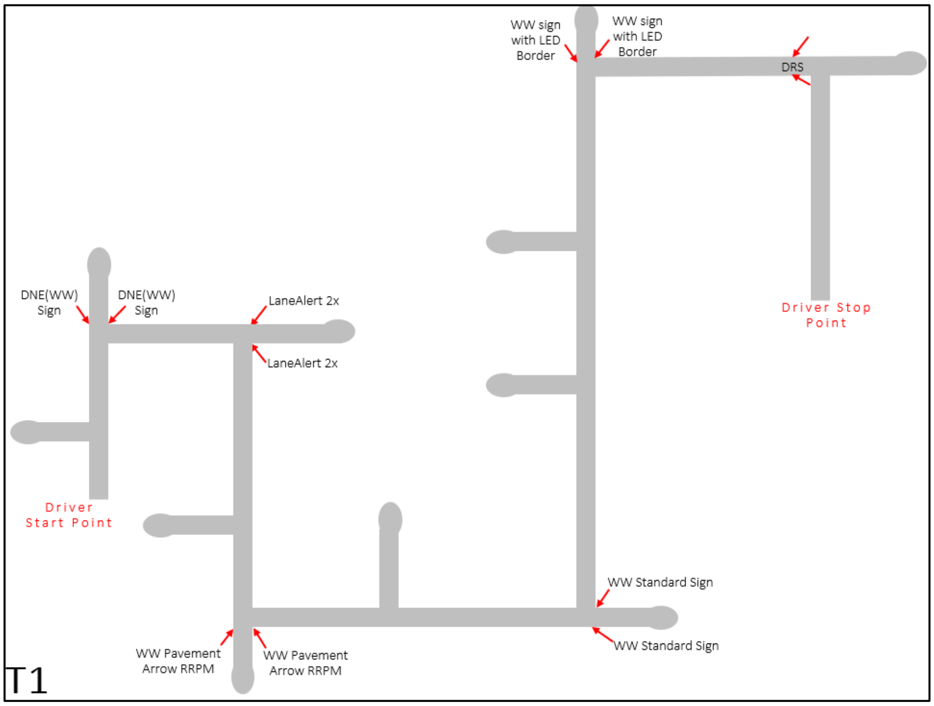


Figure 4.8 Testing Scenario One

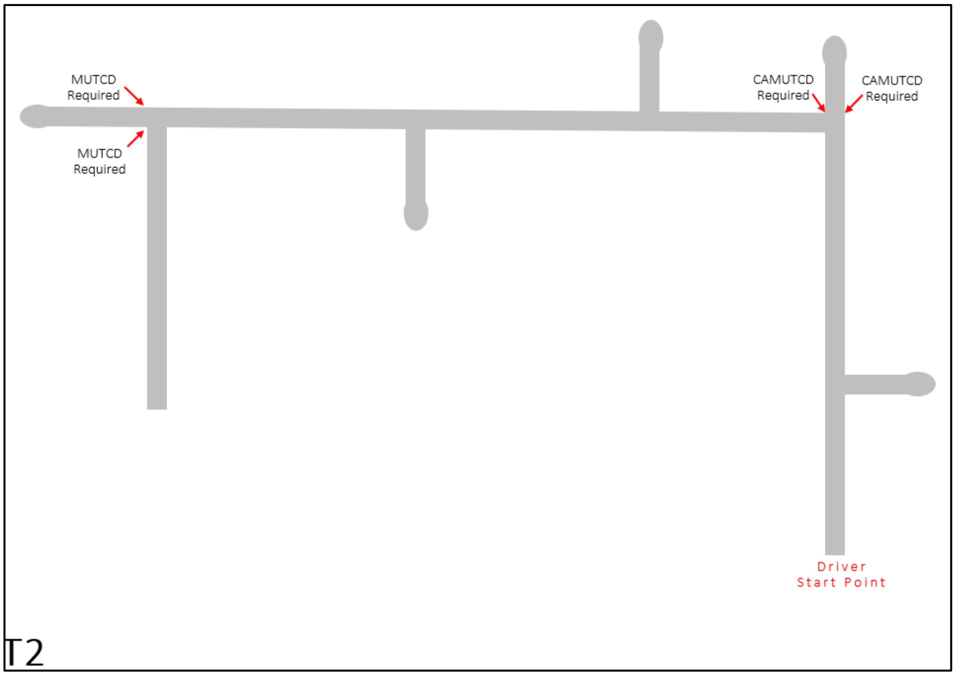


Figure 4.9 Testing Scenario Two

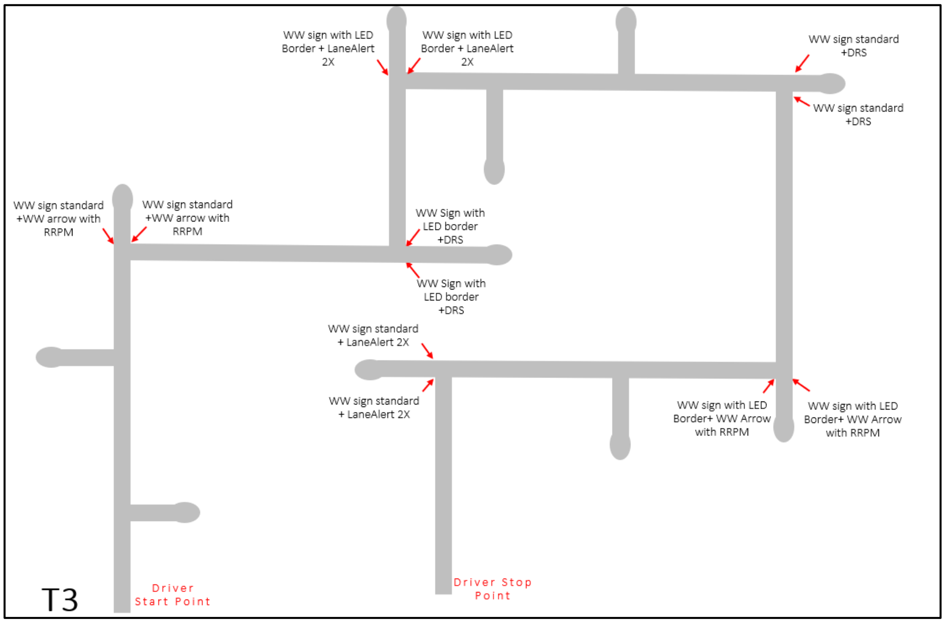


Figure 4.10 Testing Scenario Three

4.4 Lab Session Procedures

Based on the screening results, eligible individuals were invited to participate in the study and asked to attend three in-person lab sessions. The familiarization session is always the first session that requires attending, and participants were randomized to experience the alcohol and non-alcohol sessions in a counterbalanced order. Consider dosing participants with a relatively high BrAC for this study, and there would be a stark difference in perceived intoxication between a 0.00 and a 0.12 estimated BrAC. The placebo condition was not employed, and the participant were informed regarding which session they will attend.

4.4.1 Familiarization session

The first session is a familiarization session, which is common among alcohol and driving simulation studies to avoid potential confounds in driving performance related to first exposure to the driving simulator and other kinds of devices. During this session, participants were provided with and sign the informed consent. After that, the researchers were verify inclusion criteria (relevant drinking history, driver's license status, age, etc.), which were self-reported by participants during the screening process, and collect relevant demographic information. Two eye tests - standard visual acuity test and color blindness - are prepared for participants to ensure participants have at least a minimal level of acceptable vision (20/40 and not color blind).

Participants were also got familiar with all the devices used in the testing session. First, participants learned how to blow the breathalyzer. After that, participants were required to wear the eye-tracking system and complete the training scenario on the driving simulator. Finally, participants became familiarized with the Go/No-Go and Grooved Pegboard task, which were commonly applied in previous alcohol and driving simulator studies (*Van Dyke & Fillmore, 2014, 2017*). The Go/No-Go test is used to assess inhibitory control, which has been shown to be related to impulsive decision-making and behaviors. The Grooved Pegboard Task is a behavioral task used to assess motor coordination. Both tasks were served as a validity check for the study.

The results can be used to compare the driving simulator performance, motor control, and inhibitory control between alcohol and non-alcohol sessions.

4.4.2 Testing sessions

The testing sessions contained the non-alcohol dosing session and alcohol dosing session. The non-alcohol dosing session and alcohol dosing session were separated by a maximum of one week in order to reduce the effect caused by the outside environment (e.g., participant drug use). As a requirement for both sessions, participants were required to abstain from alcohol and all other drugs for 24 hours and food for 4 hours prior to each testing session.

For the alcohol session, the participant's weight was measured at the beginning of the session to calculate the amount of alcohol consumption. The participants were required to complete three testing scenarios with the eye-tracking glasses right after they reach the target BrAC level, which usually takes approximately 60-70 minutes. During that period, participants' BrAC was sampled every 10 minutes until participants are within 0.01 of the target BrAC, after which testing will begin. The real-time BrAC level was measured at the beginning of each scenario. As for the non-alcohol session, the participant was weighed as well upon arrival, and a breath alcohol concentration test was conducted using the breathalyzer to ensure that no alcohol has been consumed prior to the session. Participants consumed the same volume of liquid as the alcohol does session to standardize the procedure within both sessions, but with no alcohol in the beverage. Then the participants were required to wear eye-tracking glasses and finish three testing scenarios on the driving simulator after 60 minutes post-beverage consumption.

After participants completed driving simulator tasks, they also needed to complete the Go/No-Go Task and the Grooved Pegboard Task to assess inhibitory control and measure motor coordination, respectively. It should also be noted that participants were allowed to leave the lab after their BrAC level drops below 0.03 in the alcohol session for safety concerns.

Chapter 5 Data Collection and Analysis

This chapter provides detailed information regarding data collection and analyzed methods applied to different criteria, which were identified and used to evaluate the effectiveness of TCD(s) in the driving simulator study. Two types of data were collected for this study - eye-tracking data and driving-simulator data – for further analysis.

5.1 Data Collection

5.1.1 Eye-Tracking Data

The driver's eye movement data were collected by Tobii Pro Glasses 2 eye tracker manufactured by Tobii, Sweden. The eye-tracking device helps to collect the participant gaze sample with a sampling rate of 50 Hz, which means that it can capture 50 individual gaze points per second. The gaze points show what the eyes are looking at. If a series of gaze points are very close to each other in time and/or space, the cluster of gaze points forms a fixation, indicating where the eyes are locked toward an object (*Farnsworth, 2022*). The eye-tracking device finally delivered the video data which contained the driver's fixation point denoted as a red circle on it for each scenario during each session. As a result, a total of 210 videos were collected in the study.

After that, 180 videos excluding training session videos were transferred into the data analysis software named *Tobii Pro Lab* (*Tobii AB, 2014*) for further data reduction, which contains more than 1,500 minutes of videos. The TCD(s) contained in the video data can be regarded as dynamic stimuli since it changes (from small to large and from far to close) all the time. As a result, the mapping procedures were conducted to aggregate participants' fixation points on the static snapshots that contain the target TCD (s). during the mapping procedures, two criteria need to be determined for the study:

- Time of Interest (TOI), allows researchers to organize the recording data according to intervals of time during which meaningful behaviors and events take place (*Tobii Academy, 2022*). For this study, the TOI was defined as a period that starts when the TCD first can be seen on TV monitors and ends when the participant makes either correct (make a left/right turn going the right way)or wrong (going the wrong way) decision. The researcher tried to ensure that each TOI has a similar period within each scenario and under both conditions, which will aid the accuracy of further analysis. Table 5.1 shown below listed the average TOI for proposed TCD (s) under different conditions.

Table 5.1 Average TOI for Proposed TCD(s) under Different Conditions

Scenario	TCD	TOI (s)	
		NONALC	ALC
1	DNEWW	27.94	28.48
	WW	21.28	20.94
	WWflashing	22.34	21.51
	DRS	13.36	12.41
	RRPM	19.29	17.24
	LaneAlert	17.95	17.24
2	MUTCD	26.90	25.86
	CAMUTCD	24.10	24.01
3	WW+DRS	13.01	13.43
	WW+LaneAlert2X	13.06	13.42
	WW+RRPM	13.73	14.50
	WWFlashing+DRS	15.37	14.71
	WWFlashing+LaneAlert2X	14.35	15.46
	WWFlashing+RRPM	14.55	15.25

- Area of Interest (AOI) allows researchers to define areas of the stimulus based on research needs (*Tobii Academy, 2022*), and by doing this, the eye movement on a defined area can be calculated precisely. For this study, the AOI was defined as a single TCD or combined TCDs.

As shown in **Figure 5.1**, within a defined TOI, the video data on the left-hand side was automatically mapped on the corresponding snapshot on the right-hand side by the software. Then, the researcher reviewed all mapped points again and made modifications (deleted the automatic mapping point and add a manual mapping point at the right location on the snapshot) if the automatic mapping point was not located in the correct location.

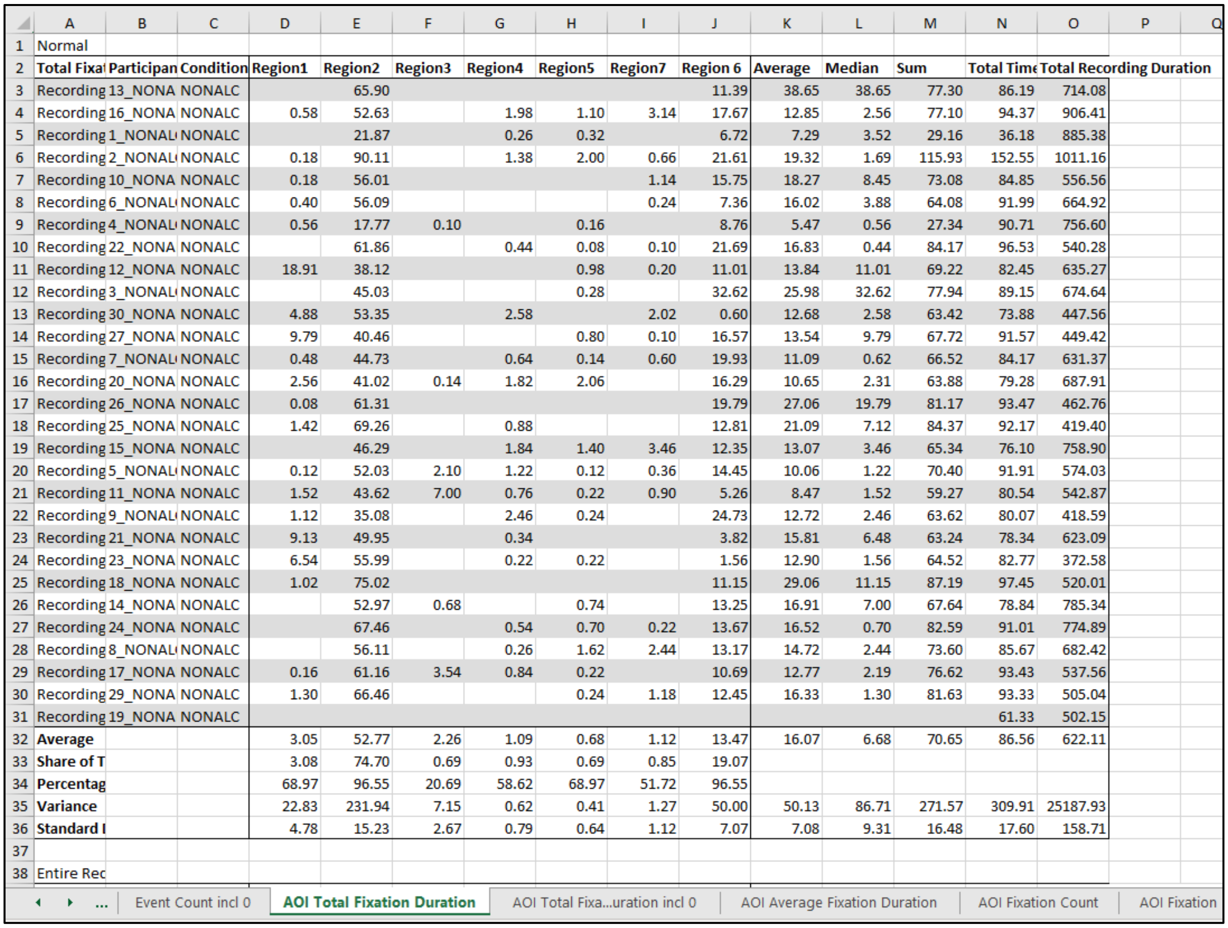
Recording Recording002
Participant 16_NONALC
Duration 00:15:06.407
Date & Time 6/16/2022 2:02 PM

Show snapshot ●
Automatically step to next fixation ●

There are no custom Times of Interest available in this project.

Figure 5.1 Illustration of Mapping Fixation Points on The Snapshot.

After mapping all the fixation points within the defined TOI onto the snapshot, the data matrices can be exported after selecting the participant conditions and AOIs. The software exported data with excel formats that contain several variables in it such as total interval, total fixation count, total fixation duration, etc. For each variable, a table was generated that contains the results for each AOI and participant. **Figure 5.2** illustrates how the eye-tracking data is organized after being exported from the software.

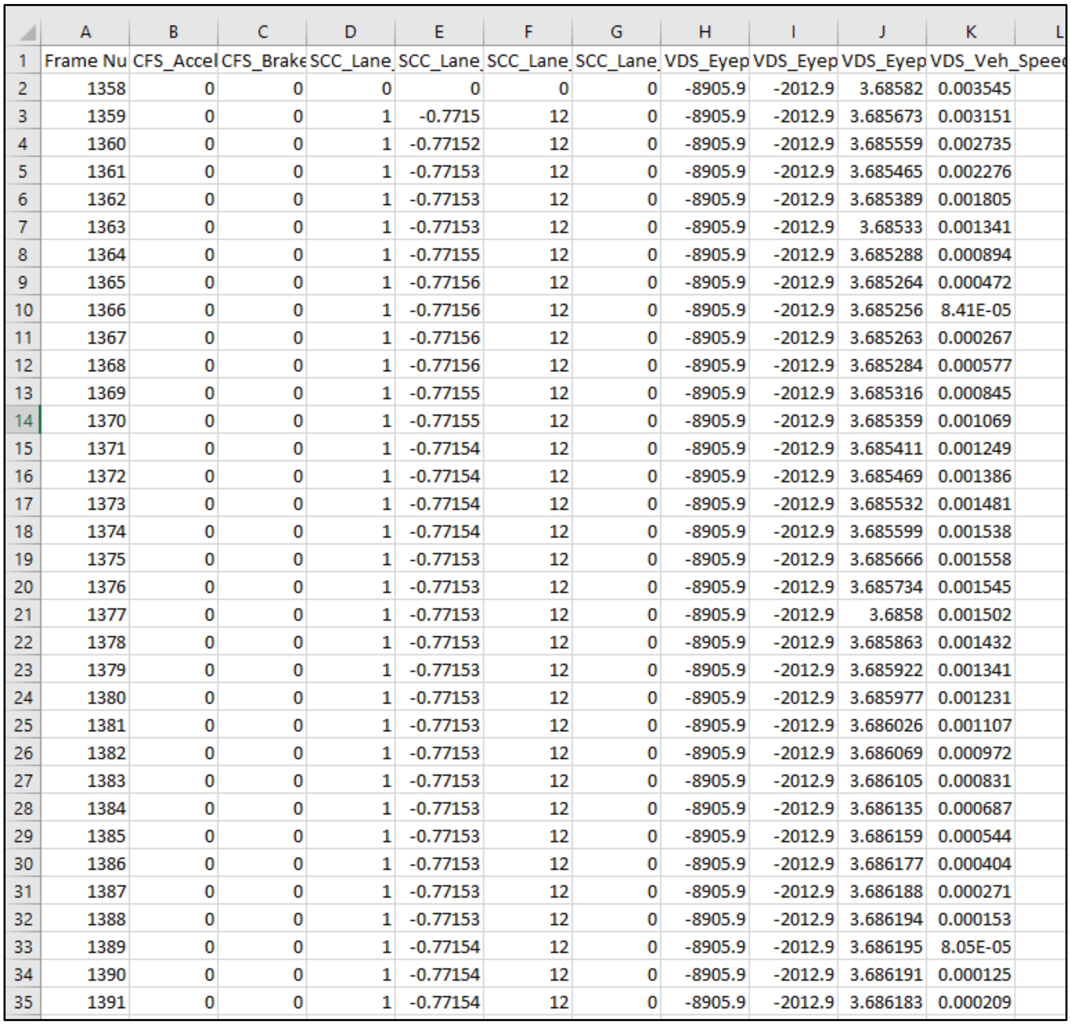


	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	Normal																
2	**Total Fixat**	**Participan**	**Condition**	**Region1**	**Region2**	**Region3**	**Region4**	**Region5**	**Region7**	**Region 6**	**Average**	**Median**	**Sum**	**Total Time**	**Total Recording Duration**		
3	Recording	13_NONA	NONALC		65.90					11.39	38.65	38.65	77.30	86.19	714.08		
4	Recording	16_NONA	NONALC	0.58	52.63		1.98	1.10	3.14	17.67	12.85	2.56	77.10	94.37	906.41		
5	Recording	1_NONAL	NONALC		21.87		0.26	0.32		6.72	7.29	3.52	29.16	36.18	885.38		
6	Recording	2_NONAL	NONALC	0.18	90.11		1.38	2.00	0.66	21.61	19.32	1.69	115.93	152.55	1011.16		
7	Recording	10_NONA	NONALC	0.18	56.01				1.14	15.75	18.27	8.45	73.08	84.85	556.56		
8	Recording	6_NONAL	NONALC	0.40	56.09				0.24	7.36	16.02	3.88	64.08	91.99	664.92		
9	Recording	4_NONAL	NONALC	0.56	17.77	0.10		0.16		8.76	5.47	0.56	27.34	90.71	756.60		
10	Recording	22_NONA	NONALC		61.86		0.44	0.08	0.10	21.69	16.83	0.44	84.17	96.53	540.28		
11	Recording	12_NONA	NONALC	18.91	38.12			0.98	0.20	11.01	13.84	11.01	69.22	82.45	635.27		
12	Recording	3_NONAL	NONALC		45.03			0.28		32.62	25.98	32.62	77.94	89.15	674.64		
13	Recording	30_NONA	NONALC	4.88	53.35		2.58		2.02	0.60	12.68	2.58	63.42	73.88	447.56		
14	Recording	27_NONA	NONALC	9.79	40.46			0.80	0.10	16.57	13.54	9.79	67.72	91.57	449.42		
15	Recording	7_NONAL	NONALC	0.48	44.73		0.64	0.14	0.60	19.93	11.09	0.62	66.52	84.17	631.37		
16	Recording	20_NONA	NONALC	2.56	41.02	0.14	1.82	2.06		16.29	10.65	2.31	63.88	79.28	687.91		
17	Recording	26_NONA	NONALC	0.08	61.31					19.79	27.06	19.79	81.17	93.47	462.76		
18	Recording	25_NONA	NONALC	1.42	69.26		0.88			12.81	21.09	7.12	84.37	92.17	419.40		
19	Recording	15_NONA	NONALC		46.29		1.84	1.40	3.46	12.35	13.07	3.46	65.34	76.10	758.90		
20	Recording	5_NONAL	NONALC	0.12	52.03	2.10	1.22	0.12	0.36	14.45	10.06	1.22	70.40	91.91	574.03		
21	Recording	11_NONA	NONALC	1.52	43.62	7.00	0.76	0.22	0.90	5.26	8.47	1.52	59.27	80.54	542.87		
22	Recording	9_NONAL	NONALC	1.12	35.08		2.46	0.24		24.73	12.72	2.46	63.62	80.07	418.59		
23	Recording	21_NONA	NONALC	9.13	49.95		0.34			3.82	15.81	6.48	63.24	78.34	623.09		
24	Recording	23_NONA	NONALC	6.54	55.99		0.22	0.22		1.56	12.90	1.56	64.52	82.77	372.58		
25	Recording	18_NONA	NONALC	1.02	75.02					11.15	29.06	11.15	87.19	97.45	520.01		
26	Recording	14_NONA	NONALC		52.97	0.68		0.74		13.25	16.91	7.00	67.64	78.84	785.34		
27	Recording	24_NONA	NONALC		67.46		0.54	0.70	0.22	13.67	16.52	0.70	82.59	91.01	774.89		
28	Recording	8_NONAL	NONALC		56.11		0.26	1.62	2.44	13.17	14.72	2.44	73.60	85.67	682.42		
29	Recording	17_NONA	NONALC	0.16	61.16	3.54	0.84	0.22		10.69	12.77	2.19	76.62	93.43	537.56		
30	Recording	29_NONA	NONALC	1.30	66.46			0.24	1.18	12.45	16.33	1.30	81.63	93.33	505.04		
31	Recording	19_NONA	NONALC											61.33	502.15		
32	**Average**			3.05	52.77	2.26	1.09	0.68	1.12	13.47	16.07	6.68	70.65	86.56	622.11		
33	**Share of T**			3.08	74.70	0.69	0.93	0.69	0.85	19.07							
34	**Percentag**			68.97	96.55	20.69	58.62	68.97	51.72	96.55							
35	**Variance**			22.83	231.94	7.15	0.62	0.41	1.27	50.00	50.13	86.71	271.57	309.91	25187.93		
36	**Standard I**			4.78	15.23	2.67	0.79	0.64	1.12	7.07	7.08	9.31	16.48	17.60	158.71		
37																	
38	Entire Rec																

Figure 5.2 Sample of the Eye-Tracking Data Output.

5.1.2 Driving Simulator Data

The software MiniSim V2.3 was used to perform scenarios on the TV monitors during the lab testing and was programmed to collect the vehicle's real-time position, velocity, acceleration, brake force, etc. Data were collected at a rate of 60 HZ for each scenario, which means that 60 data points were collected in one second. All data files were saved as .daq files which are readable by the driving simulator. In order to export data, the data files should be opened into the ISAT software. Then in the data export menu list, variables that will be used for further analysis were selected. Finally, the data would be exported as .csv file, as shown in **Figure 5.3**.



	A	B	C	D	E	F	G	H	I	J	K	L
1	Frame Nu	CFS_Accel	CFS_Brake	SCC_Lane_	SCC_Lane_	SCC_Lane_	SCC_Lane_	VDS_Eyep	VDS_Eyep	VDS_Eyep	VDS_Veh_Spee	
2	1358	0	0	0	0	0	0	-8905.9	-2012.9	3.68582	0.003545	
3	1359	0	0	1	-0.7715	12	0	-8905.9	-2012.9	3.685673	0.003151	
4	1360	0	0	1	-0.77152	12	0	-8905.9	-2012.9	3.685559	0.002735	
5	1361	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.685465	0.002276	
6	1362	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.685389	0.001805	
7	1363	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.68533	0.001341	
8	1364	0	0	1	-0.77155	12	0	-8905.9	-2012.9	3.685288	0.000894	
9	1365	0	0	1	-0.77156	12	0	-8905.9	-2012.9	3.685264	0.000472	
10	1366	0	0	1	-0.77156	12	0	-8905.9	-2012.9	3.685256	8.41E-05	
11	1367	0	0	1	-0.77156	12	0	-8905.9	-2012.9	3.685263	0.000267	
12	1368	0	0	1	-0.77156	12	0	-8905.9	-2012.9	3.685284	0.000577	
13	1369	0	0	1	-0.77155	12	0	-8905.9	-2012.9	3.685316	0.000845	
14	1370	0	0	1	-0.77155	12	0	-8905.9	-2012.9	3.685359	0.001069	
15	1371	0	0	1	-0.77154	12	0	-8905.9	-2012.9	3.685411	0.001249	
16	1372	0	0	1	-0.77154	12	0	-8905.9	-2012.9	3.685469	0.001386	
17	1373	0	0	1	-0.77154	12	0	-8905.9	-2012.9	3.685532	0.001481	
18	1374	0	0	1	-0.77154	12	0	-8905.9	-2012.9	3.685599	0.001538	
19	1375	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.685666	0.001558	
20	1376	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.685734	0.001545	
21	1377	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.6858	0.001502	
22	1378	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.685863	0.001432	
23	1379	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.685922	0.001341	
24	1380	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.685977	0.001231	
25	1381	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.686026	0.001107	
26	1382	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.686069	0.000972	
27	1383	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.686105	0.000831	
28	1384	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.686135	0.000687	
29	1385	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.686159	0.000544	
30	1386	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.686177	0.000404	
31	1387	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.686188	0.000271	
32	1388	0	0	1	-0.77153	12	0	-8905.9	-2012.9	3.686194	0.000153	
33	1389	0	0	1	-0.77154	12	0	-8905.9	-2012.9	3.686195	8.05E-05	
34	1390	0	0	1	-0.77154	12	0	-8905.9	-2012.9	3.686191	0.000125	
35	1391	0	0	1	-0.77154	12	0	-8905.9	-2012.9	3.686183	0.000209	

Figure 5.3 Sample of the Driving Simulator Data Output.

Each .csv file represents one participant under a certain scenario and condition, and as a result, 180 files excluded from the training session were manually exported to the desired location. As illustrated in **Figure 5.3**, within each file, 11 variables were selected for further analysis such as real-time coordinates, brake force, and speed, which are shown as a column. Each row can be regarded as one data point collected in 0.017 seconds (60 Hz). The number of data points collected by each participant is highly dependent on how much time he/she spends on the driving simulator. The longer the time, the greater the data point will be collected. For this study, more than 5,506,580 data points were collected as the raw dataset.

5.2 Data Analysis Method

For this study, the data analysis methods were applied for eye-tracking and driving simulator data to achieve three purposes: i) summarize the general information regarding participants and BrAC levels; ii) identify the forward driving scene for both normal and alcohol-impaired conditions, and iii) evaluate the effectiveness of TCD(s) using three criteria. The detailed statistical methods adopted for each purpose are listed below.

5.1.1 Summarize the General Information

Descriptive statistics were used to summarize the general information. Descriptive statistics can be regarded as the initial step for data analysis, which aims to provide an understanding of the basic features of the dataset (*Sheshkin, 2007*). Participant demographic information such as age, race, and visual acuity was summarized in this section. Additionally, the actual BrAC level for each scenario during the alcohol session was also summarized in the section with the calculation of mean value, standard deviation (SD), and maximum and minimum values.

5.1.2 Forward Driving Scene under Both Conditions

The eye-tracking data, drivers' fixation points, were used to illustrate the forward driving scene under normal and alcohol-impaired conditions. the researcher defined a TOI with no visual cue on the roadway in the scenario that contains the single TCD and then mapped fixation points for all participants under the same conditions into one snapshot. After that, the heatmap was generated for both normal and alcohol-impaired conditions. The heatmap aggregates the viewing behavior of all participants over a certain period and displays it on a static image (*Tobii Connect,* *2022*). It uses a scheme of different colors to depict the amount of fixations that different parts of AOI received (*Tobii Connect, 2022*). Colors used on the heatmap such as red and yellow indicated areas that attracted more fixations. On the contrary, the green color on the heatmap shows the areas with fewer fixations. The usage of the heatmap can better visualize the fixation data and aid to identify whether the forward driving scene was changed after drinking the alcohol.

Besides, in order the quantify the visualization results, seven regions were defined on the snapshot and the amount of the fixations can be obtained within each region. Then the percentage of total fixation points for each region under different conditions was calculated, and the forward driving scene shifted when the percentage of fixations in a certain region increased or decreased. After that, the Chi-Square test was applied to the results. The Chi-square test was usually performed for between-group comparisons involving non-continuous categorical variables, which was calculated by the following equation:

$$\chi^2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\frac{(Y_{ij}-E_{ij})^2}{E_{ij}} \qquad \textbf{Equation 5-1}$$

Where,

$\chi^2 = Chi - square\ test\ statistic$

$Y_{ij} = Observed\ cell\ count$

$E_{ij} = Extimated\ expected\ cell\ count$

The result of the Chi-square test is used to measure the discrepancy between the observed and expected fixation count statistics (*Spiegelman et al., 2011*). The greater the chi-squared value, the more considerable discrepancy between groups, and the null hypothesis is rejected (*Spiegelman et al., 2011*). For this study, the Chi-square test was used to evaluate whether the percentage of fixation points in the seven regions was dependent on different conditions, and the result was calculated using a 95% of confidence interval.

5.1.3 Measures of Effectiveness for TCD(s)

In order to evaluate the effectiveness of TCD(s), three measures of effectiveness (MOEs) were identified to quantify drivers' behaviors: i) the number of WWD events, ii) fixation durations, and iii) brake response. These three criteria were also widely used in the past driving simulator and eye-tracking studies and the detailed analysis is summarized as follows:

5.1.3.1 Number of WWD events

The WWD event was defined as the driver did not make a left/right turn at the T-intersection and passing through the TCD(s). The number of WWD events was captured by manually reviewing all the video data collected by the eye-tracking device. It can be regarded as a simple criterion commonly used in the driving simulator study to evaluate the effectiveness of countermeasures (*Lin et al., 2017; Seitzinger, et al. 2015)*. The more WWD events were captured for the TCD(s), the less effectiveness of it (them), since it may not be able to stop the WWD. For this study, the number of WWD events was counted for each TCD(s), for each condition, and for each scenario. For each scenario, the comparisons were made between normal and alcohol-impaired conditions for a certain TCD(s). Or the comparisons were made among TCD(s) under certain conditions.

5.1.3.2 Fixation durations

Visual characteristics are important indicators to evaluate drivers' cognitive activities, which can well reflect the visual effect of TCD(s). The concepts of fixation point number. Fixation point order, fixation duration, pupil size, sight angle, and other eye movement parameters and the objects they can represent have been demonstrated in detail in previous studies (*Jacob, and Karn, 2003; Mele and Federici, 2012; and Khan and Lee, 2019*). Fixation frequency, fixation duration, and spatial distribution were significantly correlated with drivers' performance in driving tasks. Specifically, more complex cognitive activities are often accompanied by reduced eye movements, prolonged gaze duration, and reduced spatial distribution of gaze (*Reimer, 2009; Bian and Andersen, 2017*).

For this study, the total fixation duration was collected for all proposed TCD(s), and the average fixation duration was collected for the single TCD(s), based on eye-tracking data. The total duration can be defined as how long the participant spends on the TCD(s) during the defined TOI (*Geisen and Bergstrom, 2017*). The total duration was made by several fixation durations and the longer total fixation duration indicates the area that generates interest (Burridge, 2014). In other words, the TCD(s) with longer total fixation duration indicated more attraction to the drivers. Additionally, the average fixation duration was applied for single TCD(s). The average fixation duration refers to the average time for each fixation, and an increased average fixation duration is associated with processing and suggests complexity (*Tullis and Albert, 2013*; *Geisen and Bergstrom, 2017*).

The datasets exported from the Tobii Pto Lab already contain the raw data of Total fixation duration and average fixation duration. However, it should be reorganized due to the data reduction. For this study, participants with low gaze samples (less than 70%) were excluded from the analysis. Low gaze samples usually resulted in fewer or no fixation points in the video data, which means that the eye-tracking device did not capture the participants' eyeballs properly, which should be removed due to the low quality of the data. Additionally, the participant who did not have any fixation points located in the AOIs was also excluded from the analysis. **Table 5.2** shown below lists the sample size used for each TCD(s) under different conditions.

Table 5.2 Eye-Tracking Data Sample Size for Each TCD(s)

Scenario	TCD(s)	Sample Size	
		NONALC	ALC
Single TCD	DNEWW	27	26
	WW	27	25
	WWflashing	27	25
	DRS	24	20
	RRPM	22	23
	LaneAlert	21	19
MUTCD VS. CAMUTCD	MUTCD	28	26
	CAMUTCD	26	25
Sign & Pavement Marking Combination	WW+DRS	26	26
	WW+LaneAlert	26	27
	WW+RRPM	26	27
	WWflashing+DRS	26	27
	WWflsfhing+LaneAlert	26	27
	WWflashing+RRPM	26	27

For the total fixation duration and average fixation duration, the independent samples T-tests and the Analysis of Variance (ANOVA) tests were conducted for multiple comparisons.

The Independent samples T-Test was applied for between-group comparisons with continuous predictor variables (total fixation duration and average fixation duration). It compares the means of two or more unrelated datasets (*Field et al., 2012*). The T-Test statistic can be calculated using **Equation 5-2**.

$$t = \frac{d_{obs} - d_{exp}}{standard\ error\ estimate}$$ **Equation 5-2**

There are a variety of assumptions that need to be satisfied before running The Independent samples T-Test, such as the assumption of normality and the assumption of independence. As described in the previous chapter regarding participant recruitment, participants possessed no prior knowledge of the study purpose and any scenario before the driving simulator study. Each testing session only had one participant and the order of the testing session and scenarios were all counterbalanced. As a result, each driving simulator test was unrelated to all other assessments based on participants. As for the assumption of normality, the normality tests were required to determine if data were normally distributed since the validity of the T-Test depends on the distribution of the data. For this study, the Shapiro-Wilk test was used for normality tests. The Shapiro-Wilk test was widely recommended for the normality test and it provides a better power than other normality tests such as the Kolmogorov-Smirnov normality test (*STHDA, 2022*). The general idea of Shapiro-Wilk's method is to compare the sample distribution to a normal one to ascertain whether data show or not a serious deviation from normality (*STHDA, 2022*). The null hypothesis of Shapiro-Wilk's test is that:

- The sample distribution of drivers' total fixation duration for X is normal under Y condition.
- The sample distribution of drivers' average fixation duration for Z is normal under Y condition.

where X represents the proposed TCD(s) in all scenarios (14 in total), Z represents the proposed single TCDs in scenario 1, and Y represents drivers' conditions (alcohol or non-alcohol). If the test is significant (p-value is less than 0.05), the null hypothesis should be rejected, which means that the sample distribution is non-normal.

If the sample data satisfy the assumption of normality, the Independent T-tests were used to evaluate the following null hypotheses and the null hypothesis was not rejected when the p-value exceeded 0.05:

- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the DNEWW sign.

- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the WW sign.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the WW flashing sign.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the DRS.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the RRPM.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the LaneAlert 2X.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the MUTCD combination.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the CAMUTCD combination.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the WW sign and DRS combination.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the WW sign and RRPM combination.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the WW sign and LaneAlert 2X combination.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the WW flashing sign and DRS combination.

- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the WW flashing sign and RRPM.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' total fixation duration time for the WW flashing sign and LaneAlert 2X .
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' average fixation duration time for the DNEWW sign on the same post.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' average fixation duration time for the WW sign.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' average fixation duration time for the WW flashing sign.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' average fixation duration time for the DRS.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' average fixation duration time for the RRPM.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' average fixation duration time for the LaneAlert 2X.
- There is no significant difference between MUTCD and CAMUTCD combinations regarding drivers' total fixation duration under alcohol conditions.
- There is no significant difference between MUTCD and CAMUTCD combinations regarding drivers' total fixation duration under non-alcohol conditions.

For the data that did not satisfy the assumptions of normality, the non-parametric test- the Mann-Whitney U test- was adopted for hypothesis testing. The Mann-Whitney U test aims to compare outcomes between two independent samples when the dependent variable is continuous, but not normally distributed (*Agresti, 1996*). For the null hypothesis listed above, which did not meet the normality requirement, it should be rejected when the p-value is less than 0.05.

Additionally, the one-way analysis of variance (ANOVA) was applied to total fixation duration and average fixation duration to identify the difference among TCD(s). ANOVA is a statistical technique that is applied to check if the means of two or more groups are statistically significant from each other, which can be calculated as:

$$F = \frac{MSB}{MSW}$$ **Equation 5-3**

Where,

$F = Coefficient\ of\ ANOVA$

$MSB = Mean\ sum\ of\ squares\ between\ the\ group$

$MSW = Mean\ sum\ of\ squares\ within\ groups$

Further, in order to examine whether the differences between groups were significant, Tukey's multiple comparison test was conducted for the study after the AVOVA test. Tukey's multiple comparison test is a single-step multiple comparison procedure that compares all possible pairs of means and identifies any difference between two means that is greater than the expected standard error. Tukey's multiple comparison test is similar to the T-Test, which can be calculated as:

$$q_s = \frac{Y_A - Y_B}{SE}$$ **Equation 5-4**

Where,

$Y_A = The\ larger\ of\ the\ two\ means\ being\ compared$

$Y_B = The\ sialler\ of\ the\ two\ means\ being\ compared$

$SE = Standard\ error\ of\ the\ sum\ of\ the\ means$

If the sample data satisfy the assumption of normality, the ANOVA test was used to evaluate the following null hypotheses, and the null hypothesis was not rejected when the p-value exceeded 0.05:

- There is no significant difference between the DNEWW sign, the WW sign, and the WW flashing sign regarding drivers' average fixation duration time under non-alcohol conditions.
- There is no significant difference between the DNEWW sign, the WW sign, and the WW flashing sign regarding drivers' average fixation duration time under alcohol conditions.
- There is no significant difference between the DRS, the RRPM, and the LaneAlert 2X regarding drivers' average fixation duration time under non-alcohol conditions.
- There is no significant difference between the DRS, the RRPM, and the LaneAlert 2X regarding drivers' average fixation duration time under alcohol conditions.
- There is no significant difference between the WW sign and DRS combination, the WW sign and RRPM combination, and the WW sign and LaneAlert 2X combination regarding drivers' average fixation duration time under non-alcohol conditions.
- There is no significant difference between the WW sign and DRS combination, the WW sign and RRPM combination, and the WW sign and LaneAlert 2X combination regarding drivers' average fixation duration time under alcohol conditions.
- There is no significant difference between the WW flashing sign and DRS combination, the WW flashing sign and RRPM combination, and the WW flashing sign and LaneAlert

2X combination regarding drivers' average fixation duration time under non-alcohol conditions.

- There is no significant difference between the WW flashing sign and DRS combination, the WW flashing sign and RRPM combination, and the WW flashing sign and LaneAlert 2X regarding drivers' average fixation duration time under alcohol conditions.

For the data that did not satisfy the assumptions of normality, the non-parametric test- the Kruskal-Wallis test- was adopted for hypothesis testing. The Kruskal-Wallis test is the non-parametric equivalent of the ANOVA test, which aims to compare whether samples originate from the same distributions (*Kruskal and Wallis, 1952)*. For the null hypothesis listed above, which did not meet the normality requirement, it should be rejected when the p-value is less than 0.05.

5.1.3.3 Hard brake response distance

The hard brake response distance can be used as another MOE to identify the effectiveness of TCD(s), which is calculated using the driving simulator data. The hard brake response distance can be used to indicate the driver's reaction to TCD(s) and was used in past studies to analyze the driver's reaction based on testing purposes (*Lin et al., 2017; Seitzinger, et al. 2015*). Past studies also indicate that the longer the brake response distance, the earlier the driver got a reaction.

For this study, the brake application status was first dispatched for each TCD(s) under difference conditions. The variable named brake force, which listed the force applied on the brake pedal at a certain distance was used for the study. First, the brake force was transferred to the brake application with "1" (apply brake) and "0" (not apply brake). Then the analysis zone was defined based on the coordination. For this study, the analysis zone started from 1000 ft away from the TCD(s) and ended at the 300 ft pass through the TCD(s). After that, the percentage of people use the brake at each point can be calculated as:

$$\% \, of \ people \ apply \ brake = \frac{Number \ of \ people \ hit \ the \ brake \ at \ a \ cetain \ point}{30} \times 100\% \quad \textbf{Equation 5-5}$$

Then the distribution of brake usage, in terms of the percentage of people applying brake versus distance to the TCDs can be visualized. To better interpret the results, the corresponding distance that most people apply the brake for TCD(s) under certain conditions was summarized in the table.

The hard brake can be defined as 5% of the maximum force (max force=180 lbs; 3% is ~10lb of pressure) according to past literature (*Lin et al., 2017*). As a result, the hard brake distance is the corresponding distance that the driver applied the hard brake before TCD(s). For this study, the analysis zone of the hard brake started from 1000 ft away from the TCD(s) and ended at the TCD(s) (0 ft). The participants who did not apply the hard brake were removed for further analysis for both conditions. **Table 5.3** shown below lists the sample size used for each TCD(s) under different conditions.

Table 5.3 Driving Simulator Data Sample Size for Each TCD(s)

Scenario	TCD(s)	Sample Size	
		NONALC	ALC
Single TCD	DNEWW	22	22
	WW	21	21
	WWflashing	20	20
	DRS	14	14
	RRPM	19	19
	LaneAlert	17	17
MUTCD VS. CAMUTCD	MUTCD	23	23
	CAMUTCD	23	23
Sign & Pavement Marking Combination	WW+DRS	26	26
	WW+LaneAlert	24	24
	WW+RRPM	23	23
	WWflashing+DRS	22	22
	WWflsfhing+LaneAlert	23	23
	WWflashing+RRPM	23	23

The Paired-Sample T-test was performed on the hard brake response distance data to compare the sample means from two conditions with identical participants (*Field et al., 2012*). The Paired-Samples T-Test is appropriate for analyses involving the following: i) paired data; ii) comparisons between two groups; and iii) a continuous outcome with normal distribution. Therefore, checks on the data for normality were completed using the Shapiro-Wilk test and following the same process as that for the Independent T-Test described previously. The null hypothesis of Shapiro-Wilk's test is that:

- The sample distribution of drivers' hard brake response distance for X is normal under Y condition.

where X represents the proposed TCD(s) in all scenarios (14 in total), and Y represents drivers' conditions (alcohol or non-alcohol). If the test is significant (p-value is less than 0.05), the null hypothesis should be rejected, which means that the sample distribution is non-normal.

If the sample data satisfy the assumption of normality, the Paired-Samples T-tests were used to evaluate the following null hypotheses and the null hypothesis was not rejected when the p-value exceeded 0.05:

- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' driver's hard brake response distance for the DNEWW sign.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the WW sign.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the WW flashing sign.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the DRS.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the RRPM.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the LaneAlert 2X.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the MUTCD combination.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the CAMUTCD combination.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the WW sign and DRS combination.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the WW sign and RRPM combination.

- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the WW sign and LaneAlert 2X combination.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the WW flashing sign and DRS combination.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the WW flashing sign and RRPM.
- There is no significant difference between alcohol and non-alcohol drivers regarding drivers' hard brake response distance for the WW flashing sign and LaneAlert 2X .
- There is no significant difference between MUTCD and CAMUTCD combinations regarding drivers' hard brake response distance under alcohol conditions.
- There is no significant difference between MUTCD and CAMUTCD combinations regarding drivers' hard brake response distance under non-alcohol conditions.

For the data that did not satisfy the assumptions of normality, the non-parametric test- the Wilcoxon Signed-Rank test- was adopted for hypothesis testing, which is used to compare two related (or paired) samples that violated the assumption of normality. The Wilcoxon Signed-Rank test draws conclusions by analyzing the magnitude of the observed difference between to paired data samples. For the null hypothesis listed above, which did not meet the normality requirement, it should be rejected when the p-value is less than 0.05.

Additionally, the ANOVA was applied to hard brake response distance to identify the difference among TCD(s). Further, Tukey's multiple comparison test was conducted for the study after the AVOVA test to examine whether the differences between groups were significant. If the sample data satisfy the assumption of normality, the ANOVA test was used to evaluate the following null hypotheses, and the null hypothesis was not rejected when the p-value exceeded 0.05:

- There is no significant difference between the DNEWW sign, the WW sign, and the WW flashing sign regarding drivers' hard brake response distance under non-alcohol conditions.
- There is no significant difference between the DNEWW sign, the WW sign, and the WW flashing sign regarding drivers' hard brake response distance under alcohol conditions.
- There is no significant difference between the DRS, the RRPM, and the LaneAlert 2X regarding drivers' hard brake response distance under non-alcohol conditions.
- There is no significant difference between the DRS, the RRPM, and the LaneAlert 2X regarding drivers' hard brake response distance under alcohol conditions.
- There is no significant difference between the WW sign and DRS combination, the WW sign and RRPM combination, and the WW sign and LaneAlert 2X combination regarding drivers' hard brake response distance under non-alcohol conditions.
- There is no significant difference between the WW sign and DRS combination, the WW sign and RRPM combination, and the WW sign and LaneAlert 2X combination regarding drivers' hard brake response distance under alcohol conditions.
- There is no significant difference between the WW flashing sign and DRS combination, the WW flashing sign and RRPM combination, and the WW flashing sign and LaneAlert 2X combination regarding drivers' hard brake response distance under non-alcohol conditions.
- There is no significant difference between the WW flashing sign and DRS combination, the WW flashing sign and RRPM combination, and the WW flashing sign and LaneAlert 2X regarding drivers' hard brake response distance under alcohol conditions.

As described in the previous section, the non-parametric test- the Kruskal-Wallis test- was adopted for hypothesis testing if the data did not satisfy the assumptions of normality. For the null hypothesis listed above, which did not meet the normality requirement, it should be rejected when the p-value is less than 0.05.

Chapter 6 Results and Discussion

This chapter summarizes the results of the driving simulator study in three sections: i) general information about participants such as age and the BrAC level; ii) the results on drivers' fixation point distribution for alcohol and non-alcohol drivers; iii) the results on the effectiveness of TCDs based on the driving simulator and eye-tracking data.

6.1 General Information

A total of 680 individuals completed the online screening survey and 83 of them were qualified and contacted to participate in the lab session. Finally, 30 of them completed all three lab testing sessions. The average age of them was 24.67 with a standard deviation (SD) of 7.35. The age ranged from 21 to 59, and only one participant was 59. Most of the participants were college students in their 20s. The average visual acuity was 20/18, and 80% of the participants are Caucasian.

The target BrAC level for this study was set to 0.12 g/dL. Based on the online screening survey results, the average self-reported BrAC for study eligibility was estimated as 0.19 g/dL, which was calculated according to participants' self-reported drinking activities. The researcher reviewed BrAC level data measured immediately before each testing scenario started and computed the average BrAC level for each scenario. **Table 6.1** contains the overall BrAC level descriptive statistics.

Table 6.1 Overall BrAC Level Descriptive Statistics

Scenario	Target Level (g/dL)	Average (g/dL)	SD (g/dL)	Minimum (g/dL)	Maximum (g/dL）
1	0.12	0.109	0.04	0.012	0.177
2	0.12	0.107	0.04	0.017	0.173
3	0.12	0.113	0.04	0.007	0.179

As shown in the table, the average BrAC level for scenarios 1, 2, and 3 were 0.109 g/dL, 0.107 g/dL, and 0.113 g/dL, respectively. The SD for each scenario was 0.04. The average BrAC level for this study was very close to the target level. **Table 6.1** also provided the maximum and minimum BrAC levels obtained during the lab testing. It should be noted that the minimum BrAC level of 0.007 was for one participant who was sick after the first dose of alcohol.

6.2 Fixation Point Distribution for Alcohol and Non-alcohol Drivers

One past study found that alcohol-impaired drivers could more likely focus on pavement surfaces (*Finley et al., 2014*). In this study, the eye-tracking data was analyzed to develop the heatmap of drivers' fixation points under all three scenarios, as shown in **Figure 6.1.**

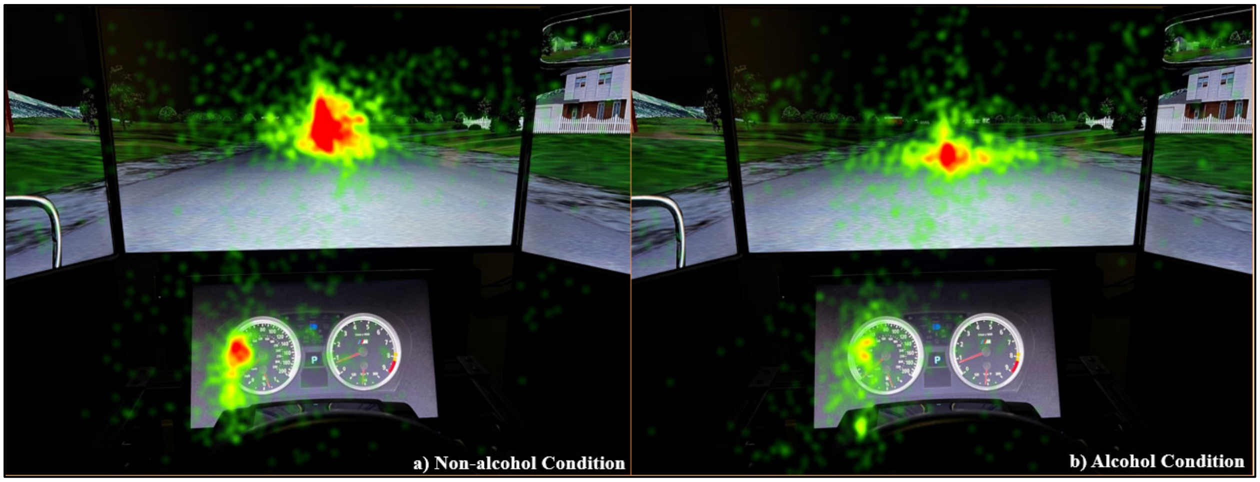


Figure 6.1 Drivers' Fixation Distribution Heatmap under a) Non-alcohol and b) Alcohol

The heatmaps aggregated the drivers' fixation points to help to visualize the fixation distribution for the entire trip. The colors such as red and yellow indicate the areas that attracted more fixations. The figure reveals that drunk drivers' fixation points are distributed closer to the pavement surface than in non-alcohol conditions.

A three-step approach was applied to examine if there is a significant difference between alcohol and non-alcohol drivers' fixation distribution, including i) define seven regions in front of the driver; ii) estimate the percentage of the fixation points in each region; and iii) conduct a chi-square test to determine if the distribution of fixation points in the seven regions are statistically different between alcohol and non-alcohol drivers.

Figure 6.2 illustrates the seven regions in the driver's front view and dashboard of the vehicle. Region 1 indicated the area in front of the vehicle inside the headlight shade area. Region 2 showed the area of the far roadway horizon. Region 3 was above all other regions and included the sky area. Regions 4 and 5 included the area that contained left and right fixation points. Region 6 covered the vehicle's dashboards, and region 7 included the rare mirror of the vehicle.

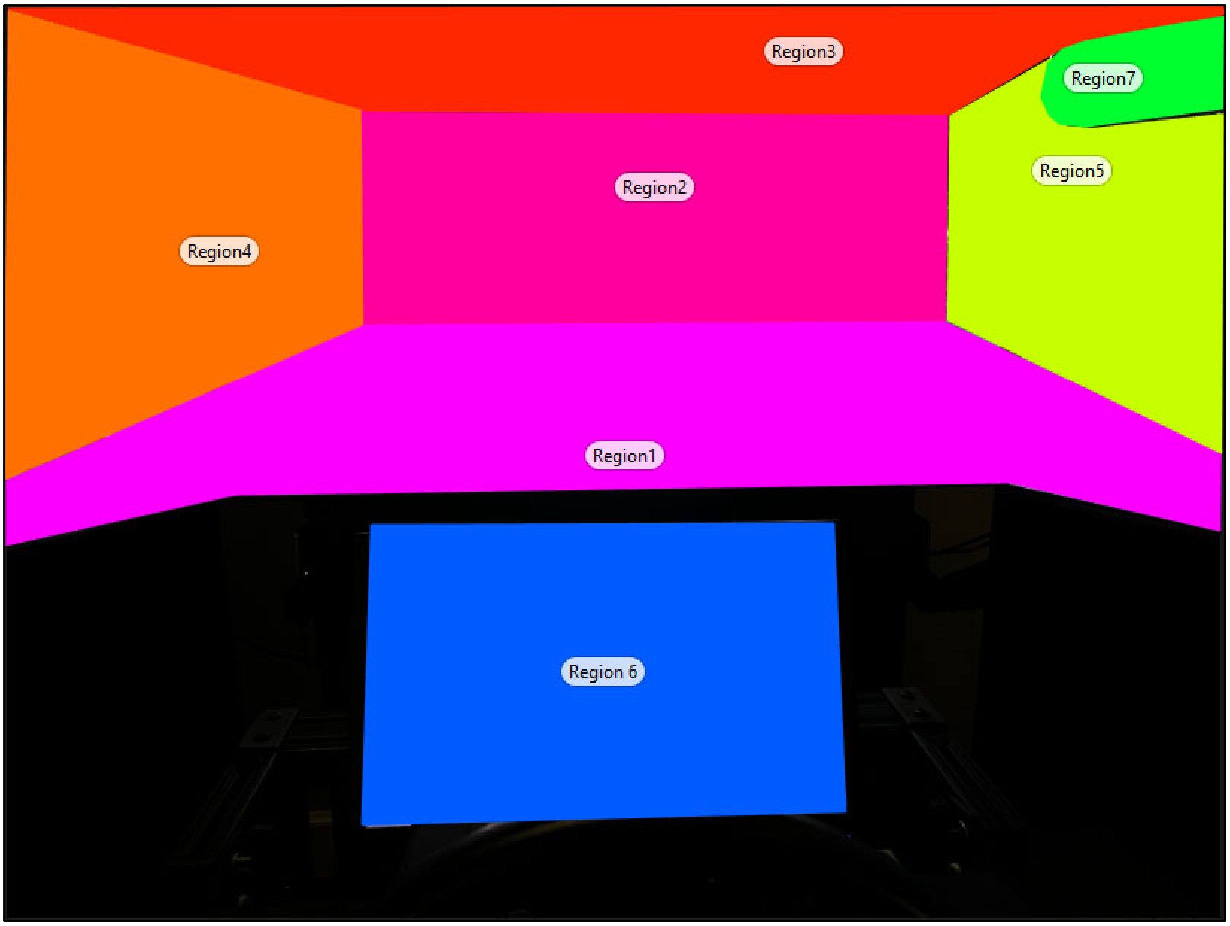


Figure 6.2 Defined Seven Regions for Fixation Distribution Analysis

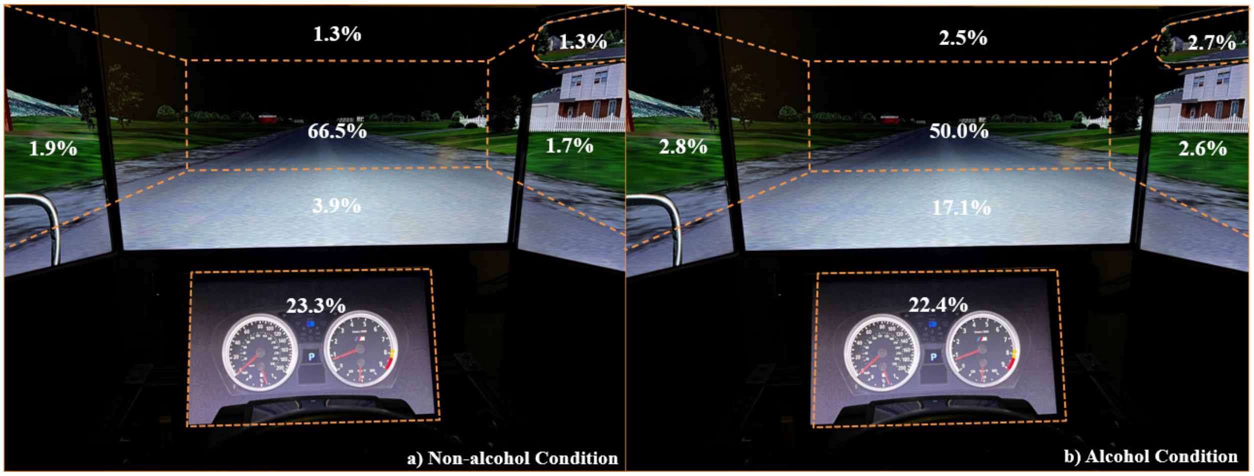


Figure 6.3 Percentage of the Fixation Point at Each Region Under a) Non-alcohol Condition; and b) Alcohol Condition

Figure 6.3 showed the percentage of the fixation point at each region. It can be found that the percentage of the fixation point at the far roadway horizon (Region 1) drop from 66.5% to 50% when drivers are under alcohol condition. On the contrary, the percentage of fixation points in front of the vehicle (Region 2) increased dramatically from 3.9% to 17.1% for alcohol drivers. It can be concluded that alcohol drivers tend to look less toward the far roadway horizon, and more toward the pavement area in front of the vehicle, which is consistent with the past study (*Finley et al., 2014*). Additionally, the percentage of fixation points in regions 3, 4, and 5 under alcohol conditions (2.5%, 2.8%, and 2.6%, respectively) was higher than expected. This may be due to the slow eye movement and recognition capability of alcohol drivers, which needs more time to check out the surrounding condition. Similar results were also found in the past study conducted in Texas (*Finley et al., 2014*), while the researchers summarized that may be due to participants keep searching for the signs even though there were no visual cues.

Finally, a bivariate chi-square test was applied to determine if the distributions of fixation points in the seven regions were dependent on drivers' conditions (alcohol and non-alcohol) ($\chi^2 = 378.72, df = 6, p - value < 2.2 \times 10^{16}$). Since the P-value is less than 0.05, it can be concluded that the proportion of drivers' fixation points in each region varies significantly between alcohol and non-alcohol driving conditions.

6.3 Measures of Effectiveness for TCD(s)

In this study, three variables were used to evaluate the effectiveness of TCD (s): the number of WWD events, fixation durations collected by the eye-tracking device, and brake status collected by the driving simulator

6.3.1 Number of WWD Events

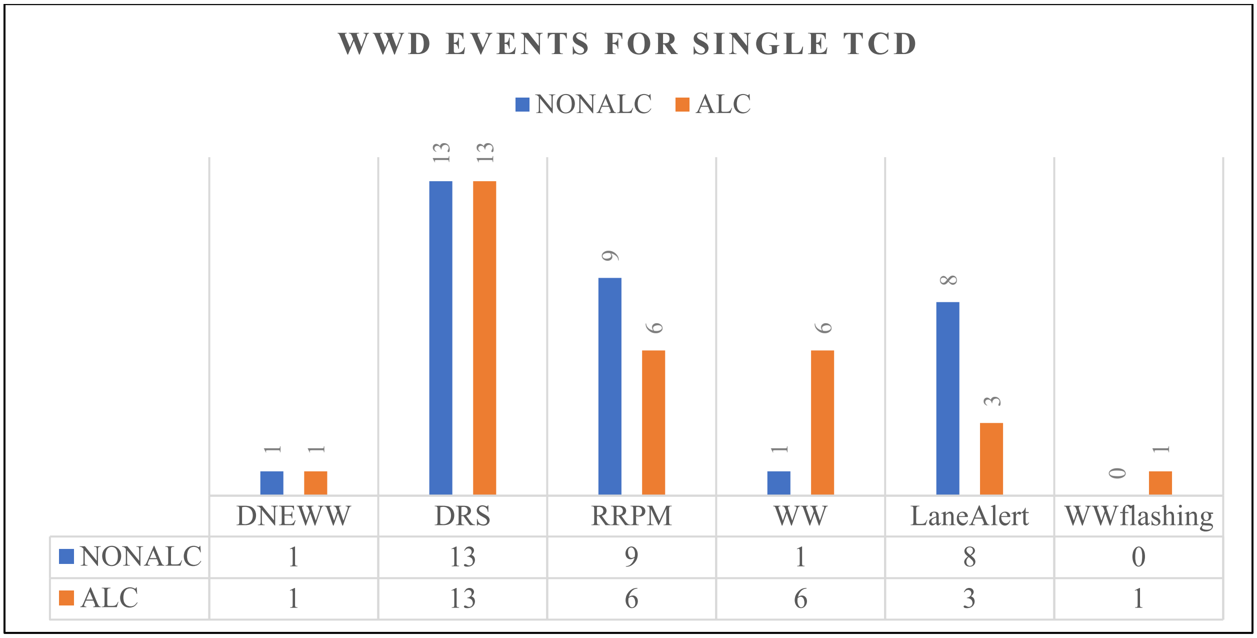


Figure 6.4 WWD Events for Single TCD

Figure 6.4 illustrated the number of WWD events captured when drivers face a single TCD. A total of 62 WWD events were recorded from scenario 1 where only one TCD was added to face the drivers, including 26 for DRS; 15 for RRPM; 11 for LaneAlert; 7 for WW sign, 2 for DNE/WW sign; and 1 for flashing WW sign. Among them, 32 WWD events were made by alcohol drivers; and 30 by non-alcohol drivers. Overall, signs worked better than pavement markings with only 10 WWD events for three types of signs and 52 for three types of pavement markings. DRS had the most WWD events since its purpose was to generate sounds and vibrations to alert drivers for other regulatory/warning signs There were also a large number of WWD incidents when facing the other two types of pavement markings: RRPM (15) and LaneAlert 2X (11). However, the number of WWD events by alcohol drivers is less than those by non-alcohol drivers. This may be due to alcohol drivers' fixation areas toward more to the pavement surface. On the contrary, fewer WWD events were found when drivers faced single signs, especially under non-alcohol conditions. Compared with pavement markings, signs can be noticed at further distances, so drivers can be prepared in advance. Among the three proposed signs, alcohol-impaired drivers have more chance of going to the WW when facing the WW sign, and the number of WWD events increased from one to six.

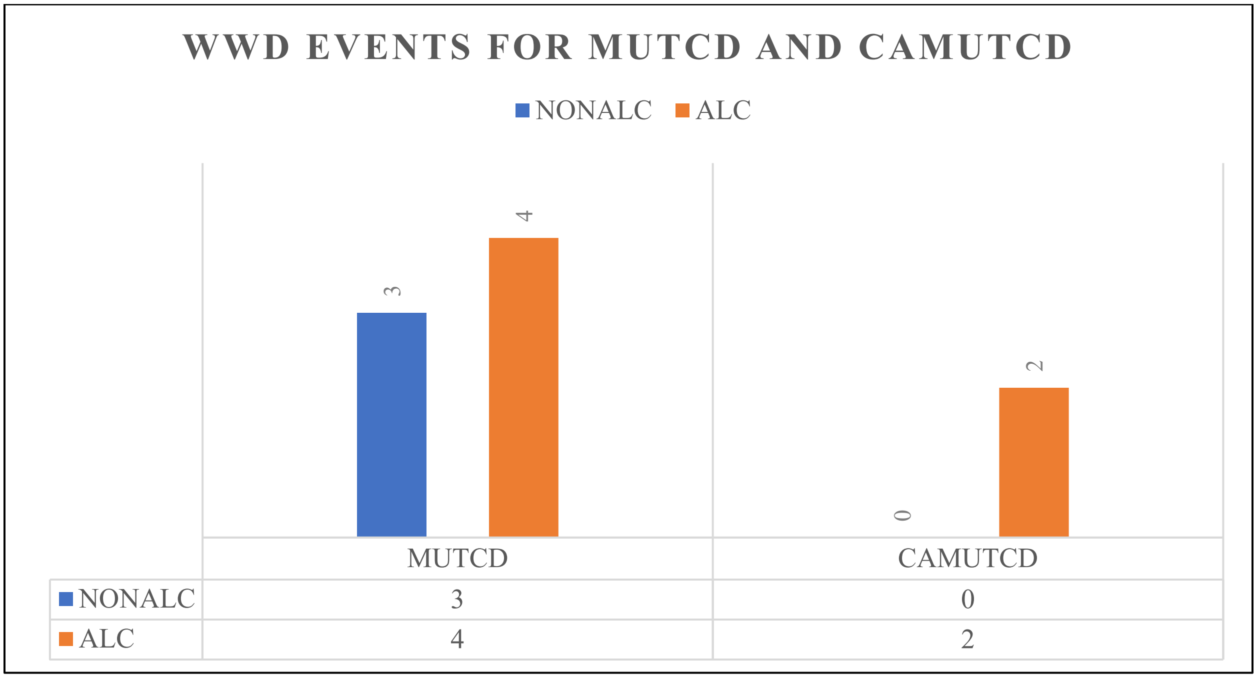


Figure 6.5 WWD Events for MUTCD and CAMUTCD

Similarly, the WWD events captured for TCD combinations based on MUTCD and CAMUTCD were listed in **Figure 6.5**. It can be summarized that three WWD events were found when normal drivers facing to the MUTCD combination, and four WWD events were found when drivers were under alcohol-impaired conditions. As for the TCD combinations followed by CAMUTCD requirements, no WWD events were found under normal conditions, and two WWD events were found under alcohol conditions. Compared to the number of WWD events counted for the single TCD, fewer WW entries were found in this scenario, which reveals that the TCD combinations can better prevent WWD than the single TCD. Additionally, the results also indicate that the TCD combinations followed by MUCTD may not sufficiently prevent WWD evens. However, TCD combinations followed by CAMUTCD reduced the number of WWD events for both alcohol and non-alcohol drivers.

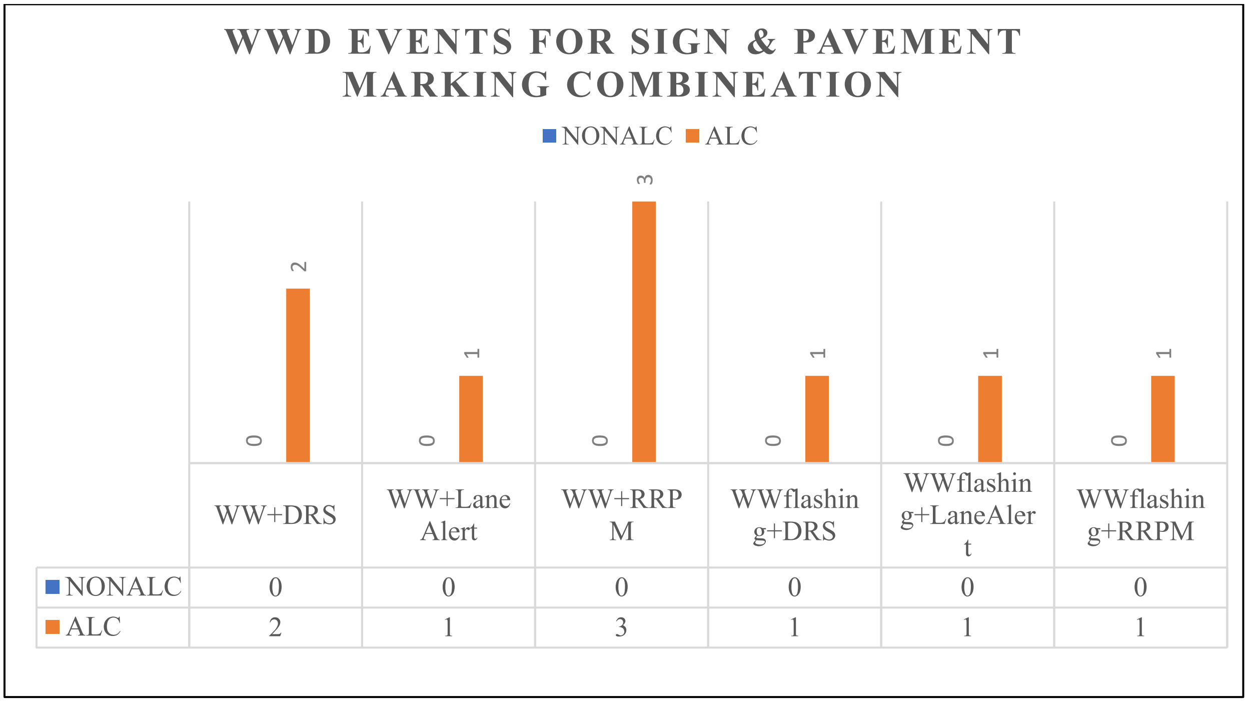


Figure 6.6 WWD Events for Sign and Pavement Marking Combinations

Lastly, as for scenario 3 which contained six sign and pavement marking combinations, **Figure 6.5** shows summarized the number of WWD events for each combination. Although no WWD events were found for all sign and pavement marking combinations under non-alcohol conditions, nine WWDs were founded when drivers were alcohol-impaired. Additionally, the results showed that the combination with WW flashing sign reduced the number of WWD entries from six to three for alcohol drivers compared to the combinations with the traditional WW sign. It can be concluded that the combination with WW flashing sign had the potential to keep alcohol drivers from WWD.

6.3.2 Fixation Duration Using Eye-tracking Data

As mentioned in the last chapter, the fixation durations can be applied as a MOE to evaluate the effectiveness of TCD (s). **Table 6.2** listed the p-values of the Shapiro-Wilk test for each TCD(s) under different conditions.

Table 6.2 Shapiro-Wilk Test Results for Each TCD(s) Using Eye-Tracking Data

Scenario	Variable	TCD	P-value	
			NONALC	ALC
Single TCD	Total Fixation Duration	DNEWW	0.117	0.267
		WW	0.330	0.612
		WWflashing	0.732	0.112
		DRS	0.373	0.865
		RRPM	0.244	0.055
		LaneAlert	0.104	0.460
Single TCD	Average Fixation Duration	DNEWW	0.979	0.007
		WW	0.339	0.028
		WWflashing	0.145	0.515
		DRS	0.128	0.005
		RRPM	0.048	0.000
		LaneAlert	0.004	0.087
MUTCD VS. CAMUTCD	Total Fixation Duration	MUTCD	0.379	0.189
		CAMUTCD	0.227	0.763
Sign & Pavement Marking Combination	Total Fixation Duration	WW+DRS	0.207	0.350
		WW+LaneAlert2X	0.338	0.3214
		WW+RRPM	0.116	0.524
		WWFlashing+DRS	0.659	0.641
		WWFlashing+LaneAlert2X	0.195	0.743
		WWFlashing+RRPM	0.229	0.092

It can be found that the p-value for each TCD(s) regarding total fixation duration is large than 0.05, which means the sample of total fixation duration for each TCD(s) follows the normal distribution assumption, and the Independent T-Test and ANOVA test can be applied for the following analysis. However, for average fixation duration, the p-value for RRPM and LaneAlert under non-alcohol conditions and the p-value for DNEWW, WW, DRS, and RRPM under alcohol conditions are less than 0.05, which means that these samples do not follow the normal distribution assumption. Therefore, the Mann-Whitney U test was adopted for single TCDs alcohol and non-alcohol comparison except WW flashing sign. Additionally, the Kruskal-Wallis test was adopted for group comparison, except sign group during non-alcohol conditions.

For the single TCD, **Table 6.3** listed the total fixation duration for each TCD under different conditions as well as the unpaired t-test results conducted to compare the difference between the two conditions. **Figure 6.7** illustrates the same information for better visualization.

Table 6.3 Total Fixation Duration for Single TCD and T-Test Results

	NONALC		ALC		T Stat	P-value
	N	Mean	N	Mean		
DNEWW	27	8.24	26	6.07	2.80	0.0071*
WW	27	5.35	25	4.23	1.77	0.0828
WWFlashing	27	6.09	25	4.20	2.92	0.0052*
DRS	24	2.52	20	2.47	0.11	0.9138
RRPM	22	4.20	23	1.81	2.75	0.0088*
LaneAlert	21	2.88	19	2.68	0.42	0.67941
Note: * means that p-value less than 0.05.						

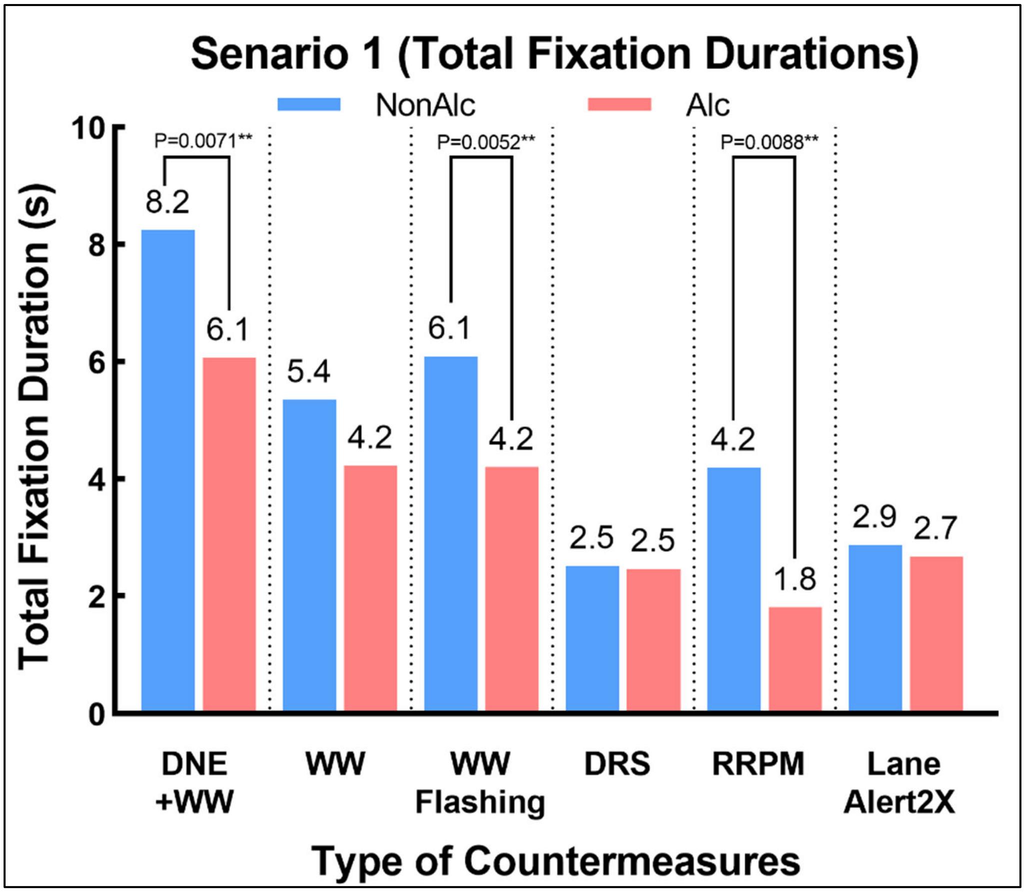


Figure 6.7 Total Fixation Duration for Single TCD

The total fixation duration is summarized as the total time duration participants spend on each TCD with the defined TOI, on average. The key finding can be summarized as two points. First, the results revealed that normal drivers will spend more time on TCD than alcohol-impaired drivers. In other words, the proposed single TCDs are more attractive to normal drivers than to drunk drivers. The unpaired T-test was applied to test whether there exists a statistically significant difference in the total fixation duration between non-alcohol and alcohol conditions. The results show that the total fixation duration was significantly different for DNE and WW signs on the same post (DNEWW, p=0.0071); WW sign with flashing border (WW Flashing, p = 0.0052); and retroreflective raised pavement marker system (RRPM, p = 0.088). The rest of the

TCD did not have any statistically significant difference in the total fixation duration between the two conditions.

Besides, it should be noticed that signs are more attractive than pavement markings for both normal and alcohol-impaired conditions since drivers had longer total fixation duration on signs than pavement markings. The reason is that signs can be visible from a far distance, which can attract drivers for a long time. While the pavement markings are only able to be captured when drivers are approaching them, which means that drivers had less time to focus on the TCD before they make decisions (going the right way or wrong way).

Although the total fixation duration can help us to understand whether the proposed single TCD was attractive for drivers. It is necessary to dive into the depth and identify whether the single TCD is easily understood by drivers. As a result, the average fixation duration was calculated for each participant for both conditions. **Table 6.4** listed the average fixation duration for each TCD under different conditions as well as the Mann-Whitney U test results conducted to compare the difference between the two conditions. **Figure 6.8** illustrates the same information for better visualization.

Table 6.4 Average Fixation Duration for Single TCD and Mann-Whitney U Test Results

	NONALC		ALC		W	P-value
	N	Mean	N	Mean		
DNEWW	27	0.98	26	1.40	154.00	0.0003*
WW	27	0.84	25	1.63	126.5	0.0001*
DRS	24	0.75	20	1.28	121.00	0.0043*
RRPM	22	0.82	23	1.11	202.50	0.2566
LaneAlert	21	1.07	19	1.87	98.50	0.0054*
Note: * means that p-value less than 0.05.						

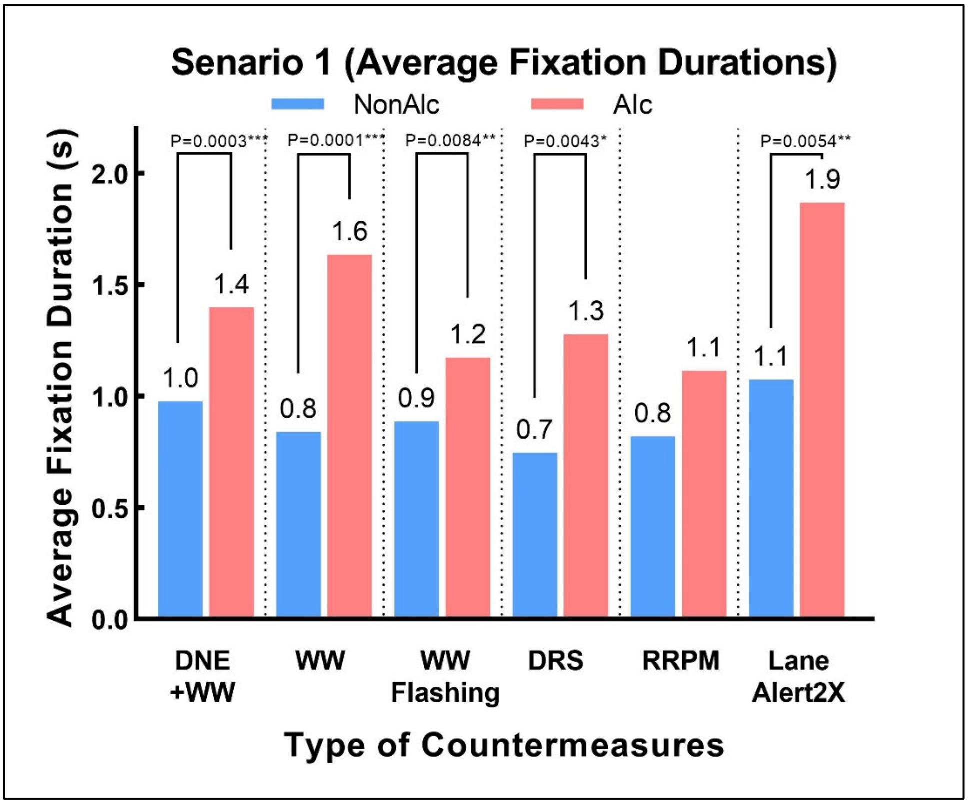


Figure 6.8 Average Fixation Duration for Single TCD

The Independent T-Test conducted for WW flashing sign shows that the p-value is 0.0084 with a T stat of -2.75. The results indicated that there is a significant difference between alcohol and non-alcohol conditions for the WW flashing sign regarding average fixation duration. **Table 6.4** and **Figure 6.7** suggested that drivers typically have longer average fixation durations under alcohol-impaired conditions than normal conditions, which indicates that drunk drivers may need more time for understanding those single TCDs. Further, the Mann-Whitney U test was conducted to identify whether there is any significant difference in the average duration between normal and intoxicated conditions for proposed TCDs. The results indicate that all the single TCDs are statistically significant between the two conditions, except RRPM.

In order to evaluate the effectiveness of the single TCD, the one-way ANOVA test was conducted for the average fixation duration among signs under non-alcohol conditions.

Additionally, the Kruskal-Wallis test was conducted for the average fixation duration among signs under alcohol conditions, and among pavement markings under both conditions. After that, Dunn's multiple comparisons test was applied between two TCDs within each group to determine whether the differences between TCDs were significant. The results of the Kruskal-Wallis test and Dunn's multiple comparisons test are listed in **Table 6.5**, as shown below. Additionally, **Figure 6.9** illustrates the results in a bar chart.

Table 6.5 Results of Kruskal-Wallis Test and Dunn's Comparison Test for Single TCD

Condition	**Group**	**Kruskal-Wallis Stat**	**P-value**	**Dunn's Multiple Comparisions Test**			
				Comparsion		**Mean Rank Diff**	**P-Value**
ALC	Signs	3.645	0.167	DNE	WW	-2.053	0.99
				DNE	WW Flashing	9.127	0.4199
				WW	WW Flashing	11.18	0.2202
NONALC	Pavement Markings	4.167	0.1245	DRS	RRPM	-3.144	0.99
				DRS	LaneAlert	-11.6	0.1392
				RRPM	LaneAlert	-8.451	0.4652
ALC	Pavement Markings	10.09	0.0064	DRS	RRPM	4.816	0.99
				DRS	LaneAlert	-12.6	0.0877
				RRPM	LaneAlert	-17.42	0.0055*

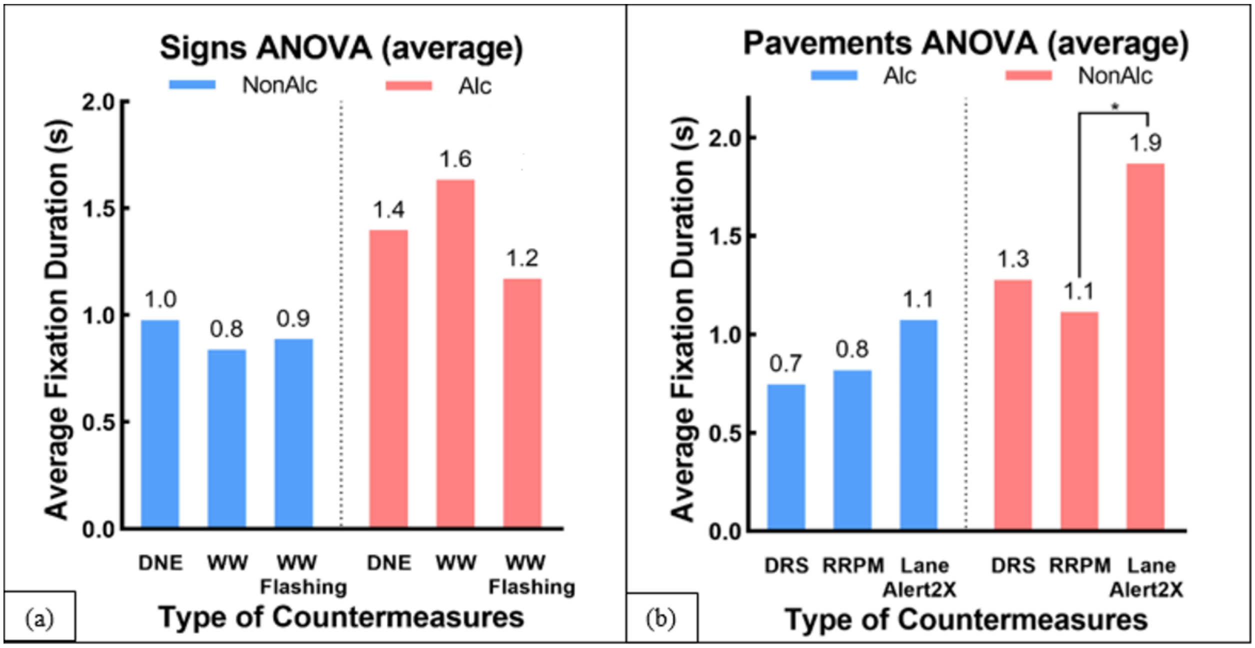


Figure 6.9 Results of ANOVA and Kruskal-Wallis Test and Between Group Comparison Test for a) Signs; and b) Pavement Markings

Based on **Table 6.5 and Figure 6.9**, for single signs, it is found that drivers tend to spend similar times with 1.0 seconds for DNEWW sign, 0.8 seconds for WW sign, and 0.9 seconds for WW flashing sign under normal conditions. Drivers spend relatively less time on WW signs, which may be because the WW sign is most commonly used in deterring WWD and drivers get used to it. As for alcohol drivers, the average fixation duration for the WW sign was significantly increased to 1.6 seconds, which indicates that drivers need a longer time to understand it. It should also be noticed that drivers spend the least amount of time understanding the WW flashing signs (1.2 seconds) under alcohol conditions, compared to WW signs. As for single pavement markings, the results indicate that divers spend less time on DRS (0.7 seconds) and more time on the LaneAlert 2X (1.1 seconds) for pavement markings under non-alcohol conditions. The results are in accord with the expectations since the DRS and RRPM used vibration and red retro-reflectivity, respectively, to warn drivers to keep away from WWD. However, drivers have to capture and read the warning message on the LaneAlert 2X to understand the current situation when approaching it, which may take a relatively long time. Additionally, when drivers are under alcohol-impaired conditions, the average fixation duration for LaneAlert 2X increased dramatically from 1.1 seconds to 1.9 seconds. On the contrary, the least average fixation duration was applied on the RRPM.

The ANOVA test indicates that when drivers are under normal conditions, there is no significant difference in average fixation duration among signs (p = 0.325). According to the Kruskal-Wallis Test, there are no significant differences in average fixation duration among signs under alcohol conditions (p = 0.167), and among pavement markings under non-alcohol conditions (p = 0.1245). There is a statistically significant difference among pavement markings under alcohol-impaired conditions (p = 0.0064). Further, Dunn's multiple comparison tests show that the average fixation duration of alcohol drivers is signification different between RRPM and LaneAlert 2X, which can be concluded as LaneAlert needs a significantly longer time to understand drunk drivers than RRPM.

For the combined TCDs followed by MUTCD and CAMUTCD, **Table 6.6** listed the total fixation duration for each combination under different conditions as well as the unpaired T-test results conducted to compare the difference between the two conditions. **Figure 6.10** illustrates the same information for better visualization.

Table 6.6 Total Fixation Duration for MUTCD and CAMUTCD and T-Test Results

	NONALC		**ALC**		**T Stat**	**P-value**
	N	**Mean**	**N**	**Mean**		
MUTCD	28	8.04	26	3.05	6.16	<0.0001*
CAMUTCD	26	9.13	25	5.27	4.49	<0.0001*
Note: * means that p-value less than 0.05.						

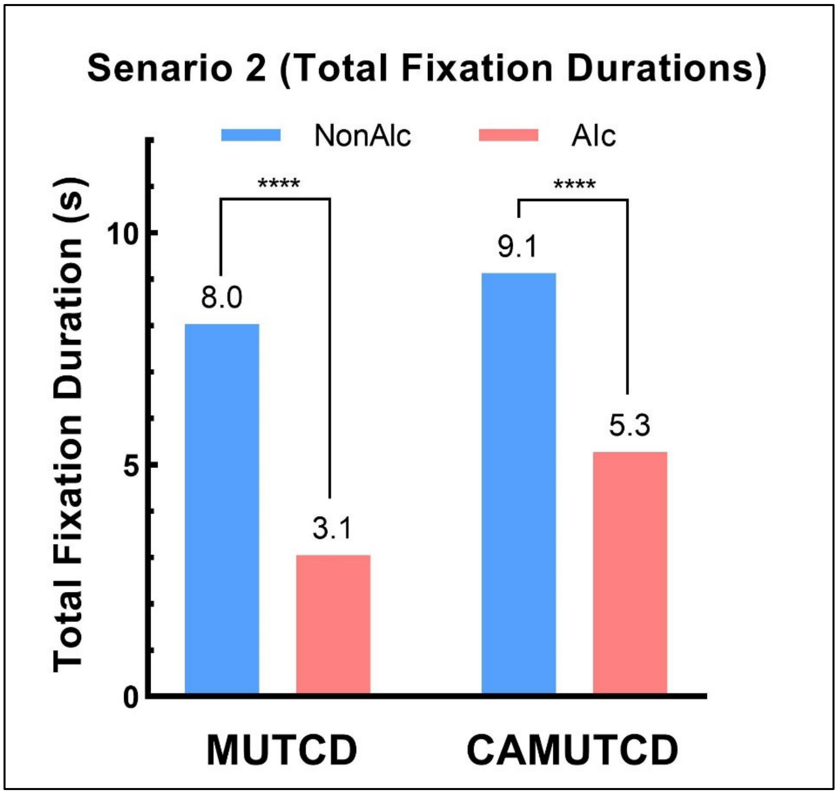


Figure 6.10 Total Fixation Duration for MUTCD and CAMUTCD Combinations

The table and the figure illustrated that normal drivers usually spend an average of 8.04 seconds on the MUTCD combination while it drops to 3.1 seconds after the alcohol was consumed. As for the CAMUTCD combination, normal drivers spend an average of 9.13 seconds on it, while the mean total fixation duration for alcohol-impaired drivers is only 5.27 seconds. The unpaired T-test was applied to the results to identify whether there is any significant difference between different conditions for each TCD combination. Since the p-value for both MUTCD and CAMUTCD combinations are less than 0.0001, it can be concluded that drivers spend less time on TCD combinations under alcohol-impaired conditions compared with the normal conditions.

Additionally, in order to evaluate the effectiveness of the TCD combinations followed by MUTCD and CAMUTCD, another unpaired t-test was conducted for the total fixation duration between combinations under certain conditions. The results of the T-test test are listed in **Table 6.7**, as shown below. Additionally, **Figure 6.11** illustrates the same information for better visualization.

Table 6.7 T-Test Results for MUTCD and CAMUTCD Comparison

	Comparison		T Stat	P-Value
NONALC	MUTCD	CAMUTCD	1.053	0.2972
ALC	MUTCD	CAMUTCD	4.318	<0.0001*
Note: * means that p-value less than 0.05.				

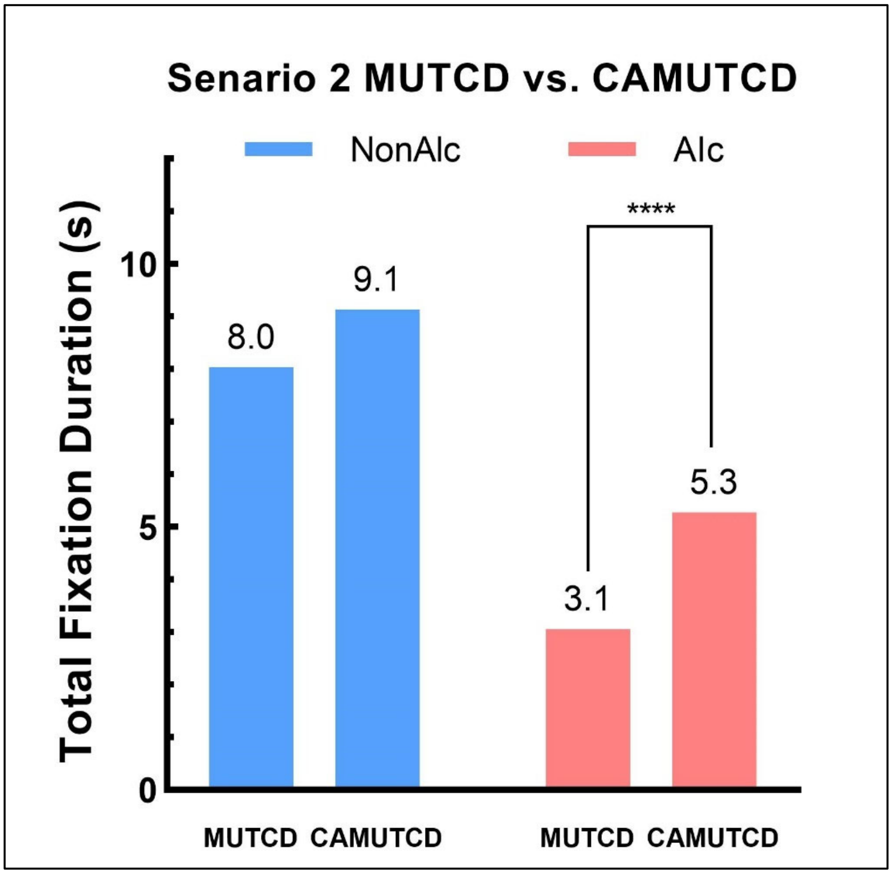


Figure 6.11 T-Test Results for MUTCD and CAMUTCD Comparison

It is found that the combination followed by the CAMUTCD is more attractive than the combination followed by the MUTCD. The results show that drivers will spend an average of 1.1

seconds more on CAMUTCD combination under normal conditions compared to MUTCD. Similarly, drunk drivers spend 2.2 seconds more on the CAMUTCD combination. The t-test results indicate that there is no statistically significant difference in total fixation duration between MUTCD and CAMUTCD combinations under normal conditions. However, when drivers got drunk, there is a statistically significant difference in total fixation duration between MUTCD and CAMUTCD combinations under normal conditions, which can be concluded as alcohol-impaired drivers looked at CAMUTCD combinations longer than MUTCD combinations.

Finally, for the sign and pavement combinations, **Table 6.8** listed the total fixation duration for each combination under different conditions as well as the unpaired T-test results conducted to compare the difference between the two conditions. **Figure 6.12** illustrates the same information for better visualization.

Table 6.8 Total Fixation Duration for Sign and Pavement Marking Combinations and T-Test Results

	NONALC		ALC		T Stat	P-value
	N	Mean	N	Mean		
WW+DRS	22	2.77	18	2.14	1.87	0.0694
WW+LaneAlert	23	2.70	19	1.80	2.53	0.0157*
WW+RRPM	26	2.31	24	1.58	2.00	0.0511
WWflashing+DRS	25	3.28	23	2.92	0.74	0.4656
WWflsfhing+LaneAlert	25	3.09	24	1.94	2.53	0.0148*
WWflashing+RRPM	25	3.44	26	2.75	1.54	0.1291
Note: * means that p-value less than 0.05.						

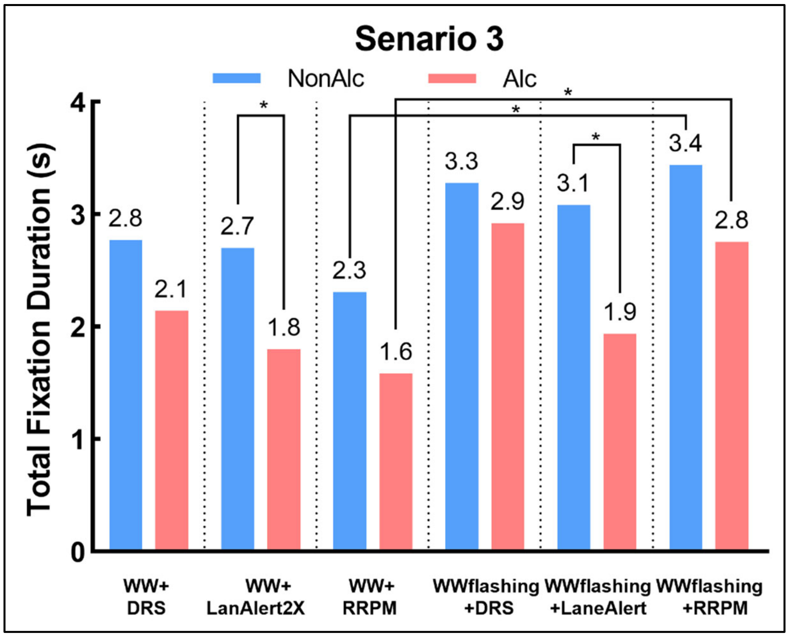


Figure 6.12 Total Fixation Duration for Sign and Pavement Marking Combinations

According to **Table 6.8** and **Figure 6.12**, it is found that normal drivers spend more time on sign and pavement marking combinations than alcohol-impaired drivers. In other words, the proposed sign and pavement marking combinations are more attractive to normal drivers than to drunk drivers. The results are consistent with the previous results for single TCD and TCD combinations followed by MUTCD and CAMUTCD. After that, the unpaired T-test was applied to test whether there exists a statistically significant difference in the total fixation duration between non-alcohol and alcohol conditions. The results show that the total fixation duration was significantly different for WW sign and LaneAlert 2X combinations (WW + LaneAlert, p=0.0157); and WW flashing sign and LaneAlert 2X combinations (WWflashing + LaneAlert, p = 0.0148). The rest of the TCD(s) did not have any statistically significant difference in the total fixation duration between the two conditions.

Additionally, **Figure 6.12** illustrates that the combinations with WW flashing sign tend to have longer total fixation duration compared to the combinations with the traditional WW sign.

For example, for non-alcohol conditions, drivers' average fixation duration of the WW flashing sign and DRS combination is 3.3 seconds, whereas the average fixation duration of the WW sign and DRS combination is 2.8 seconds. As a result, the unpaired T-test was conducted for those combinations with the same pavement markings but different signs in order to determine whether the WWflafhing sign can attract more attention. As shown in the figure, only the comparisons between the WW sign and RRPM combination and the WW flashing sign and RRPM combination are statistically significantly different at a 95% confidence interval. The rest of the combinations did not have any significant differences.

In order to evaluate the effectiveness of the sign and pavement marking combinations, the one-way ANOVA test was conducted for the total fixation duration among the traditional WW sign and the WW flashing sign under different conditions. After that, Tukey's multiple comparisons test was applied between two combinations within each group to determine whether the differences between combinations were significant. The results of the ANOVA test and Tukey's multiple comparisons test are listed in **Table 6.9**, as shown below. Additionally, **Figure 6.13** illustrates the same information for better visualization.

Table 6.9 Results of ANOVA Test and Tukey's Comparison Test for Sign and Pavement Combinations

Condition	Group	F	P-value	Tukey's Multiple Comparisons Test			
				Comparison		Mean Diff	P-Value
NONALC	WW	0.84	0.4352	DRS	LaneAlert	0.07	0.9836
				DRS	RRPM	0.46	0.4663
				LaneAlert	RRPM	0.39	0.5677
ALC	WW	1.84	0.1677	DRS	LaneAlert	0.34	0.5141
				DRS	RRPM	0.56	0.1428
				LaneAlert	RRPM	0.22	0.7276
NONALC	WWflashing	0.25	0.7806	DRS	LaneAlert	0.19	0.9215
				DRS	RRPM	-0.16	0.9456
				LaneAlert	RRPM	-0.35	0.7619
ALC	WWflashing	3.22	0.0461*	DRS	LaneAlert	0.98	0.05*
				DRS	RRPM	0.17	0.9134
				LaneAlert	RRPM	-0.82	0.117
Note: * means that p-value less than 0.05.							

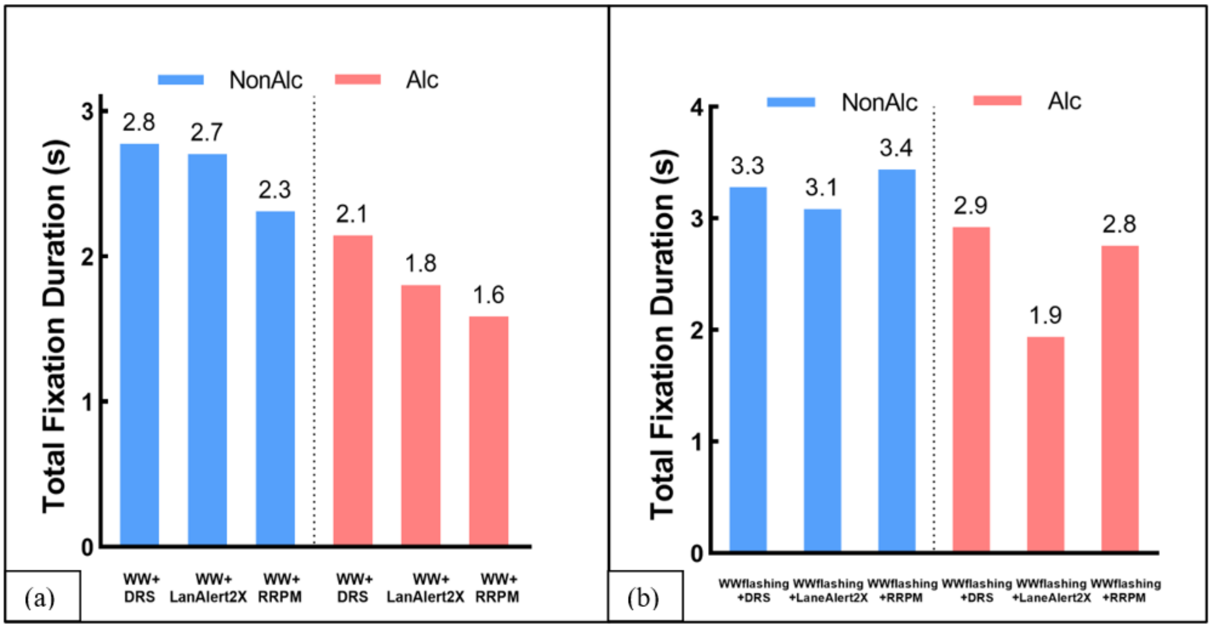


Figure 6.13 Results of ANOVA Test and Tukey's Comparison Test for a) WW Sign; and b) WW Flashing Sign

Based on **Table 6.9 and Figure 6.13**, for the combinations with the WW sign, it is found that the combination of the WW sign and DRS attracts the driver's attention for the longest time for both conditions. Then it follows with the WW sign and LaneAlert 2X combination. The WW sign and RRPM combination is the one with the least total fixation duration for both conditions. As for the combinations with the WW flashing sign, it is found that WW flashing sign and RRPM is the combination that attracts drivers the most under normal conditions, and it also has a similar performance with the WW flashing sign and DRS combination under alcohol-impaired conditions. Additionally, the WW flashing sign and LaneAlert 2X is the combination with the least total fixation duration for both conditions.

The ANOVA test indicates that there is no significant difference in total fixation duration among combinations with WW signs for both normal and alcohol-impaired conditions ($p = 0.4352$, and $p = 0.1677$, respectively). However, the ANOVA test shows there are statistically significant differences among combinations with WW flashing signs under alcohol-impaired conditions (p = 0.0461). Further, Tukey's multiple comparisons tests show that the total fixation duration of drunk drivers is signification different between DRS and LaneAlert 2X combinations, which can be concluded as the DRS increase the total fixation duration for WW flashing sign for alcohol-impaired drivers.

6.3.3 Brake Response Using Driving Simulator Data

The braking usage distributions for each TCD (s) were depicted, which aims to visualize how many participants applied brake at each point when approaching the TCD (s). **Figure 6.14** shows an example of braking usage distributions of DNEWW and DRS for normal and alcohol-impaired conditions. The rest of the braking usage distributions can be found in **Appendix I**. The corresponding distances that most of the people (as a percentage) applied brake for each TCD (s) are summarized in **Table 6.10** for a better understanding of the figure.

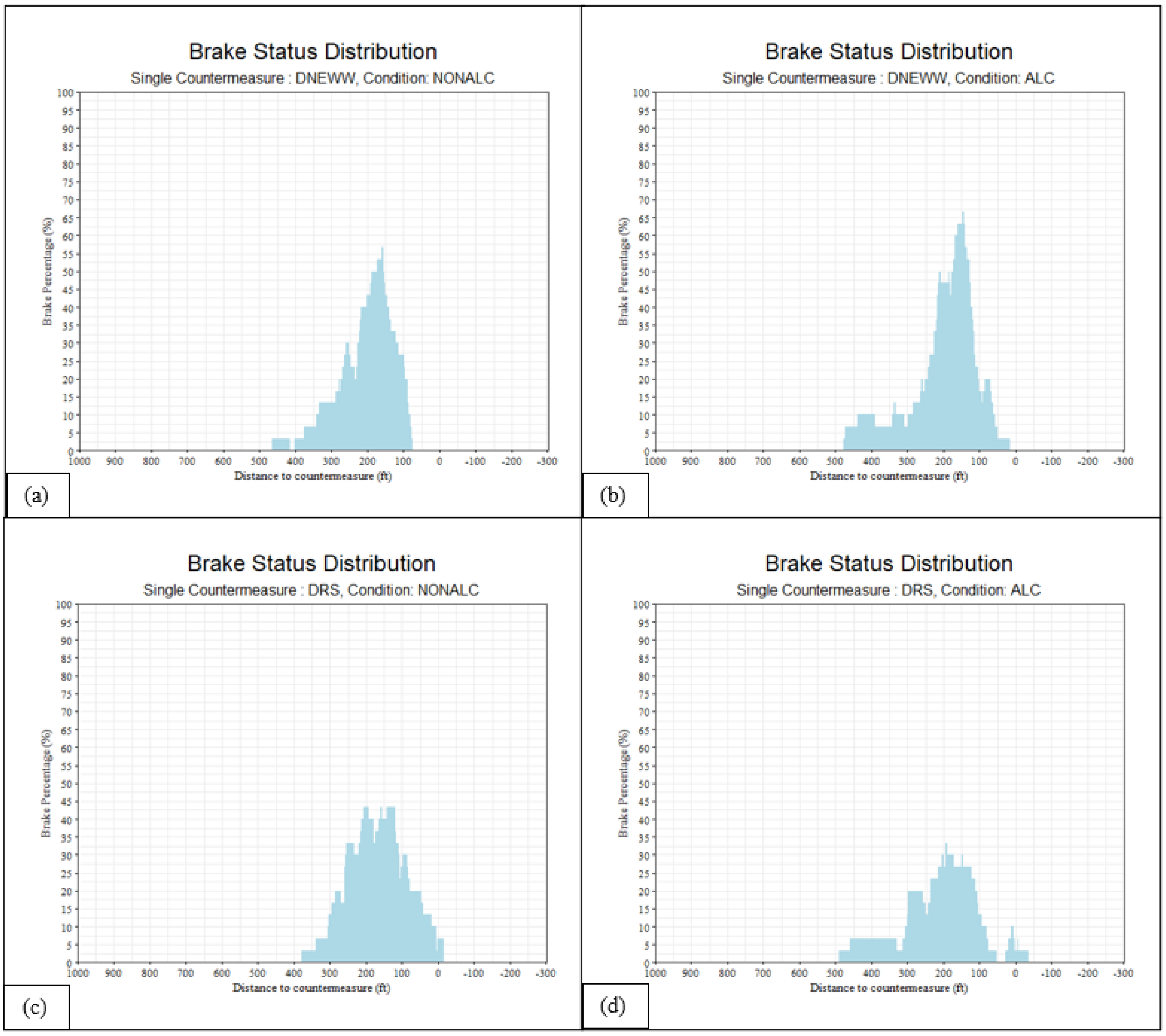


Figure 6.14 Brake Status Distribution

Table 6.10 Distance to the TCD When Most of the People Applied Brake

Scenarios	TCD (s)	NONALC		ALC	
		Distance to Countermeasure (ft)	Percentage of People Applied Brake	Distance to Countermeasure (ft)	Percentage of People Applied Brake
1	DNEWW	219	53%	201	46%
	WW	199	57%	167	60%
	WW Flashing	215	60%	231	60%
	DRS	176	63%	228	53%
	RRPM	215	70%	200	57%
	LaneAlert 2X	215	50%	186	43%
2	MUTCD	137	70%	208	63%
	CAMUTCD	179	60%	200	63%
3	WW+DRS	219	53%	201	46%
	WW+LaneAlert2X	215	60%	231	60%
	WW+RRPM	215	70%	200	57%
	WWFlashing+DRS	199	57%	167	60%
	WWFlashing+LaneAlert2X	215	60%	231	60%
	WWFlashing+RRPM	215	50%	186	43%

According to **Figure 6.14**, it is found that drivers start to apply the brake at a similar distance when facing the DNEWW for both normal and alcohol-impaired conditions. However, normal drivers tend to stop using the brake pedal earlier than alcohol-intoxicated drivers, who tend to stop using the brake pedal at a very close distance. **Table 6.10** also shows that most of the drivers (53%) applied the brake when they are 219 ft away from the sign under normal conditions, while most of the drunk drivers (46%) applied the brake when they are 201ft away from the DNEWW sign. It can be concluded that normal drivers have a little bit earlier response to the brake pedal when facing the DNEWW sign. As for the DRS, on the contrary, the drunk driver responded earlier than the normal drivers due to the further distance starting to hit the brake and the further distance that most drivers apply the brake than normal drivers.

Table 6.10 indicates that for the scenario with a single TCD, it is found that most of the drunk drivers applied the brake pedal at relatively further distances than normal drivers when facing the WW flashing sign and the DRS. As for the comparison among TCDs under the same conditions, WW flashing sign has the furthest distance (231 ft) and LaneAlert 2X has the nearest distance (186 ft) when most of the drunk drivers applied the brake. And under normal conditions, the DNEWW sign has a relatively furthest distance (219 ft) when most of the drivers applied the brake, then followed by the WW flashing sign (215 ft), RRPM (215 ft), and LaneAlert 2X (215 ft). As for the scenario with TCD combinations followed by MUTCD and CAMUTCD, the results show that most of the drunk drivers applied the brake pedal at relatively further distances than normal drivers for both combinations. When talking about the comparison between combinations under certain conditions, it is found that most drivers applied the brake pedal at relatively further distances when facing the TCD combination followed by CAMUTCD under both conditions (179 ft for non-alcohol conditions and 200 ft for alcohol conditions). As for the scenario that contains sign and pavement marking combinations, the results reveal that most of the drunk drivers applied the brake pedal at relatively further distances than normal drivers when facing the combinations with LaneAlert 2X (231 ft both WW+LaneAlert2X and WWFlashing+LaneAlert2X). When comparing among TCDs under the same condition, it can be concluded that the combinations with LaneAlert 2X have the furthest distance (231 ft both WW+LaneAlert2X and WWFlashing+LaneAlert2X) when most of the drunk drivers applied the brake. And under normal conditions, the WW sign and DRS combination have a relatively furthest distance (219 ft) when most of the drivers applied the brake. The combination of the WW flashing sign and DRS has the nearest distance (199 ft for non-alcohol and 167 ft for alcohol) when most of the drivers applied the brake under both conditions.

Additionally, the researcher also analyzed the brake pedal usage condition after drivers drove WW for every single TCD due to the largest number of WWD events captured for this scenario. The results indicated that no driver applied the brake after passing the DNEWW sign and WW flashing sign since few WW entries were found for these two TCDs. As for the WW sign, one participant was found to apply the brake right after passing it under the alcohol-impaired condition. Additionally, one participant was was found to apply the brake after passing the WW sign 191 ft under the normal condition. As for the pavement markings, two drivers were founded to apply the brake when passing the DRS to 33 ft under alcohol-impaired conditions and to 13 ft under normal conditions. When passing the RRPM, drivers drove a certain distance before applying the brake (190 ft for alcohol-impaired conditions, and 96 ft for normal conditions). As for the LaneAlert 2X, one normal driver was found to apply the brake right after passing the TCD to 22 ft. Two drunk drivers were found applying the brake right after passing the TCD to 96 ft.

As for the hard brake response distance, **Table 6.11** listed the p-values of the Shapiro-Wilk test for each TCD(s) under different conditions.

Table 6.11 Shapiro-Wilk Test Results for Each TCD(s) Using Driving Simulator Data

Scenario	Variable	TCD	P-value	
			NONALC	ALC
Single TCD	Hard Brake Response Distance	DNEWW	0.189	0.139
		WW	0.073	0.154
		WWflashing	0.088	0.016
		DRS	0.398	0.349
		RRPM	0.157	0.374
		LaneAlert	0.368	0.338
MUTCD VS. CAMUTCD	Hard Brake Response Distance	MUTCD	0.895	0.681
		CAMUTCD	0.086	0.999
Sign & Pavement Marking Combination	Hard Brake Response Distance	WW+DRS	0.240	0.197
		WW+LaneAlert2X	0.083	0.9729
		WW+RRPM	0.290	0.709
		WWFlashing+DRS	0.267	0.647
		WWFlashing+LaneAlert2X	0.587	0.730
		WWFlashing+RRPM	0.583	0.113

It can be found that all the p-value are large than 0.05, which means the sample of fixation duration for each TCD(s) follows the normal distribution assumption. Therefore, the Paired-Samples T-Test and the ANOVA test can be applied for the following analysis.

Table 6.12 Hard Brake Response Distance for Single TCD and T-Test Results

	NONALC		ALC		T Stat	p-value
	N	Mean	N	Mean		
DNEWW	22	243.82	22	244.41	-0.02	0.98
WW	21	265.67	21	262.05	0.17	0.87
WWFlashing	20	252.90	20	279.40	-0.88	0.39
DRS	14	227.93	14	265.00	-0.79	0.45
RRPM	19	259.26	19	290.42	-1.43	0.17
LaneAlert	17	258.11	17	256.17	0.07	0.95
Note: * means that p-value less than 0.05.						

Table 6.12 listed the hard brake response distance for each single TCD as well as the Paired T-test results conducted to compare the difference between the two conditions. The results show that drivers tend to have long hard brake response distances under alcohol conditions, except WW sign and LaneAlert 2X. It may be because alcohol drivers have less capability to control the vehicle and they may hit the break harder than non-alcohol drivers. However, the Paired-Samples T-Test results reveal that there is no significant difference between alcohol and non-alcohol drivers for every single TCD regarding the hard brake response distance.

Table 6.13 Results of ANOVA Test and Tukey's Comparison Test for Single TCD

Condition	**Group**	**F**	**P-value**	**Tukry's Multiple Comparisions Test**			
				Comparsion		**Mean Diff**	**P-Value**
NONALC	Signs	0.4281	0.6537	DNE	WW	-21.85	0.6285
				DNE	WW Flashing	-9.08	0.9242
				WW	WW Flashing	12.77	0.8588
ALC	Signs	0.68	0.5105	DNE	WW	-17.64	0.8233
				DNE	WW Flashing	-34.99	0.4782
				WW	WW Flashing	-17.35	0.8357
NONALC	Pavement Markings	0.5909	0.5578	DRS	RRPM	-31.33	0.5895
				DRS	LaneAlert	-30.18	0.619
				RRPM	LaneAlert	1.152	0.9992
ALC	Pavement Markings	0.7543	0.5758	DRS	RRPM	-25.42	0.6912
				DRS	LaneAlert	8.833	0.957
				RRPM	LaneAlert	34.25	0.4669

Table 6.13 listed the comparison results of hard brake response distance among sign and pavement marking groups under both conditions. According to **Table 6.12**, under non-alcohol conditions, drivers have the farthest hard brake response distance when facing the WW sign (266 ft) and have the closest hard brake response distance when facing the DNEWW sign (244 ft). As for alcohol conditions, drivers have the farthest hard brake response distance when facing the

WW flashing sign (279 ft) and have the closest hard brake response distance when facing the DNEWW sign (244 ft). As for the pavement marking groups, drivers have the farthest hard brake distance when facing RRPM for both conditions (259 ft for non-alcohol conditions and 290 for non-alcohol conditions). On the other hand, drivers have the closest hard brake distance when facing DRS (227 ft) under non-alcohol conditions and facing LaneAlert 2X (256 ft) under alcohol conditions. However, the results listed in **Table 6.13** show that there is no significant difference regarding the hard brake response distance among sign and pavement marking groups under both conditions.

Table 6.14 Hard Brake Response Distance for MUTCD and CAMUTCD and T-Test Results

	NONALC		**ALC**		**T Stat**	**p-value**
	N	**Mean**	**N**	**Mean**		
MUTCD	23	238.52	23	268.74	-1.45	0.16
CAMUTCD	23	250.48	23	245.61	0.26	0.80
Note: * means that p-value less than 0.05.						

Table 6.14 listed the hard brake response distance for MUTCD and CAMUTCD combinations as well as the Paired T-test results conducted to compare the difference between the two conditions. The results show that drivers tend to have long hard brake response distances under alcohol conditions for MUTCD, and tend to have less hard brake distance under alcohol conditions for CAMUTCD. However, the Paired-Samples T-Test results reveal that there is no significant difference between alcohol and non-alcohol drivers for every single TCD regarding the hard brake response distance.

Table 6.15 T-Test Results for MUTCD and CAMUTCD Comparison

	MUTCD		CAMUTCD		T Stat	p-value
	N	Mean	N	Mean		
NONALC	23	238.52	23	250.48	-0.46181	0.65
ALC	23	268.74	23	245.61	1.096964	0.28
Note: * means that p-value less than 0.05.						

Table 6.15 listed the hard brake response distance for MUTCD and CAMUTCD combinations as well as the Paired T-test results conducted to compare the difference between the TCDs. According to **Table 6.15**, under non-alcohol conditions, drivers have the farthest hard brake response distance when facing the CAMUTCD combinations (250 ft) and have the closest hard brake response distance when facing the MUTCD combinations (239 ft). As for alcohol conditions, drivers have the farthest hard brake response distance when facing the MUTCD combinations (269 ft) and have the closest hard brake response distance when facing the CAMUTCD combinations (246 ft). However, the Paired-Samples T-Test results reveal that there is no significant difference between two combinations for both conditions regarding the hard brake response distance.

Table 6.16 Hard Brake Response Distance for Sign and Pavement Marking Combinations and T-Test Results

	NONALC		ALC		T Stat	p-value
	N	Mean	N	Mean		
WW+DRS	26	230.81	26	231.58	-0.04	0.97
WW+RRPM	23	242.22	23	246.00	-0.14	0.89
WW+ LaneAlert2X	24	232.83	24	242.04	-0.76	0.45
WWFlashing+DRS	22	238.45	22	277.95	-1.54	0.14
WWFlashing+RRPM	23	234.74	23	289.96	-2.71	0.01*
WWFlashing+ LaneAlert2X	23	281.17	23	305.30	-1.19	0.25
Note: * means that p-value less than 0.05.						

Table 6.17 Results of ANOVA Test and Tukey's Comparison Test for Sign and Pavement Combinations

Condition	Group	F	P-value	Tukry's Multiple Comparisions Test			
				Comparsion		Mean Diff	P-Value
NONALC	WW	0.1251	0.8826	DRS	RRPM	-11.41	0.8836
				DRS	LaneAlert	-2.026	0.996
				RRPM	LaneAlert	9.384	0.9225
ALC	WW	0.2306	0.7947	DRS	RRPM	-14.42	0.7922
				DRS	LaneAlert	-10.46	0.8819
				RRPM	LaneAlert	3.958	0.9832
NONALC	WWflashing	3.043	0.0545	DRS	RRPM	3.715	0.9831
				DRS	LaneAlert	-42.72	0.1143
				RRPM	LaneAlert	-46.43	0.0743
ALC	WWflashing	0.627	0.5374	DRS	RRPM	-12.00	0.8765
				DRS	LaneAlert	-27.35	0.5078
				RRPM	LaneAlert	-15.35	0.8024

Table 6.16 listed the hard brake response distance for each single TCD as well as the Paired T-test results conducted to compare the difference between the two conditions. **Table 6.17** listed the comparison results of hard brake response distance among sign and pavement marking groups under both conditions using ANOVA tests. The results show that drivers tend to have long hard brake response distances under alcohol conditions, which is in accord with the results obtained from scenario 1. However, the Paired-Samples T-Test results reveal that there is no significant difference between alcohol and non-alcohol drivers for every single TCD regarding the hard brake response distance. According to **Table 6.16**, under both conditions, drivers have the farthest hard brake response distance when facing the WW sign and RRPM combination (242 ft for non-alcohol conditions, and 246 ft for alcohol conditions). Drivers have the closest hard brake response distance when facing the WW sign and DRS combination (231 ft for non-alcohol conditions and 232 ft for alcohol conditions). As for the WW flashing sign combinations, drivers have the farthest hard brake distance when facing WW flashing sign and

LaneAlert 2X combinations in both conditions (281 ft for non-alcohol conditions and 305 for non-alcohol conditions). On the other hand, drivers have the closest hard brake distance when facing the WW flashing sign and RRPM combination (235 ft) under non-alcohol conditions and facing WW flashing sign and DRS combination (278 ft) under alcohol conditions. However, the results listed in **Table 6.17** show that there is no significant difference regarding the hard brake response distance among sign and pavement marking groups under both conditions.

Table 6.18 T-Test Result for WW Sign Combinations and WW Flashing Sign Combinations

	Combine with WW		Combine with WWflashing		T Stat	p-value
	N	Mean	N	Mean		
NONALC	75	242	75	256	-1.2574	0.11
ALC	71	257	71	275	-1.5945	0.05*
Note: * means that p-value less than 0.05.						

Since there is no difference among WW sign combinations and WW flashing sign combinations under both conditions, then another Paired T-test was conducted in order to compare whether there is any significant difference between WW sign combinations and WW flashing sign combinations. According to **Table 6.18**, it is found that there is no significant difference between WW sign combinations and WW flashing sign combinations regarding hard brake response distance under non-alcohol conditions. However, when drivers are under alcohol conditions, the p-value equals 0.05, which means that there is a significant difference between WW sign combinations and WW flashing sign combinations. In other words, the WW flashing sign can help alcohol drivers increase 7% of hard brake response distance than the WW sign.

Chapter 7 Conclusions

This research conducted a first-ever study to design and conducted the driving simulator study by giving real alcohol to participants in order to identify the effectiveness of engineering traffic control devices for WWD from a driver behavior perspective. Key findings from this study can be utilized by transportation agencies to better improve off-ramps and prevent WWD events.

The research contains two tasks. For the first task, the researcher extracted 17 years (2004-2020) of WWD fatal crash data nationwide from the FARS database and updated the trend and distribution of WWD fatal crashes, which haven't been updated since 2014. Additionally, this research also identified the crash-prone factors for WWD fatal crashes using both supervised and unsupervised methods. The results are not only used for the further driving simulator study design, but also help readers understand the national trend of WWD fatal crashes and the risk factors that cause WWD fatal crashes, which may support the decision-making for FHWA, state DOTs, and local governments. Some key findings are concluded as follows:

- An average of 302 WWD fatal crashes happened each year, which caused an average of 409 people to die annually. In other words, the fatality rate for WWD fatal crashes is 1.36, which is relatively higher than the overall fatality rates (calculated as 1.11) on divided highways. The results provide evidence that WWD crashes are more severe than other types of crashes.
- Trends for fatal crashes show that the number of overall fatal crashes decreased from 2005 to 2009 but increased after 2011 to reach the same level as 2005 and reached to the peak in 2020. Observing the trends for WWD fatal crashes, it is found that although the number of WWD fatal crashes follows the same trend as

total fatal crashes, the overall WWD fatal crashes increased substantially from 2004 to 2020. The 17-year scope of this study shows that the number of WWD fatal crashes has not been declining over the years; in fact, the percentage of fatal crashes comprising WWD crashes has increased.

- WWD fatal crashes are highly related to alcohol involvement than expected. The results indicated that more than 60% of WWD fatal crashes were caused by alcohol-impaired drivers. For those alcohol-related WWD fatal crashes, 77% of them were founded recorded BrAC levels in the database. Among these WWD fatal crashes with recorded BrAC levels, 32% of them had BrAC levels less than 0.08. About 40% of them had BrAC levels below 0.12 across the nation.
- The results of the binomial logistic regression model identified the key contributing factors which increased the odds of WWD crash significantly. Those factors include no passenger in the vehicle, weekends, early morning (0:00-5:59), late-night (18:00-23:59), no lighting conditions, DUI drivers, severe weather conditions, young drivers, old drivers, male drivers, hillcrest roadway, and sag roadway.
- MCA results revealed four clouds of variables, when variables within each cloud happened together, the WWD fatal crashes were more likely to happen. Especially for cloud one, which is the key reference used for the driver simulator scenario development. Cloud 1 contains categories: “DUI_yes,” “0:00-5:59,” “25-34,” “injury,” “24 or less,” “urban,” “dark_Lit,” and “45-50 mph.” This suggests that a large portion of WWD fatal crashes occurred when younger drivers drove

after drinking alcohol during the midnight and early morning in an urban area, despite a relatively lower speed limit and good street lighting.

As for the driving simulator study, this research conducted the real alcohol testing session and evaluated the effectiveness of TCD(s) based on the number of WWD events, fixation durations, and brake response. The results can be used to identify the difference between normal and alcohol-impaired drivers. More importantly, the results can aid the TCD selection to better improve off-ramps, and prevent WWD events. Some key findings are summarized as follows:

- Alcohol-impaired drivers tend to look less toward the far roadway horizon, and more toward the pavement area in front of the vehicle. The results showed that the percentage of the fixation point at the far roadway horizon drops from 66.5% to 50% when drivers are under alcohol conditions. On the contrary, the percentage of fixation points in front of the vehicle increased dramatically from 3.9% to 17.1% for alcohol-impaired drivers. The proportion of drivers' fixation points in each region varies significantly between alcohol and non-alcohol driving conditions.
- Based on the number of WWD events, it can be concluded that signs worked better than pavement markings. For pavement markings, the number of WWD events by alcohol drivers is less than those by non-alcohol drivers due to the shift of the forward scene. Additionally, alcohol-impaired drivers have more chance of going to the WW when facing the WW sign. The TCD combinations followed by MUCTD may not sufficiently prevent WWD events. However, TCD combinations followed by CAMUTCD reduced the number of WWD events for both alcohol and non-alcohol drivers. Additionally, the combination with WW flashing sign reduced the number of WWD entries from six to three for alcoholic

drivers compared to the combinations with the traditional WW sign. It can be concluded that the combination with WW flashing sign had the potential to keep alcohol-impaired drivers from WWD.

- The total fixation durations for each TCD(s) revealed that normal drivers will spend more time on TCD(s) than alcohol-impaired drivers. In other words, the proposed TCD(s) are more attractive to normal drivers than to drunk drivers. This finding is consistent throughout all scenarios. For single TCDs, signs are more attractive than pavement markings for both normal and alcohol-impaired conditions since drivers had a longer total fixation duration on signs than pavement markings. There is no statistically significant difference in total fixation duration between MUTCD and CAMUTCD combinations under normal conditions. However, when drivers got drunk, there is a statistically significant difference in total fixation duration between MUTCD and CAMUTCD combinations under normal conditions, which can be concluded as alcohol-impaired drivers looked at CAMUTCD combinations longer than MUTCD combinations. As for sign and pavement marking combinations, the combinations with WW flashing sign tend to have longer total fixation duration compared to the combinations with the traditional WW sign. Additionally, there is no significant difference in total fixation duration among combinations with WW signs for both normal and alcohol-impaired conditions. WW flashing sign combined with DRS and RRPM, respectively, attract more drivers' attention, especially under alcohol-impaired conditions.

- According to the results of the average fixation duration for single TCDs, drivers typically have longer average fixation durations under alcohol-impaired conditions than normal conditions, which indicates that drunk drivers may need more time for understanding those single TCDs. When drivers are under normal conditions, there is no significant difference in average fixation duration among signs and pavement markings. However, when drivers are alcohol intoxicated, the average fixation duration of drunk drivers is signification different between WW and WW Flashing signs, which can be concluded as the flashing border reduce the average fixation duration on the WW sign for drunk drivers. Besides, it is also found that there exists a significant difference between RRPM and LaneAlert 2X, which can be concluded as LaneAlert needs a significantly longer time to understand drunk drivers than RRPM.
- As for the brake response, it is found that most of the drunk drivers applied the brake pedal at relatively further distances than normal drivers when facing the WW flashing sign and the DRS. As for the comparison among TCDs under the same conditions, WW flashing sign has the furthest distance (231 ft) and LaneAlert 2X has the nearest distance (186 ft) when most of the drunk drivers applied the brake. For the scenario with TCD combinations followed by MUTCD and CAMUTCD, the results show that most of the drunk drivers applied the brake pedal at relatively further distances than normal drivers for both combinations. The TCD combination followed by CAMUTCD can help drivers brake earlier than the MUTCD. Additionally, the combinations with LaneAlert 2X have the furthest distance when most of the drunk drivers applied the brake.

- The results of the hard brake response distance show that drivers have different behaviors when facing different TCDs under different conditions. The Paired T-Test results indicate that there is no significant difference between alcohol and non-alcohol conditions for proposed TCD(s) regarding the hard brake response distance. Additionally, the ANOVA test results also reveal that there is no significant difference between WW sign combinations and WW flashing sign combinations under both conditions. According to the comparison between WW sign combinations and WW flashing sign combinations, it is found that there is a significant difference between these two groups regarding hard brake response distance. In other words, the WW flashing sign can help alcohol drivers increase 7% of hard brake response distance than the WW sign.

Chapter 8 Limitations and Future Study

The limitations of this study as well as future studies are summarized as follows:

- The WWD crash analysis only focused on the fatal crashes, since only the fatal crashes were documented in the FARS database. As a result, future studies could expand the crash data that contain all crash severity (fatal, injury, and property damage only) using other databases such as the Highway Safety Information system (HSIS). The same procedure for WWD crash data extraction and analysis can be followed to further summarize the WWD crash data with all crash severity.
- For this study, the MCA analysis was applied to the WWD fatal crash data which was mainly for visualization purposes. Future studies could investigate how to quantify the group effect of variables in terms of WWD crashes.
- As for the driving scenario development. This study used the T-intersection to simulate the off-ramp. Additionally, the scenarios were designed to let proposed TCD(s) directly face the driver to collect enough data regarding drivers' reactions. However, it should be noted that drivers have to make a left/right turn to enter the off-ramp in real situations. Therefore, further study should be conducted to better simulate real-world situations, which also requires a larger sample size to quantify the findings.
- For this study, the data analysis of the driving simulator study mainly focused on the drivers' behaviors before going to WW. As a result, future studies could expand to identify the difference between right-way drivers and WW drivers regarding the drivers' behaviors.

- Lastly, this study only applied three MOEs to quantify driver behaviors. As a result, future studies could expand using other MOEs, such as speed change point response distance. Additionally, the correlation between MOEs could be analyzed in the further analysis.

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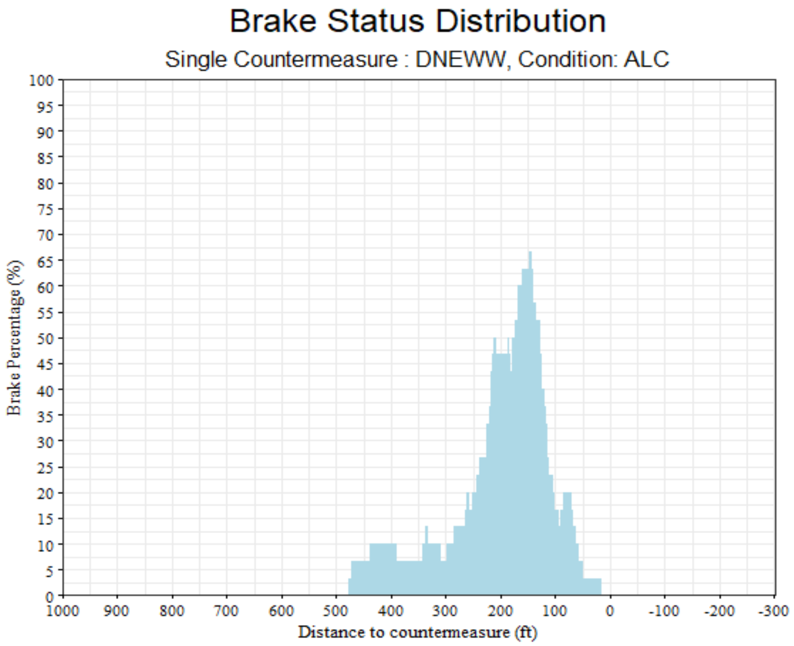
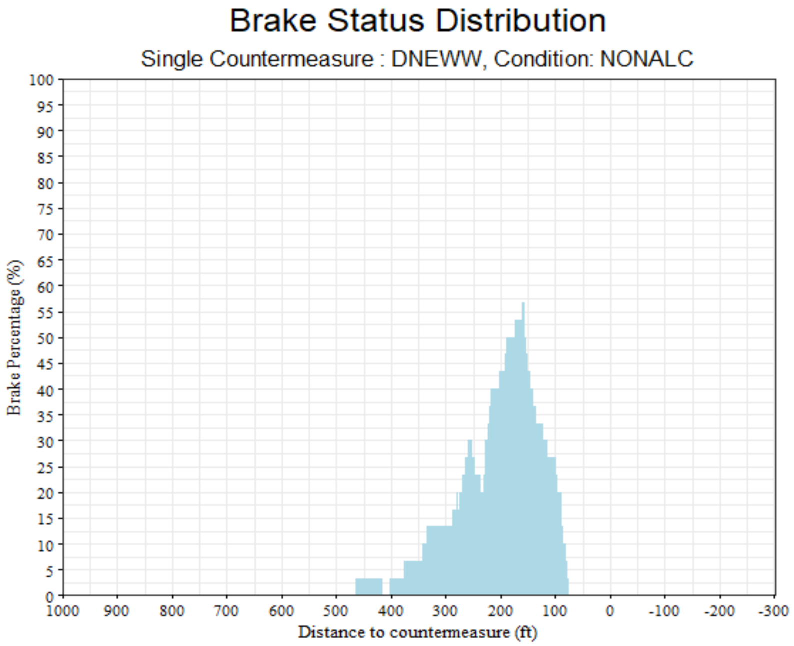
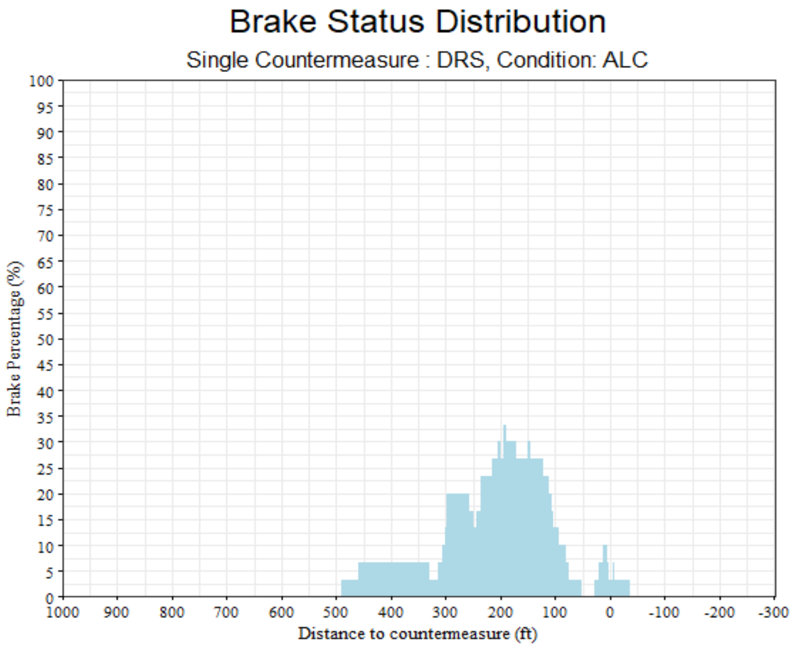
Appendix I: Braking usage distributions

Scenario 1

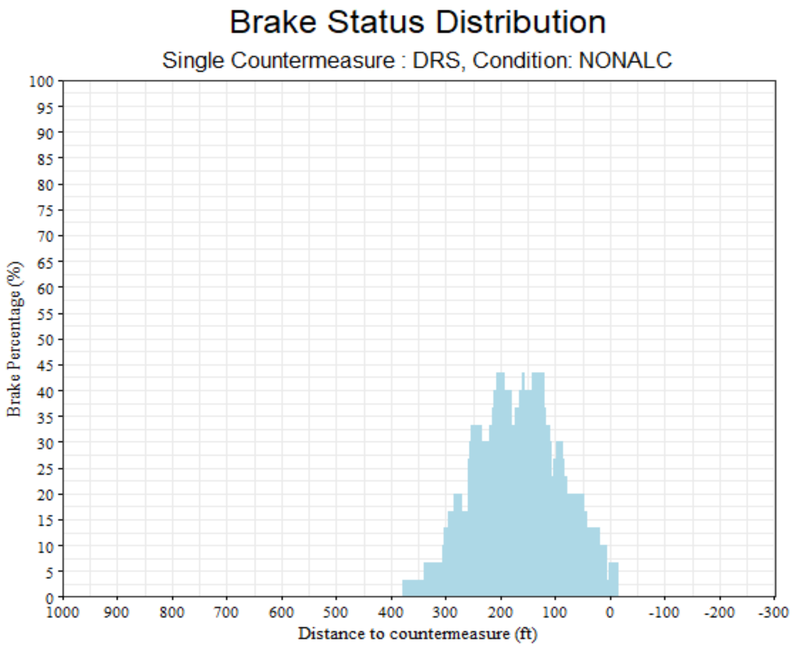






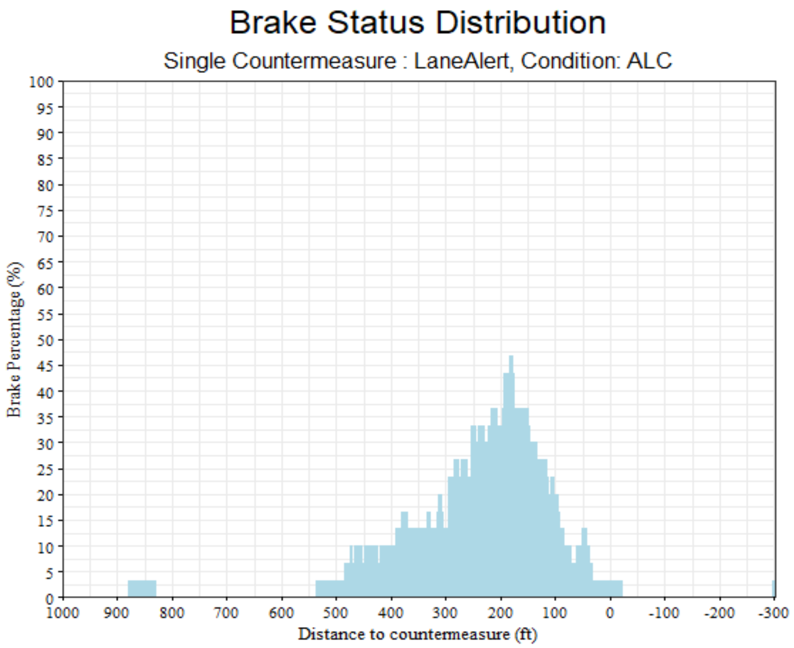
Brake Status Distribution

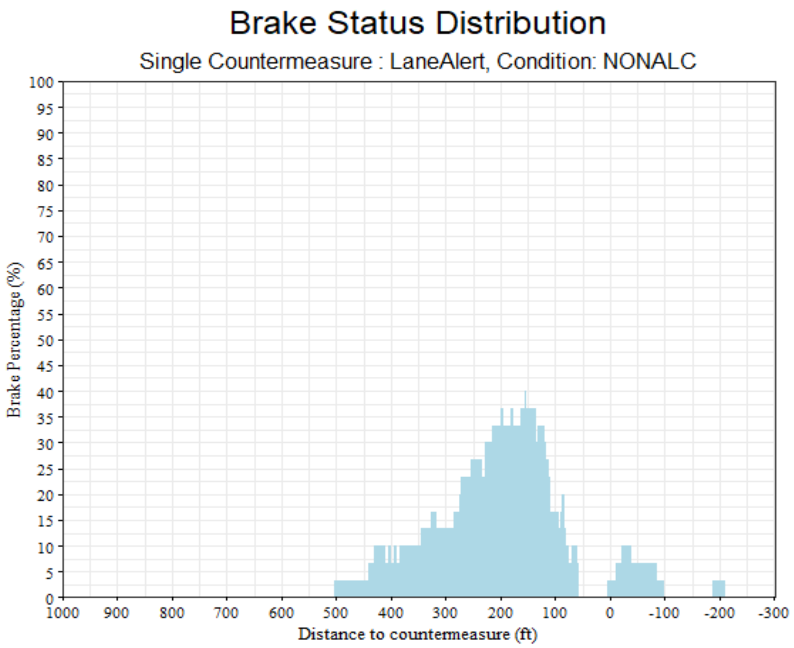
Single Countermeasure : DRS, Condition: ALC



Brake Status Distribution

Single Countermeasure : DRS, Condition: NONALC


Brake Status Distribution
Single Countermeasure : LaneAlert, Condition: ALC
Brake Percentage (%)
100
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
1000
900
800
700
600
500
400
300
200
100
0
-100
-200
-300
Distance to countermeasure (ft)


Brake Status Distribution
Single Countermeasure : LaneAlert, Condition: NONALC
Brake Percentage (%)
100
95
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75
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-100
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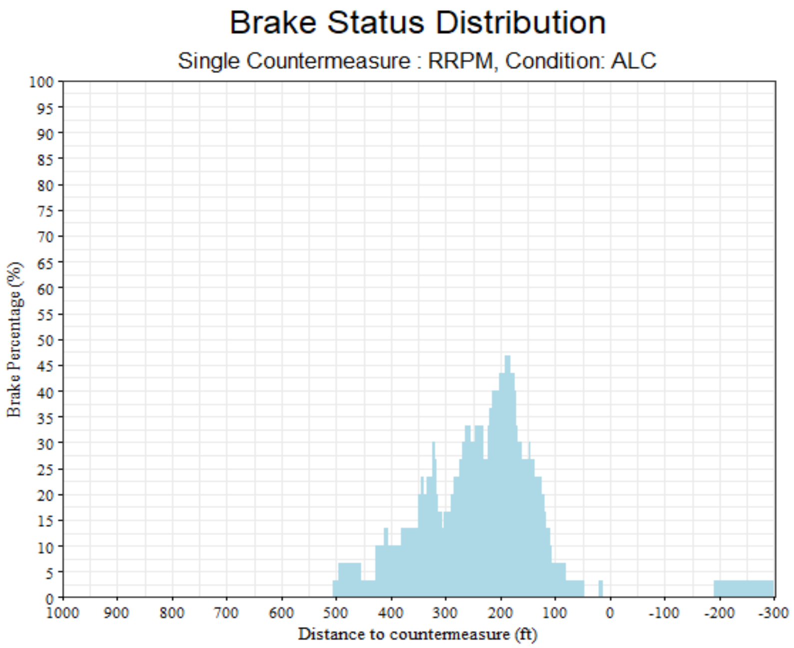
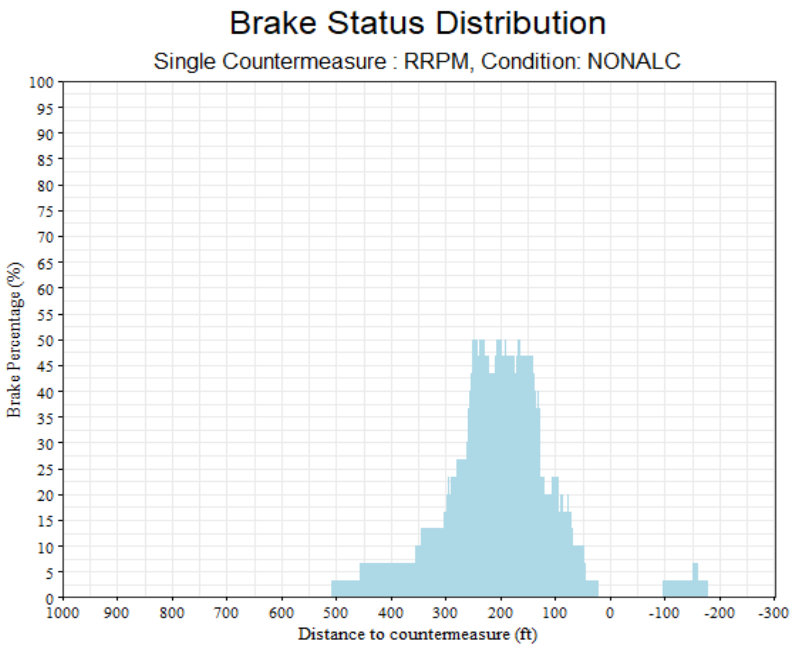
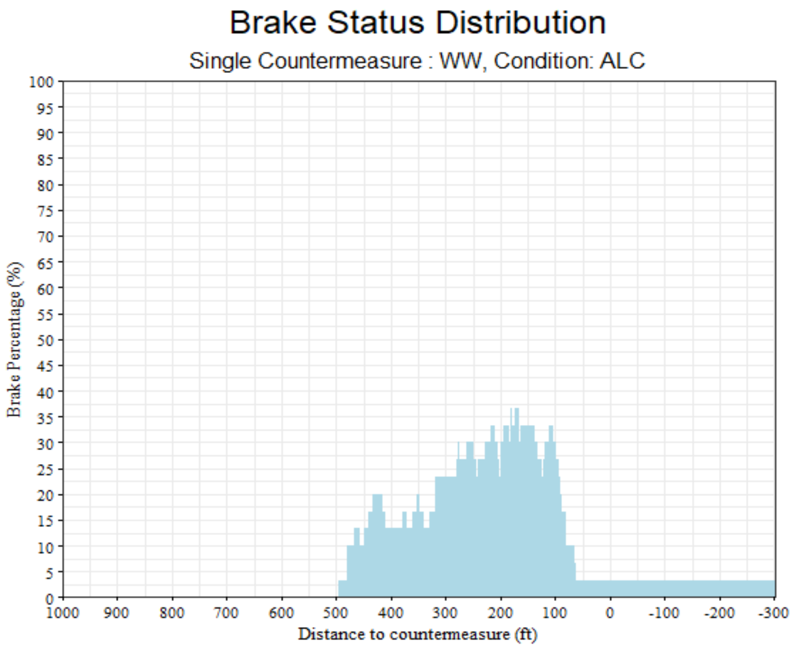
-300
Distance to countermeasure (ft)


Brake Status Distribution

Single Countermeasure : RRPM, Condition: ALC


Brake Status Distribution

Single Countermeasure : RRPM, Condition: NONALC


Brake Status Distribution
Single Countermeasure : WW, Condition: ALC
Brake Percentage (%)
0
5
10
15
20
25
30
35
40
45
50
55
60
65
70
75
80
85
90
95
100
1000
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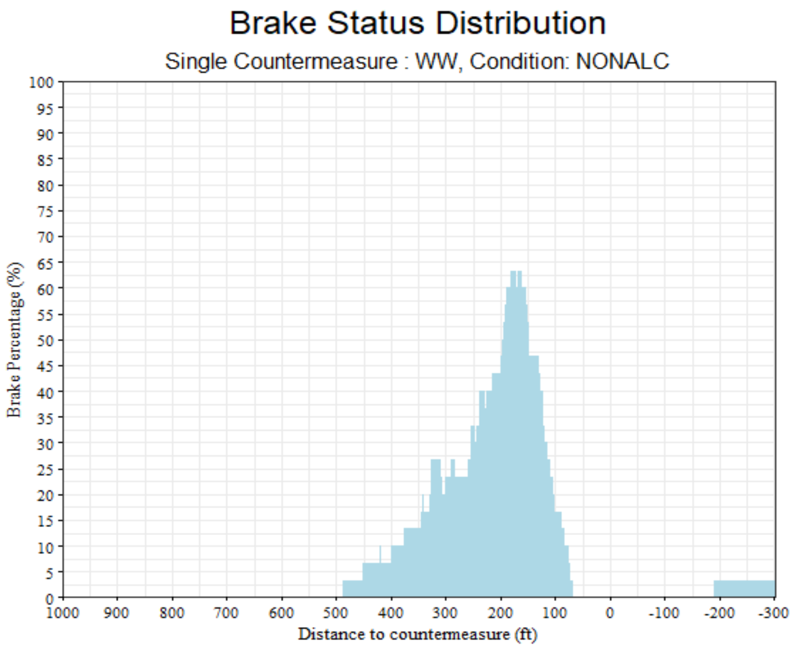
100
0
-100
-200
-300
Distance to countermeasure (ft)


Brake Status Distribution
Single Countermeasure : WW, Condition: NONALC
Brake Percentage (%)
0
5
10
15
20
25
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35
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45
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55
60
65
70
75
80
85
90
95
100
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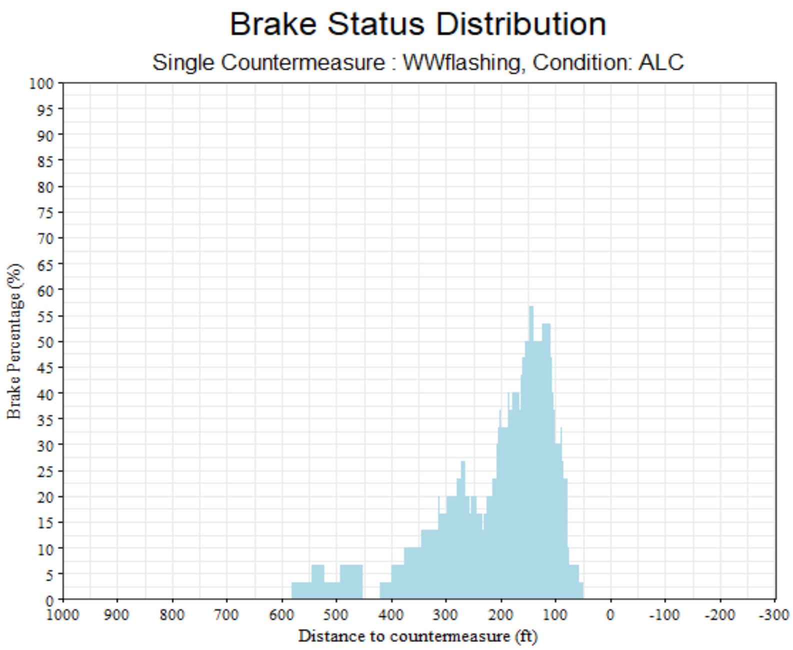
Distance to countermeasure (ft)


Brake Status Distribution
Single Countermeasure : WWflashing, Condition: ALC
Brake Percentage (%)
100
95
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85
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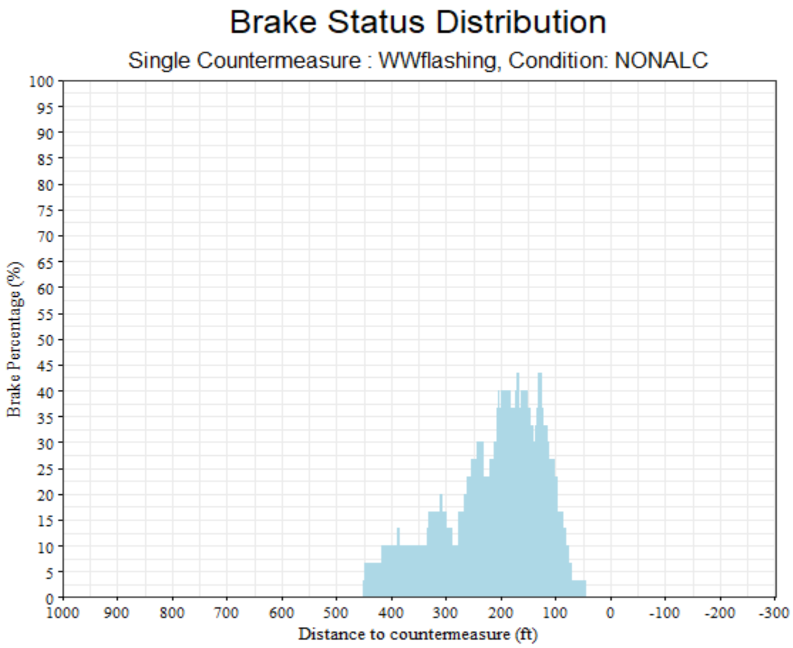
Distance to countermeasure (ft)


Brake Status Distribution
Single Countermeasure : WWflashing, Condition: NONALC
Brake Percentage (%)
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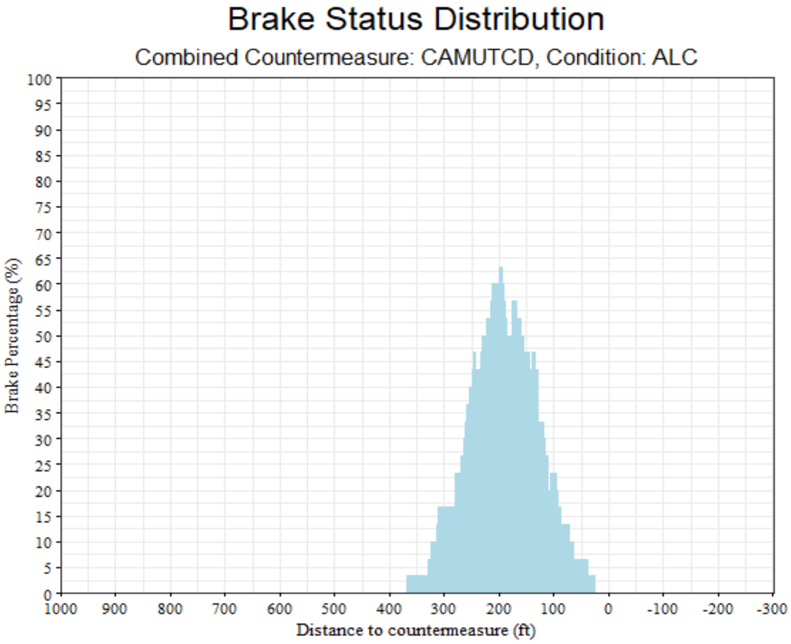
Distance to countermeasure (ft)

Scenario 2


Brake Status Distribution
Combined Countermeasure: CAMUTCD, Condition: ALC
Brake Percentage (%)
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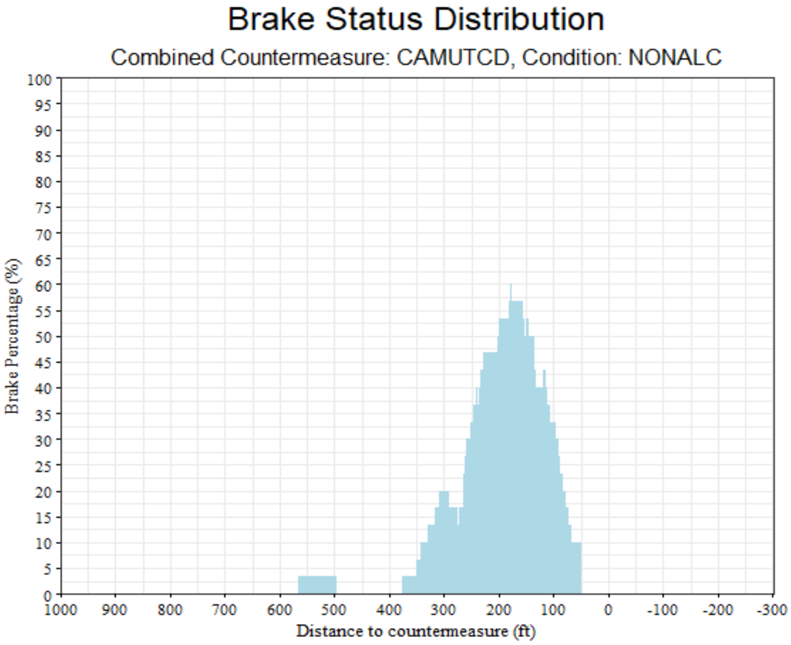
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: CAMUTCD, Condition: NONALC
Brake Percentage (%)
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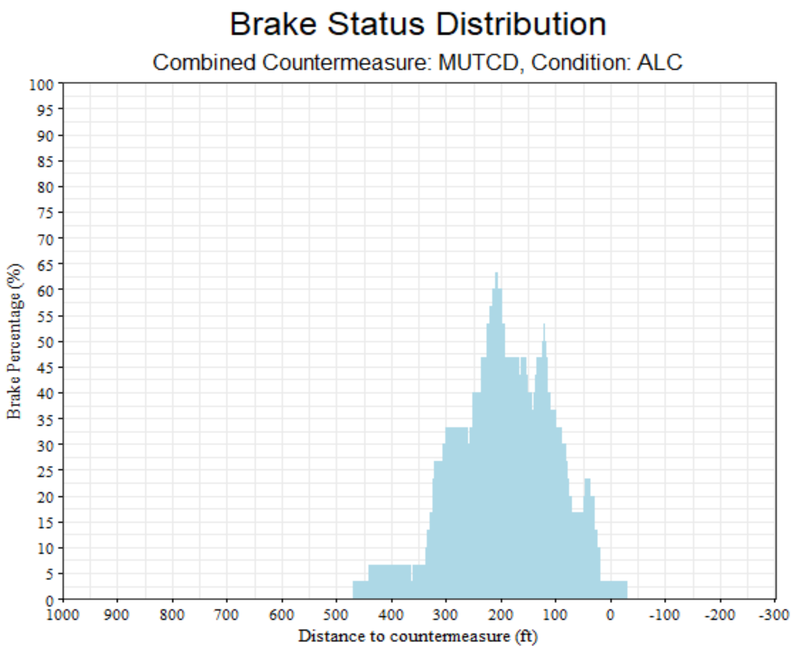
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: MUTCD, Condition: ALC
Brake Percentage (%)
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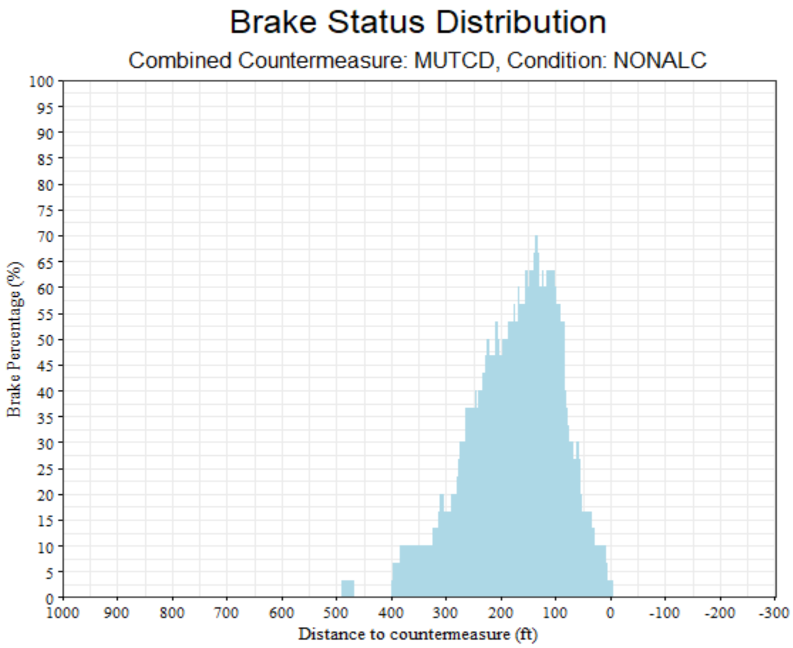
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: MUTCD, Condition: NONALC
Brake Percentage (%)
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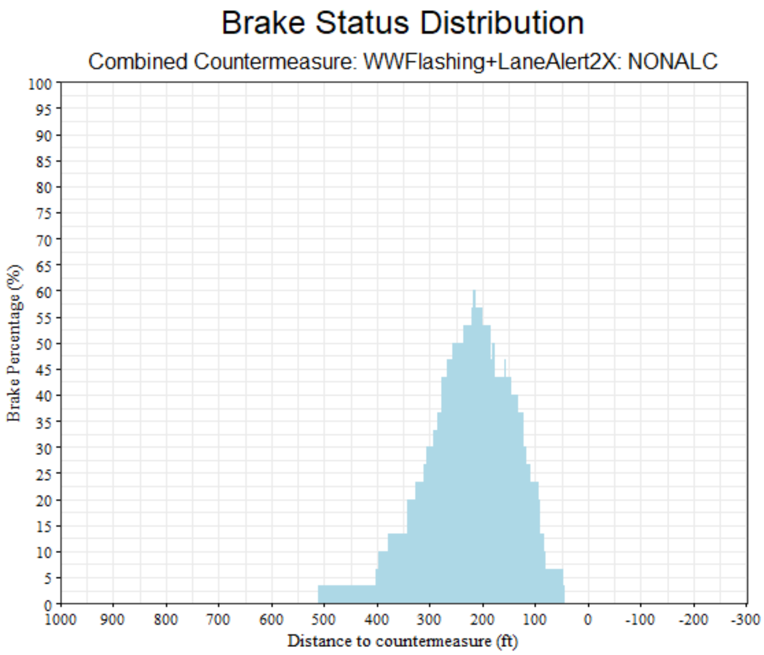
Distance to countermeasure (ft)

Scenario 3


Brake Status Distribution
Combined Countermeasure: WWFlashing+LaneAlert2X: NONALC
Brake Percentage (%)
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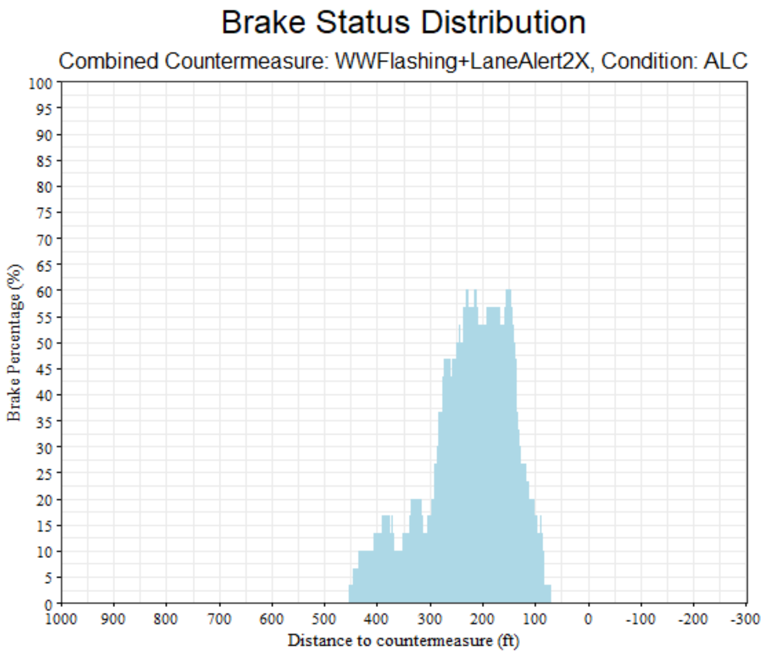
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: WWFlashing+LaneAlert2X, Condition: ALC
Brake Percentage (%)
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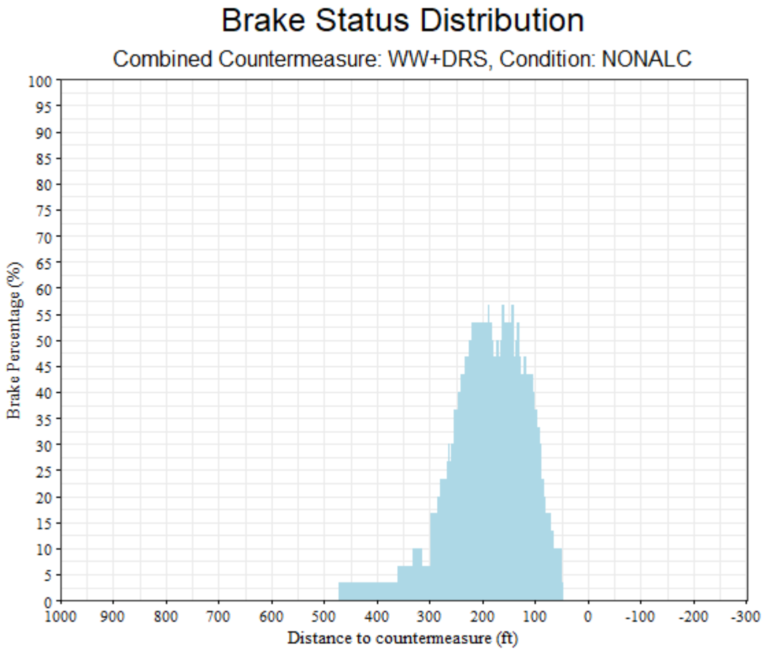
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: WW+DRS, Condition: NONALC
Brake Percentage (%)
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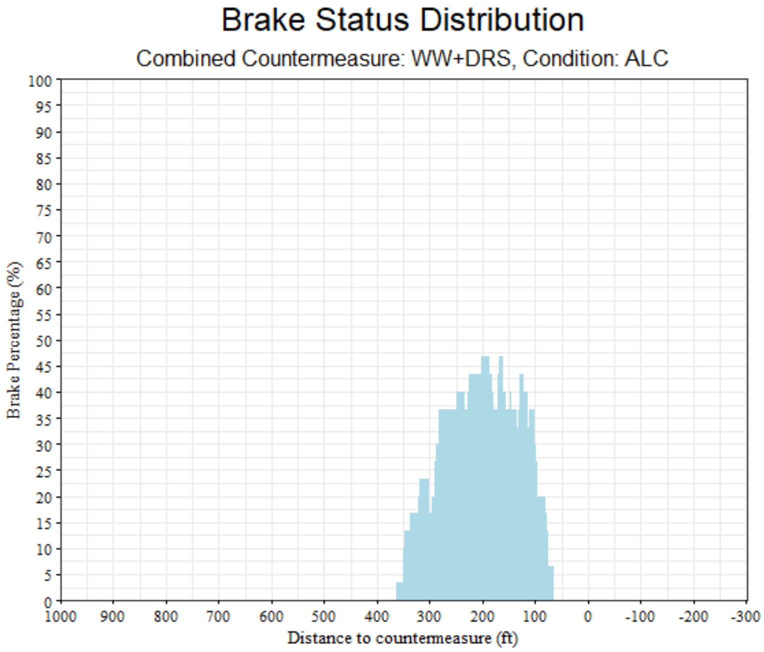
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: WW+DRS, Condition: ALC
Brake Percentage (%)
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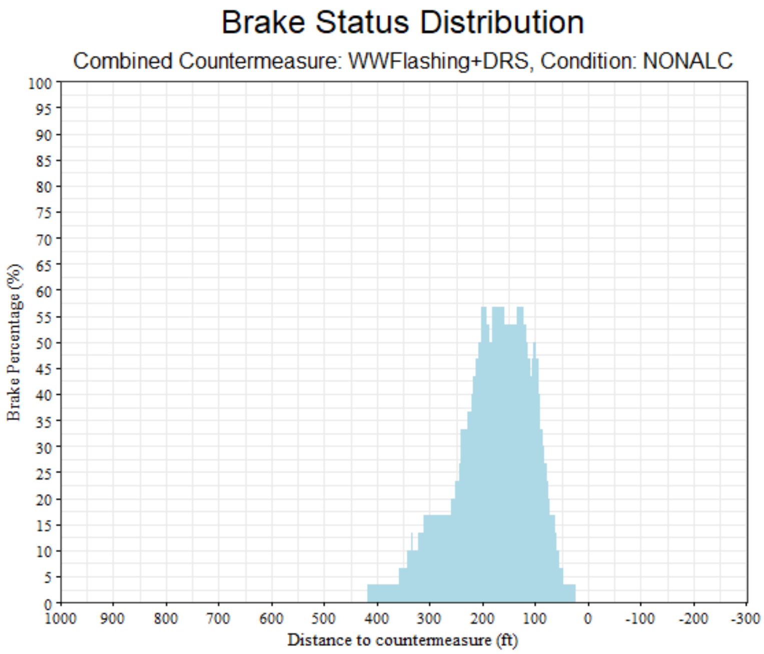
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: WWFlashing+DRS, Condition: NONALC
Brake Percentage (%)
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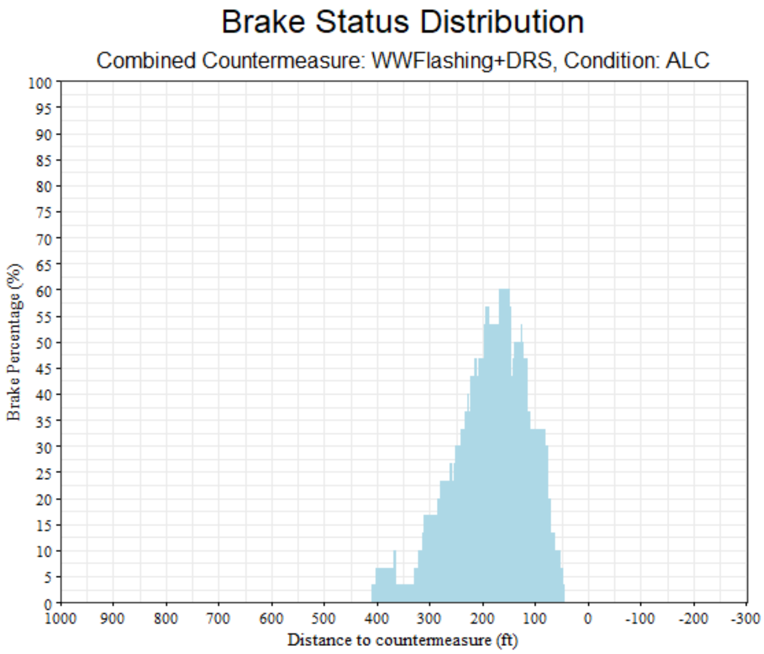
Distance to countermeasure (ft)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Brake Percentage (%)
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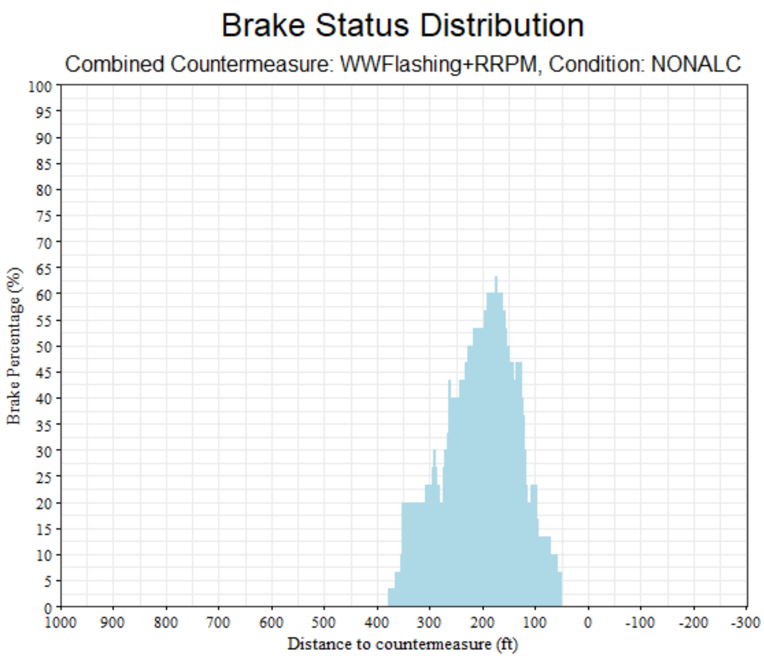
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: WWFlashing+RRPM, Condition: NONALC
Brake Percentage (%)
100
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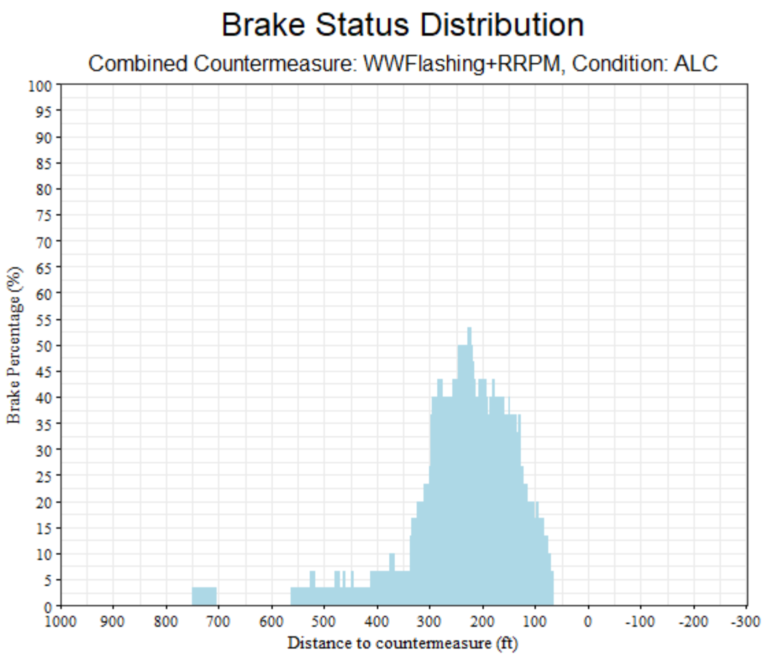
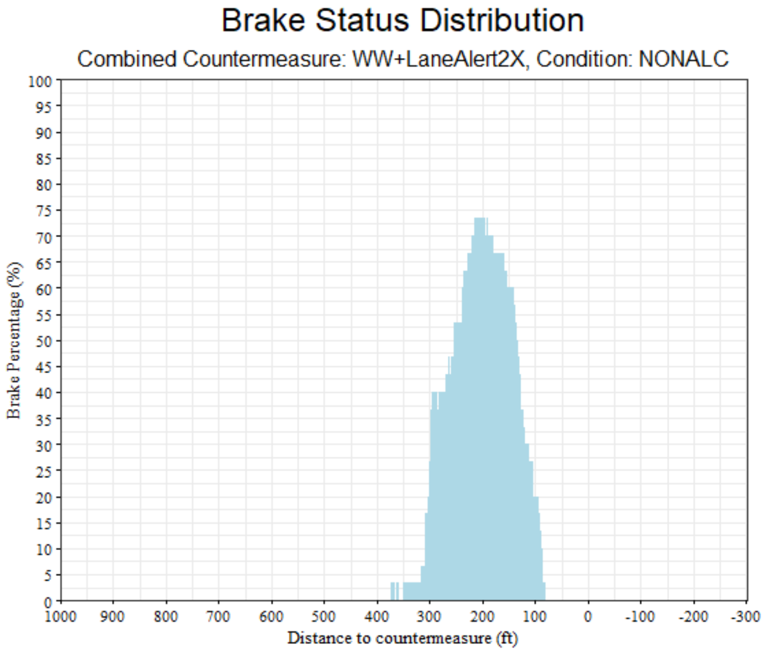
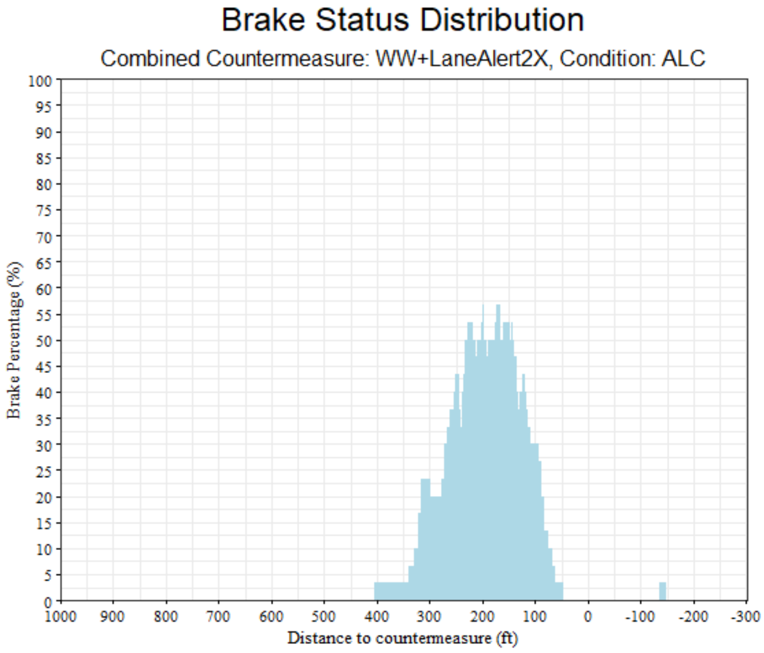
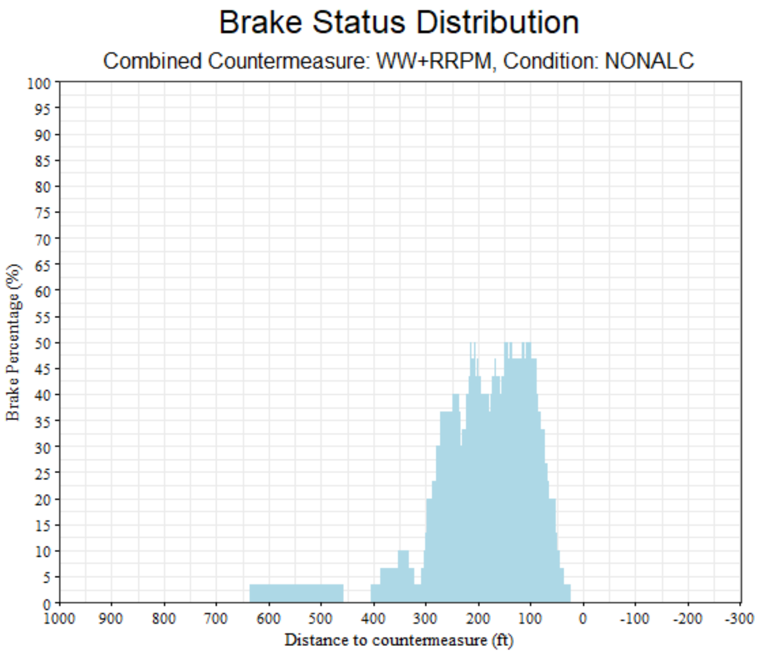
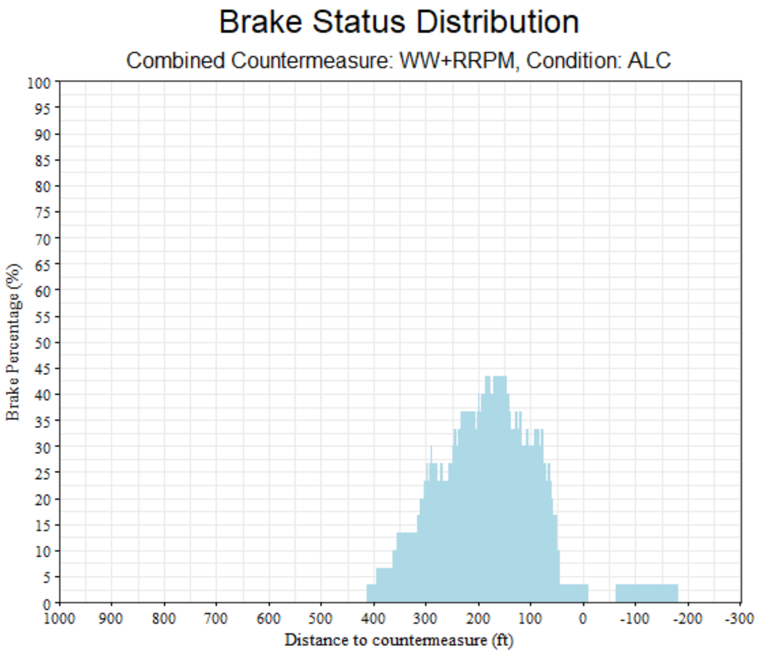
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
1000
900
800
700
600
500
400
300
200
100
0
-100
-200
-300
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: WWFlashing+RRPM, Condition: ALC
Brake Percentage (%)
100
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
1000
900
800
700
600
500
400
300
200
100
0
-100
-200
-300
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: WW+LaneAlert2X, Condition: NONALC
Brake Percentage (%)
100
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
1000
900
800
700
600
500
400
300
200
100
0
-100
-200
-300
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: WW+LaneAlert2X, Condition: ALC
Brake Percentage (%)
100
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
1000
900
800
700
600
500
400
300
200
100
0
-100
-200
-300
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: WW+RRPM, Condition: NONALC
Brake Percentage (%)
100
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
1000
900
800
700
600
500
400
300
200
100
0
-100
-200
-300
Distance to countermeasure (ft)


Brake Status Distribution
Combined Countermeasure: WW+RRPM, Condition: ALC
Brake Percentage (%)
100
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
1000
900
800
700
600
500
400
300
200
100
0
-100
-200
-300
Distance to countermeasure (ft)