Collaborative Sciences Center for ROAD SAFETY

FINAL REPORT

Safety enhancement by detecting driver impairment through analysis of real-time volatilities

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- Ahmad, N., Arvin, R., & Khattak, A. J. (2023). How is the duration of distraction related to safety-critical events? Harnessing naturalistic driving data to explore the role of driving instability. Journal of Safety Research, 85, 15–30. https://doi.org/10.1016/j.jsr.2023.01.003
- Ahmad, N., Arvin, R., & Khattak, A. J. (2022). Exploring pathways from driving errors and violations to crashes: The role of instability in driving. Accident Analysis and Prevention, 179, 106876. https://doi.org/10.1016/j.aap.2022.106876
- Ahmad, N., Khattak, A., & Bozdogan, H. (2023). Predicting safety-critical events using driver behaviors and performance: Application of machine learning. Presentation, TRBAM-23-00144.
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16. Abstract

Distracted driving can lead to driving instability and result in crashes causing injuries and the loss of valuable lives. Early detection of driver distraction is critical to alert drivers by providing feedback and warning messages. This project develops a framework to detect driver impairment using extensive real-time driver biometric information and data related to vehicle kinematics and the roadway environment. Data from multiple sources, including driver gaze data, vehicle kinematics indicators, and external factors like interaction with surrounding traffic, are collected and analyzed. The study detects deviations from regular driving events and links them with safety-critical events (SCEs). The project sheds light on the association of the duration of distracted driving, driving errors, and violations with SCEs. The study explores how inference-based statistical models and machine learning algorithms can enhance emerging driver assistance systems in automated vehicles, focusing on distracted driving. The project findings can improve traffic safety by developing more intelligent and forgiving vehicle automation features.

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List of Acronyms

ADAS	advanced driver assistance system
CV	coefficient of variation
DRT	detection response task
GBT	gradient boosting tree
KNN	k-nearest neighbors
MAD	mean absolute deviation
ML	machine learning
NB	naive Bayes
NDS	Naturalistic Driving Study
Q_{CV}	quartile coefficient of variation
SCE	safety-critical event
SHRP2	Strategic Highway Research Program 2
TDEV	Taxonomy of Driving Errors and Violations
WHO	World Health Organization

Chapter 1. Executive Summary

Overview

Distracted driving is usually associated with driving instability, which can lead to enhanced crash risk. Crashes resulting from distracted driving often result in the loss of valuable lives. Secondary activities such as cell phone use, eating, talking with passengers, adjusting vehicle infotainment controls, and looking at roadside elements or billboards are common examples of distracted driving. In 2021 alone, 3,522 road users were killed in traffic accidents due to distracted driving in the United States (Stewart, 2023). Early detection of driver distraction is critical to preventing traffic crashes due to distracted driving activities by providing feedback and warning messages to drivers and surrounding vehicles.

This project develops a framework to detect driver impairment using extensive real-time driver biometric information along with data related to vehicle kinematics and the roadway environment. The project's primary objective is to advance safety measures by closely monitoring driver behavior, examining changes in driver biometric characteristics under different distracted driving scenarios, and promptly identifying signs of driver impairment. To achieve this objective, the research team performed driving experiments in a controlled virtual environment, emulating distracted driving with varying levels of complexity through a visual detection response task (i.e., grid of arrows). By employing a multidimensional approach to data acquisition, data from multiple sources—including driver gaze data, vehicle kinematics indicators, and external factors like interaction with surrounding traffic—is collected and analyzed to detect any deviations from regular driving events using the concept of driving volatility as an indicator of safety-critical events (SCEs). The project assesses the correlations among the variations in driver biometric measures, vehicle motion indicators, and roadway surroundings with driver distraction. Finally, the driving events are classified into normal and distracted using suitable frequentist and machine learning (ML) techniques. The project's ultimate goal is to integrate early indicators of driving impairment into advanced driver assistance systems (ADAS) to provide feedback and warnings to the driver and surrounding vehicles, potentially helping to prevent accidents and improve overall safety on the road. This development holds significant promise for improving traffic safety, given the substantial interest of major automotive and information technology stakeholders in these applications, particularly those involved in fleet vehicles.

Research Questions

The project attempts to address the following research questions:

- Can driver distraction be identified from instantaneous variations in driver biometrics, vehicle kinematics, and roadway surroundings in different driving scenarios?
- How can driving events be classified as normal or distracted/impaired based on volatility measures in data streams?
- How is prolonged distracted driving associated with driving instability and SCEs?
- Are the driving errors and violations significantly associated with instability in driving parameters (vehicle speed, acceleration, jerk) which can lead to SCEs?

- Ahmad N. (2021). Role of Human Factors, Driving Instability, and Roadway Environment in Safety Critical Events: Safe System Approach. Ph.D. dissertation, University of Tennessee. https://trace.tennessee.edu/utk_graddiss/6961.

Multi-Faceted Approach

This report presents the contributions made to the existing knowledge under this project in four distinct parts. Each part is presented as a separate chapter:

Chapter 2: "Classification of driving behaviors through the analysis of real-time driver, vehicle and roadway volatilities" uses real-time large-scale multidimensional data collected through sensors that examine the variations in driver biometrics, vehicle kinematics, and roadway surroundings in different driving scenarios conducted on multimodal virtual reality (VR) simulator at the University of Tennessee, Knoxville. The study classifies driving behaviors as normal and distracted by employing a statistical model (i.e., panel ordered logistic regression) and ML techniques such as random forest and artificial neural networks, using real-time volatilities in driver biometric signals, vehicle kinematics, and roadway surroundings. The findings of the study can prove helpful in integrating early indicators of driving impairment into ADAS to provide feedback and warnings to the driver and surrounding vehicles, potentially helping to prevent accidents and improve overall safety on the road. This chapter of the report provides a detailed discussion of the study.

Chapter 3: "How is the duration of distraction-related to safety-critical events? Harnessing naturalistic driving data to explore the role of driving instability" uses naturalistic driving data collected through the Strategic Highway Research Program 2 (SHRP2) to analyze the correlation of the duration of distracted driving with SCEs directly and indirectly through driving instability. The study employed a path analysis framework to model the driving instability and SCEs jointly. The study found that the chances of a crash and near-crash increased by 34% and 40%, respectively, with a unit increase in driving instability. Moreover, the chances of both SCEs significantly increased non-linearly with an increase in distraction duration beyond 3 seconds. The study highlights the correlation between driving instability resulting from distracted driving, with the occurrence of SCEs. The findings of this study are presented in detail in this chapter of the report.

Chapter 4: "Exploring pathways from driving errors and violations to crashes: The role of instability in driving" utilizes naturalistic driving data and employs path analysis to determine the association of driving errors and violations with driving instability and their correlation with SCEs. The study found that driving errors, violations, and instability in driving speed increases the chances of crashes and near-crashes. Furthermore, driving errors and violations are associated directly with crash risk and indirectly through instability in driving speed. The paper suggests various countermeasures, such as multiple vehicle technologies like Forward Collision Warning Systems, roadway changes, policy interventions, and removing sources of external distraction such as billboards to help prevent driving errors and violations that lead to instability in driving speed and subsequently SCEs. This chapter of the report comprehensively describes various elements of the study.

Chapter 5: "Predicting safety-critical events using driver behaviors and performance: Application of machine learning," utilizes driving performance measures and measures of driving volatility for a subsample of the SHRP2 Naturalistic Driving Study (NDS) to predict the outcomes of SCEs. The study estimates an Ordered Probit model and three ML techniques, namely naive Bayes, k-nearest neighbors (KNN), and gradient boosting tree (GBT), to predict the SCEs. The study results reveal that the ML methods outperform the ordered probit model in predictions, with the gradient boosting model giving the highest out-of-sample prediction accuracy of 91.23%. The study's findings can assist in improving collision warning systems in vehicles equipped with ADAS to help prevent SCEs. The analysis is elaborated in detail in this chapter of the report.

Research Outputs

Publications and Presentations

Usman, S., A. Khattak, & S. Chakraborty (2024). *Detection of distracted driving through the analysis of real-time driver, vehicle and roadway volatilities*. Submitted for review to the Transportation Research Board Annual Meeting, Washington, D.C., 2024.

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Chapter 2

Classification of Driving Behaviors through the Analysis of Real-time Driver, Vehicle and Roadway Volatilities

Abstract

Common examples of distracted driving are secondary activities such as mobile phone use, eating, talking with passengers, adjusting vehicle infotainment controls, and looking at roadside elements or billboards. Distracted driving usually gives rise to driving instability which leads to increased crash risk and higher crash frequency. Early detection of driver distraction is critical to preventing traffic crashes due to distracted driving by providing feedback and warning messages to drivers and the surrounding vehicles. This study uses real-time multidimensional data collected through sensors that examine the variations in driver biometrics, vehicle kinematics, and roadway surroundings in different driving scenarios conducted on a multimodal VR simulator. The driving behaviors of the study participants were examined under various visual detection response tasks of increasing complexity. The study classifies driving behaviors as normal and distracted on a 5-level ordinal scale by employing a panel ordered logit model, random forest, and artificial neural network, using real-time volatilities in driver biometric signals, vehicle speed and acceleration, and roadway surroundings. The study results reveal that the driver gaze and the coefficients of variation (CVs) in vehicle speed, driver eye movements, and vehicular distances from the lane centerline and the following vehicle significantly impact distracted driving. The study's findings align with the principles of the safe systems approach by emphasizing the development of proactive safety measures in the form of feedback and warning the driver and surrounding vehicles of a potential distracted driving event, helping to foster safer user behavior and vehicles.

1. Introduction

Driver distraction can be categorized into four types: visual (taking eyes off the road), cognitive (mind preoccupied with thoughts), auditory (attention divided due to sounds such as ringing cell phone or music played in the vehicle), and physical (unable to steer with both hands due to activities like using a mobile phone, texting, or eating) according to the World Health Organization (WHO) (World Health Organization, 2010). Distracted driving due to various auxiliary tasks performed by drivers, such as talking with passengers, dialing, or texting on a mobile phone, setting vehicle infotainment system controls, looking at billboards, etc., negatively impacts drivers' abilities to perform the fundamental driving tasks safely and often leads to SCEs (Ahmad et al., 2023). In 2021 alone, 3522 road users were killed in traffic accidents due to distracted driving in the United States (Stewart, 2023). Early detection of driver distraction is critical to prevent traffic crashes by providing timely feedback and warning messages to drivers and the surrounding vehicles. In recent years, the increased use of in-vehicle and nomadic technologies has led to driver distraction and inattention (Hsieh et al., 2012). Although the existing standards of the International Organization for Standardization (ISO) to detect distracted driving address visual distraction, the effect of nonvisual, cognitively demanding activities like hands-free mobile phone conversations while driving is lightly researched. To assess the true distraction caused by such tasks, the ISO is standardizing a methodology known as the Detection Response Task (DRT). The DRT assesses the attentional effect of secondary tasks on driving performance and involves responding to visual or tactile stimuli presented at random intervals, providing a measurable indicator of distraction. It measures the number of times a visual or tactile stimulus is detected (hit rate) and the response time to this detection (Natasha et al., 2015).

This study examines drivers' behaviors under normal and different distracted driving scenarios developed using the visual DRT (grid of arrows) with varying difficulty levels to model and predict distracted driving using streams of driver biometric signals, vehicle kinematics, and roadway surroundings. The study quantifies the instantaneous variations in driver biometrics, vehicle position, speed, and acceleration by utilizing the concept of driving volatility as a surrogate measure of distracted driving. A key implication of the study is to incorporate early signs of distracted driving into ADAS. This integration aims to offer feedback and alerts to drivers and nearby vehicles, potentially reducing accidents and offering more forgiving automation technology. This advancement shows great potential for improving traffic safety, especially considering the notable interest of key stakeholders in the automotive and information technology industries, particularly those managing fleet vehicles.

2. Literature Review

Numerous studies have investigated the impact of distracted driving on various aspects of driving performance, including speed management, driver decision-making, lane-changing behavior, and more (Choudhary & Velaga, 2017; He et al., 2014; Oviedo-Trespalacios et al., 2017). One commonly observed compensatory strategy during distracted driving is lower driving speed (Leung et al., 2012; Metz et al., 2015; Yannis et al., 2010). However, studies have shown that while drivers may slow down to compensate for the increased complexity, the sudden changes in vehicle speed and acceleration tend to destabilize the vehicle (Choudhary & Velaga, 2019; He et al., 2014). Some studies have also found that distracted drivers tend to increase their headway to offset the increased workload (Santos et al., 2005; Yannis et al., 2010), although studies show mixed results regarding this strategy's effectiveness (Lee et al., 2018). In terms of lateral control, variations in the steering angle and lane excursions have been identified as potential indicators of degraded driving performance during distracted driving (Cao & Liu, 2013; Chisholm et al., 2008; Choudhary & Velaga, 2019; Rumschlag et al., 2015; Young & Salmon, 2012). The variation in lateral acceleration has also been considered in assessing vehicle performance degradation due to distracted driving (Blanco et al., 2006; Liu & Ou, 2011). Additionally, the variation in lane positioning has been analyzed in numerous studies as a measure of the effects of distraction (Irwin et al., 2015; Santos et al., 2005; Thapa et al., 2015). When analyzing visual distraction, most studies have reported increased variation compared to baseline (Irwin et al., 2015; Thapa et al., 2015), but the results have been inconsistent for phone conversations and other distractions involving cognitive attention (Cao & Liu, 2013; Garrison & Williams, 2013). Data collection methods for the detection of distracted driving include driving simulators (Ahangari et al., 2018; Dorr et al., 2014; Murphey et al., 2009), test vehicles (Feng et al., 2018; Suzdaleva & Nagy, 2018), and smartphones (Bejani & Ghatee, 2018; Mantouka et al., 2019). Test vehicles provide data that closely resemble real-world driving conditions but are limited in scope due to high costs and data collection difficulties. Data collected from smartphones are more comprehensive, capturing information from a diverse population of drivers and various types of roadways. However, the data from location-based applications on smartphones may be biased, and factors like weather conditions and global positioning system (GPS) accuracy can affect measurement accuracy (National Coordination Office for Space-Related Positioning, 2020). Notably, driving simulators are a safer and relatively low-cost option for collecting real-time driver performance and vehicle motion data (Mohammadnazar et al., 2021).

The literature review identified that most previous relevant studies focused on analyzing individual driving performance measures such as speed, lane positioning, reaction time, and steering wheel angle. However, most studies did not include information related to real-time driver biometrics including driver gaze, eye openness, etc. under different distracted driving scenarios. Instantaneous variations in drivers' vision under distracted driving conditions can readily assist in the early detection of distracted driving, which can lead to reduced SCEs if integrated into driver assistance systems in automated vehicles. This study attempts to address the research mentioned above gap by analyzing driver biometrics, including driver gaze, eye openness, etc., in addition to vehicle kinematics and roadway surroundings collected in a simulated driving environment to model distracted driving and classify the driving events into normal (baseline) and distracted driving. The study's contribution lies in incorporating the real-time driver biometric characteristics and employing the concept of driving volatility (deviations of driving parameters from normal values) as a surrogate measure of SCEs in detecting distracted driving.

3. Data Description

3.1 Data Acquisition

This study examines driver behavior under normal and different distraction scenarios using data on driver biometrics, vehicle kinematics, and roadway surroundings collected through multiple sensors in a multimodal VR simulator at the University of Tennessee, Knoxville. The simulation experiment was designed in Unreal Engine 4, a recent version of an advanced real-time 3D graphics creation tool. The simulation environment was populated with AI drivers operating with predefined parameters such as following distance, max speed, etc. The composition of the physical simulator included a car seat attached to an aluminum framing with an electronic steering wheel and pedals. Driver eye movements, a unique aspect of the study, were collected using the "HTC Vive Pro Headset," an advanced VR headset worn by the participants for immersion and eye tracking capabilities. Vehicle kinematics include speed, acceleration, and deceleration, steering wheel controller activation, and brake pedal activation. The vehicle kinematic and roadway contextual data were extracted from the simulation using Lab Streaming Layer, an open-source software designed to broadcast, coordinate, and document physiological data from various sensors. A total of 26 drivers (14 male and 12 female) participated in the study. All the drivers were above 18 and had a valid U.S. driving license. The grid of arrows visual search task was used in the study to emulate distracted driving. 4x4, 5x5, 6x6, and 8x8 grids of arrows were used to emulate distracted driving conditions with increasing complexity. Drivers were asked to detect the position of an arrow facing in a different direction than all other grid arrows. In the normal or undistracted scenario, the drivers were requested to drive normally without presenting the grid of arrows on the screen. Higher grid size usually results in higher driver reaction times in the DRT, analogous to a high level of distraction. For more details on the experimental procedure and additional ML-based analysis on the relative importance of the different sensor modalities, please refer to “Appendix A.” The drivers’ levels of distraction corresponding to the 4x4, 5x5, 6x6, and 8x8 grids of arrows were labeled as Mild, Moderate, Significant, and Severe distraction, respectively. The instantaneous variations in driver biometrics, vehicle kinematics, and roadway surroundings were quantified using various measures of variation or dispersion, indicating driving volatility during the simulated driving experiment. A description of the variables used in this study with their units and threshold values is provided in Table 1.

Table 1: Description of Variables used in the Study

Variables	**Description**	**Unit**	**Threshold Values**
Acceleration	Vehicle Acceleration	m/s^2	NA
Brake	Brake Pedal Activation	NA	0-1 (0 is unpressed, 1 is fully pressed). All other values represent intermediate brake pedal activation.
Eye Openness	Drivers’ Eye Openness	NA	0-1 (0 is closed, 1 is open). All other values represent intermediate eye openness.
Pupil Movement	Driver’s Eye Movement (Gaze)	NA	NA
Speed	Vehicle Speed	m/s	NA
Steering	Steering Wheel Controller Activation	NA	(-0.5 ---- 0.5) -0.5 all the way to the left, 0.5 all the way to the right
Throttle	Throttle Pedal Activation	NA	(0,1) 0 is unpressed, 1 is fully pressed. All other values represent intermediate throttle pedal activation.
Distance Center	Distance from left front wheel to center line of the road	1/1.5 m	NA
Distance Front	Distance to the car in front	1/1.5 m	NA
Distance Behind	Distance to the car at the back	1/1.5 m	NA

Variables	Description	Unit	Threshold Values
State (Label)	An integer classification of what level of distraction the driver was experiencing during the duration of the sample, determined by the size of the grid of arrows	NA	**0:** Undistracted **1**:4x4 grid (Mild Distraction) **2:** 5x5 grid (Moderate Distraction) **3:** 6x6 grid (High Distraction) **4:** 8x8 grid (Very High Distraction)

Note: NA means Not Applicable.

3.2 Measures of Driver, Vehicle, and Roadway Volatility

Previous literature suggests volatility functions to analyze changes in driving movement, specifically in speed, lateral acceleration, longitudinal acceleration, and vehicular jerk (Arvin et al., 2021). These functions include the coefficient of variation (CV), mean absolute deviation (MAD), quartile coefficient of variation (Qcv), and time-varying stochastic volatility (V_f). A brief mathematical description of the volatility functions is provided below:

3.2.1 Coefficient of Variation (CV): The CV captures dispersion by considering the standard deviation and the absolute mean value using the following Equation:

$$CV = SD/|\bar{x}| * 100 \tag{1}$$

3.2.2 Mean Absolute Deviation (MAD): The MAD calculates the mean distance from the central tendency of the data using Equation 2.

$$MAD = 1/n\sum|xi - \bar{x}| \tag{2}$$

This measure can simultaneously capture both positive and negative values for acceleration and deceleration, respectively.

3.2.3 Quartile Coefficient of Variation (QCV): The Qcv measures the dispersion of the data using Equation 3.

$$QCV = (Q3 - Q1/Q3 + Q1) * 100 \tag{3}$$

where Q1 and Q3 are the first and third quartiles of the data.

3.2.4 Time-Varying Stochastic Volatility (Vf): The V_f can only be applied to positive observations. Hence, it can only be applied to vehicular speed containing only positive observations. The Equation for this measure of volatility is given below:

$$Vf = \sqrt{}1/(n-1)\sum(ri - \bar{r})2 \tag{4}$$

$$ri = ln(xi/xi - 1) * 100 \tag{5}$$

where $xi - 1$ is the previous observation than xi, while $\bar{r}$ is the mean of parameter r.

In this study, the concept of temporal driving volatility, developed by Arvin et al. (2021), analyzes changes in instantaneous driving behavior over time. This approach captures driving behavior as a time-dependent variable by creating a time-series data stream. Previous literature indicates that using a 3-second time frame window to calculate driving volatility results in the highest correlation between volatility measures and crash risk compared to other time windows of 1, 2, and 5 seconds (Arvin et al., 2019). Therefore, a 3-second time window is used to calculate temporal driving volatility in this study. This study uses CV and MAD to capture the temporal variations in driver behavior and vehicle kinematics among the volatility measures.

3.3 Descriptive Statistics

The simulation experiment was performed for a total duration of 1851 seconds while the driver biometrics, vehicle motion indicators, and distances with the surrounding vehicles were recorded after every 0.1 seconds. The raw data from the driving simulator consisted of 1851/0.1 = 18510 observations. However, the data was aggregated every 3 seconds (30*0.1 sec) to compensate for very small or missing values in the data. The final dataset contains 18510/30 = 617 observations with a fixed time interval of 3 seconds. The data has volatility measures allocated to the observations using a 3-second time window. The State variable, an ordinal variable representing the level of distraction experienced by the driver during the simulation experiment, is considered the response variable predicted by the original data obtained from the simulator and the derived driving volatilities. The descriptive statistics of the variables used in the study are presented in Table 2.

Table 2: Descriptive Statistics of Predictor and Response Variables

Variables	Sample Size	Mean	SD	Minimum	Maximum
Acceleration	617	-0.10	3.88	-74.30	11.09
Brake	617	0.007	0.05	0	1
Eye Openness	617	0.81	0.33	0	1
Eye Movement	617	0.29	0.23	0	1.016
Speed	617	13.68	3.16	0.0002	26.88
Steering	617	-0.02	0.03	-0.5	0.5
Throttle	617	0.08	0.08	0	1
Distance Center	617	1.38	0.816	0	4.92
Distance Front	617	42.57	27.00	11.93	174.293
Distance Behind	617	77.73	51.71	11.77	274.78
CV-Eye movement	617	0.67	0.36	0.012	1.90
CV-Speed	617	0.092	0.078	0.003	0.42
MAD-Acceleration	617	1.64	1.61	0.05	17.08

Variables	Sample Size	Mean	SD	Minimum	Maximum
CV-Centre Distance	617	0.25	0.21	0.002	1.21
CV-Front Distance	617	0.09	0.11	.005	0.98
CV-Back Distance	617	0.06	0.11	0.001	1.08
Response Variable		Frequency		Percentage (%)	
State					
0		204		33.06	
1		123		19.94	
2		120		19.45	
3		85		13.78	
4		85		13.78	

Note: SD = Standard Deviation.

Table 3 shows the descriptive statistics of the driving volatility measures in different driving scenarios represented by the values of the State variable. Referring to Table 3, the means and standard deviations of the volatility measures relevant to vehicle kinematics and roadway surroundings increase with an increase in the level of distraction. This result implies that more variation and higher dispersion was observed in the drivers' performance in vehicle kinematics and roadway surroundings with increasing level of distraction. The descriptive statistics of the volatility measures in each distraction scenario align with general perception as higher variations in driver biometric characteristics and vehicle kinematics are generally expected in higher distracted driving environments. Furthermore, the correlations among the predictor variables were also assessed to identify the possibility of problematic multicollinearity in the ordinal logistic regression model (Table 4). Results from Table 4 suggest that the values of the Pearson Correlation Coefficients for the predictor variables lie within the interval +0.5 to -0.5, which indicates that multicollinearity does not exist among the predictor variables.

Table 3: Descriptive Statistics of Volatility Measures in Different Distraction Scenarios

Volatility Measures	**State 0 (Undistracted) N = 204**				**State 1 (Mild Distraction) N= 123**				**State 2 (Moderate Distraction) N = 120**				**State 3 (Significant Distraction) N = 85**				**State 4 (Severe Distraction) N = 85**			
	Min	Max	μ	σ	Min	Max	μ	σ	Min	Max	μ	σ	Min	Max	μ	σ	Min	Max	μ	σ
CV-Eye Movement	0.012	1.62	0.40	0.330	0.03	1.69	0.68	0.333	0.27	1.72	0.79	0.29	0.28	1.82	0.83	0.28	0.35	1.90	0.94	0.27
CV-Speed	0.003	0.34	0.06	0.05	0.02	0.35	0.08	0.06	0.033	0.36	0.10	0.068	0.0340	0.39	0.11	0.07	0.0344	0.42	0.12	0.11
MAD-Acceleration	0.05	12.88	1.47	1.44	0.06	13.31	1.56	1.53	0.07	13.89	1.63	1.55	0.09	15.15	1.86	1.73	0.12	17.08	1.95	2.00
CV-Centre Distance	0.002	1.00	0.15	0.14	0.013	1.03	0.20	0.18	0.040	1.05	0.34	0.19	0.046	1.11	0.35	0.21	0.047	1.21	0.38	0.23
CV-Front Distance	0.005	0.76	0.08	0.10	0.006	0.84	0.09	0.105	0.007	0.87	0.094	0.106	0.008	0.89	0.11	0.11	0.01	0.98	0.13	0.13
CV-Back Distance	0.001	0.38	0.04	0.07	0.0019	0.39	0.056	0.08	0.0020	0.67	0.059	0.10	0.0022	1.06	0.07	0.15	0.0025	1.08	0.10	0.15

Note: Min = Minimum; Max = Maximum; μ = Mean; σ = Standard Deviation

Table 4: Correlations among Predictor Variables

Variables	Acc/Dec	Eye Movement	Speed	Steering	Throttle	Distance Centre	Distance Front	Distance Behind	CV-Eye movement	CV-Speed	MAD-Acc/Dec	CV-Front Distance	CV-Back Distance	CV-Centre
Acc/Dec	1.000													
Eye Movement	0.0492	1.000												
Speed	0.0948	0.0204	1.000											
Steering	0.0613	0.0138	-0.1067	1.000										
Throttle	0.3252	-0.0013	0.0263	-0.0209	1.000									
Distance Centre	0.0297	0.0661	0.0647	0.0532	-0.0718	1.000								
Distance Front	0.0756	0.0312	0.1088	-0.0730	0.1397	-0.0195	1.000							
Distance Behind	0.0101	0.0153	0.3703	0.0389	-0.0594	0.2107	0.0477	1.000						
CV-Eye movement	0.0798	0.1023	0.1097	0.0105	0.0050	0.1046	-0.1056	0.0182	1.000					
CV-Speed	0.0082	0.0939	0.0794	0.0477	0.0113	0.0172	-0.0056	0.0451	0.2009	1.000				
MAD-Acc/Dec	-0.0205	-0.0327	-0.0025	0.0349	-0.0656	-0.0744	-0.0497	0.0707	0.0701	0.2382	1.000			
CV-Front Distance	0.0057	0.0038	-0.0215	0.0308	-0.0261	-0.0291	0.0006	-0.0450	0.0918	0.1482	0.2213	1.000		
CV-Back Distance	0.0065	0.0120	-0.0209	0.0402	-0.0679	-0.0828	0.0146	-0.0458	0.0893	0.0997	0.3442	0.3905	1.000	
CV-Centre Distance	0.0379	0.1716	-0.0278	0.0192	-0.0356	0.0498	0.0224	-0.0216	0.2085	0.2825	0.2251	0.2001	0.1777	1.000

Note: Acc/Dec : "Acceleration/Deceleration"

4. Methodology

The study methodology involves the estimation of a panel ordered logit model, which accounts for the ordinal nature of the dependent variable (Drivers' State) and the panel structure of the data as the data involves multiple observations collected for each driver in different driving conditions represented by the State variable. Statistical models usually have higher interpretability but lower prediction performance than ML methods. Since the real-time detection of distracted driving is necessary to develop proactive safety measures, applying prediction-based ML methods in the analysis to predict the instances of distracted driving is more appropriate. The models' predictive performance is compared, and the classification performance metrics for each category of the dependent variable obtained from all models are analyzed. Finally, conclusions are drawn from the results obtained from the frequentist and ML approaches. The overall study framework is presented in Figure 1.

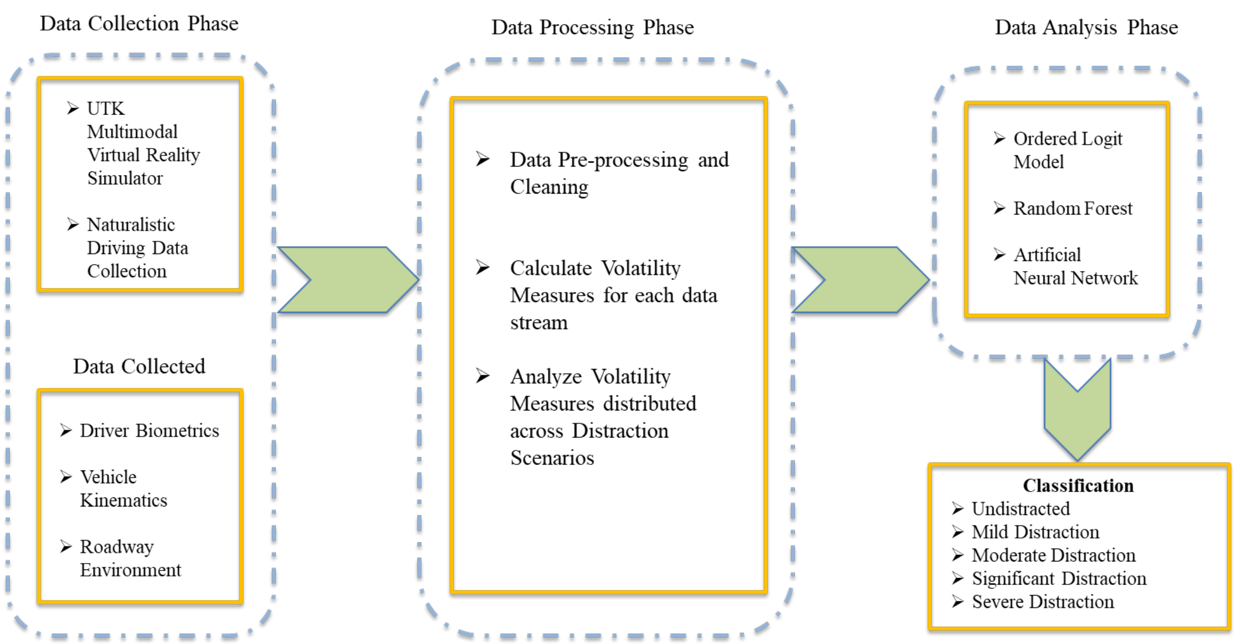

Figure 1: Overall Study Framework

4.1 Ordered Logit Model

Ordinal scales possess two key characteristics: (1) A distinct arrangement of levels is evident, indicating a clear order. (2) The precise distances between the various levels are not known. Extensive research and numerous established techniques (e.g., Multinomial Logit, MNL) exist to effectively and efficiently model categorical data by considering them nominal variables. Nevertheless, disregarding the inherent ordering information may yield dissimilar and less robust outcomes. Conversely, treating an ordered categorical variable as ordinal rather than nominal offers several advantages, including simplicity, straightforward interpretations, enhanced detection capability, increased flexibility, and a closer resemblance to conventional regression analysis (Agresti, 2010; Zheng et al., 2014). A typical mathematical formulation of the ordered logit model is given in equation 6:

$$Y = j \text{ if } \alpha_{j-1} < Y^* \leq \alpha_j \tag{6}$$

$$Y^* = \beta' X + \varepsilon \tag{7}$$

Where Y denotes the response variable, while Y^* is a continuous latent variable whose values are derived from the ordinal data. Y^* equals the product of the coefficient vector β' and explanatory variable vector X, plus an error term ε. The ordinal response, denoted as j, indicates the category where the observed Y falls. α_j represents the cut points or the boundaries of intervals on the continuous scale of Y^*, meaning that Y is assigned to category j when the latent variable falls within the j^{th} interval.

Application of logit transformation to the cumulative probabilities to preserve the ordering among the categories of the response variable results in the following:

$$\text{Logit}[P(Y\leq j)] = \log(P(Y\leq j)/1- P(Y\leq j)) \tag{8}$$

A typical equation for the ordered logit model is:

$$\text{Logit}[P(Y\leq j)] = \alpha_j + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n = \alpha_j + \beta' X \tag{9}$$

Equation (9) indicates that for different categories j of the response variable Y, the association of explanatory variables $x_1, x_2, \ldots, x_n$ is captured by coefficients β, which are important in interpreting this model.

4.2 Panel Ordered Logit Model

The data collected in this study essentially exhibit a panel structure as multiple observations in each driving scenario were recorded for each participant. The observations belonging to the same participant may be highly correlated, or observations for each participant may result in different cut points of the continuous latent response variable. As shown in Equation (9), a conventional ordered logit model cannot handle such inherent correlations or subjectivity in the data. Therefore, to solve this problem, Equation (9) is extended by introducing a random variable u_i to capture the subjectivity among different participants i, resulting in a random effects panel ordered logit model given in Equation (10).

$$\text{Logit}[P(Y_{it} \le j)] = \alpha_j + (u_i + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \ldots + \beta_n x_{nit}) = \alpha_j + u_i + \beta' X \qquad (10)$$

Where Y_{it} denotes the response corresponding to observation t for individual i. The values of the explanatory variables for each observation t of each individual i are denoted as x_{1it}, x_{2it}, ..., x_{nit}. The random effect for individual i, represented by u_i, is unobserved and typically assumed to vary among individuals according to a normal distribution ~N (0, σ_u^2). When the variance σ_u^2 increases, the correlation between two observations from the same individual also increases. The maximum Likelihood approach is used to estimate the parameters in the model.

4.3 Random Forest Classifier

The concept of random forest was first introduced by Breiman in 2001 (Fawagreh et al., 2014). A random forest consists of multiple independent basic classifiers known as decision trees. Each classifier operates on its own when presented with a test sample, and the category label of the sample is determined by aggregating the voting results from each classification. The following steps outline the process of building a random forest classifier:

(a) Choose an appropriate value for the variable “M,” which represents the number of features in each feature subset.

(b) Randomly select a new feature subset θ_k from the entire set of features, according to the chosen M value. Each subset θ_k is independent of the other subsets in the sequence θ_1, θ_2, ..., θ_k.

(c) Train the dataset using the selected feature subset to create a decision tree for each group in the training set. Each individual classifier can be represented as $f(X, \theta_k)$, where X represents the inputs.

(d) Repeat the process by selecting a new θ_k and training the data with the feature subset until all the feature subsets have been traversed. This completes the construction of a random forest classifier.

(e) Now add the test dataset and classify each sample based on the aggregated voting results from each individual classification.

Using a bagging technique, random operations are used in selecting sample subsets to create training sets from the original samples. Bagging is used again to select subsets of features from the entire set of features according to the chosen “M” value. Additionally, the importance of each feature can be ranked based on its contribution to the final decision. Incorporating random operations in the random forest greatly improves its classification performance. (Breiman, 2001; Parmar et al., 2018).

4.4 Artificial Neural Network

Artificial neural networks draw inspiration from early models of brain sensory processing. These networks can be created by simulating a network of model neurons in a computer. By employing algorithms that mimic the functioning of real neurons, we can train the network to solve a wide range of problems. A model neuron, also known as a threshold unit, receives inputs from other units or external sources, assigns weights to each input, and sums them up. If the total input exceeds a specified threshold, the unit outputs a value of one; otherwise, it outputs zero. Thus, the unit's output switches from 0 to 1 when the sum of weighted inputs matches the threshold. The points in the input space that satisfy this condition define a hyperplane. A hyperplane corresponds to a line in two dimensions, while in three dimensions, it represents a flat plane. Points on one side of the hyperplane are classified as 0, while those on the other side are classified as 1. Consequently, a threshold unit can solve a classification problem if a hyperplane can separate the two classes. In the case of a separable classification problem, we still need a way to determine the appropriate weights and threshold for the threshold unit to solve the problem accurately. This can be achieved iteratively by presenting examples with known classifications one after another. This iterative process, resembling how humans learn, is called learning or training. During computer-based learning simulations, small adjustments to the weights and threshold with each new example are made to improve the classification. Throughout the training process, the hyperplane adjusts its position until it finds the correct location in space. It undergoes minimal changes once it reaches this position (Krogh, 2008).

4.5 Performance Measures

To determine the model with the highest accuracy in predicting outcomes outside of the training sample, a confusion matrix and various performance indices are calculated using the holdout (test) sample. Table 5 presents a generalized confusion matrix for this study's five categories of the response variable. The overall out-of-sample prediction accuracy, which serves as a measure of the model's performance, can be computed as follows:

Accuracy = (Total number of correctly predicted observations) / (Total number of observations) * 100 (11)

To assess the accuracy of the model in predicting each specific class, precision and recall measures can be calculated. Both precision and recall are context-dependent and can be chosen based on the desired scope. This study employs the F1 score as a comprehensive performance measure for the prediction accuracy of each specific class. The F1 score considers both precision (false positives) and recall (false negatives) in evaluating the model’s predictive performance. The higher the F1 score of a class, the better the predictive performance of the model specific to that class.

Table 5: Generalized Confusion Matrix for Performance Evaluation of a Model

Observed Outcomes	**Predicted Outcomes**				
	Undistracted	Mild Distraction	Moderate Distraction	Significant Distraction	Severe Distraction
Undistracted	A	B	C	D	E
Mild Distraction	F	G	H	I	J
Moderate Distraction	K	L	M	N	O
Significant Distraction	P	Q	R	S	T
Severe Distraction	U	V	W	X	Y
Performance Measures					
False Positives	(F+K+P+U)	(B+L+Q+V)	(C+H+R+W)	(D+I+N+X)	(E+J+O+T)
False Negatives	(B+C+D+E)	(F+H+I+J)	(K+L+N+O)	(P+Q+R+T)	(U+V+W+X)
Precision	A/(A+F+K+P+U)	G/(B+G+L+Q+V)	M/(C+H+M+R+W)	S/(D+I+N+S+X)	Y/(E+J+O+T+Y)
Recall	A/(A+B+C+D+E)	G/(F+G+H+I+J)	M/(K+L+M+N+O)	S/(P+Q+R+S+T)	Y/(U+V+W+X+Y)
F1 Score	2*Precision*Recall Precision + Recall	2*Precision*Recall Precision + Recall	2*Precision*Recall Precision + Recall	2*Precision*Recall Precision + Recall	2*Precision*Recall Precision + Recall
Overall Accuracy	(A+G+M+S+Y) / (A+B+C+…+Y) * 100				

5. Results

5.1 Results of Panel Ordered Logit Model

The dataset (N=617) was split in an 80:20 proportion, with about 80% of the observations (N_{train} = 507) used to train the model. Approximately 20% of the observations (N_{test} = 110) were used as a holdout sample for making predictions. Table 6 presents the results of the panel ordered logit model estimated for the training dataset to quantify the impact of instantaneous variations in driver biometrics, vehicle kinematics, and roadway characteristics on drivers' states during the simulated driving experiment. All the predictor variables included in the final model were found statistically significant at a 95% and higher confidence level. Average marginal effects for the statistically significant predictor variables were also estimated. The values from μ_1 to μ_4 represent threshold values for the adjacent levels of the latent continuous response variable. Driving events with a score below -0.983 are classified as normal/undistracted. Those who receive a score between -0.983 and 0.0668 are classified as driving instances marked with mild distraction, between 0.0668 and 0.9734 as driving events corresponding to moderate distraction, between 0.9734 and 2.007 as driving events marked with significant distraction, and higher than 2.007 as driving events corresponding to severe level of distracted driving. Table 6 shows that the driver's eye movements and the CVs in drivers' eye movements, vehicle speed, vehicle distances from the lane centreline, and the following vehicle were positively associated with higher levels of driver distraction. From the marginal effects of the statistically significant predictor variables in the model, it can be observed that a unit change in the CV in drivers' eye movements is associated with an increase of 0.2816 and 0.4775 units in the probability of significant and severe levels of distraction, respectively. The marginal effects of the CV in vehicle speed indicate that a unit increase in the CV in vehicle speed is associated with an increase in the probability of significant and severe levels of driver distraction by 0.0974 and 0.1651 units. Similarly, the association of other explanatory variables with the categories of the response variable could be assessed from their respective marginal effects. Furthermore, other explanatory variables related to drivers' biometrics (eye openness) and vehicle kinematics (vehicle speed, acceleration, steering wheel angle) were found statistically insignificant and subsequently removed from the model.

Referring to the model goodness of fit statistics, the model yields a log-likelihood at convergence value of -627.472 and a Pseudo R-squared value of 0.185 which indicates a reasonable statistical fit. The model is overall statistically significant (Prob > χ^2 = 0.0000) with values of Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) as 1274.944 and 1317.229. Furthermore, a likelihood ratio test also justifies the estimation of the panel ordered logit model in comparison to the simple ordered logit model as the probability of getting a higher value than $\chi^2(1)$ = 52.72 is 0.0000, which indicates that the estimation of panel ordered logit model is more appropriate for this dataset.

Table 6: Results of Panel Ordered Logit Model for Training Dataset

Variables	Coefficient	t-stat	p-value	Marginal Effects (Level of Distraction)				
				Normal	Mild	Moderate	Significant	Severe
CV-Eye Movement	6.428	10.68	0.000	-0.8865	-0.0612	0.1886	0.2816	0.4775
CV-Speed	2.223	4.08	0.000	-0.3065	-0.0211	0.0652	0.0974	0.1651
CV-Centre Distance	4.051	6.99	0.000	-0.5586	-0.0385	0.1188	0.1774	0.3009
CV-Back Distance	1.747	2.04	0.041	-0.2409	-0.0166	0.0512	0.0765	0.1297
Eye Movement	1.142	2.05	0.041	-0.1574	-0.0108	0.0335	0.0500	0.0848
Threshold								
μ_1	-0.983							
μ_2	0.0668							
μ_3	0.9734							
μ_4	2.007							
Model Summary								
N	507							
LL at convergence	-627.4721							
LL at null	-770.3974							
Pseudo R^2	0.185							
$\chi^2(5)$	285.85							
Prob> $\chi^2(5)$	0.000							
AIC	1274.944							
BIC	1317.229							
Likelihood Ratio Test	$\chi^2(1) = 52.72$							
Panel Model vs Ordered Logit Model	Prob > $\chi^2(1) = 0.0000$							

Note: N: Number of Observations, LL: Log-likelihood, χ^2: Chi-squared

Since the objective of this project is to integrate the indicators of distracted driving in vehicles equipped with ADAS, more emphasis is placed on the ability of the model to predict incidents of distracted driving rather than inferring to distracted driving behavior. To achieve the aforementioned objective, predicted probabilities for each category of the response variable for each observation in the test dataset were obtained from the trained model. The observations were classified into the response variable categories based on the maximum value of the predicted probability for the respective category. The model was found to classify the driving events into the respective categories of distraction with 67.58% accuracy. Table 7 presents the confusion matrix obtained for the test dataset indicating the model's predictive performance.

Table 7: Confusion Matrix for Test Dataset in Ordered Logit Model

	Test Dataset (N_{test} = 110)					
Observed Outcomes	**Predicted Outcomes**					**Total**
	Undistracted	Mild Distraction	Moderate Distraction	Significant Distraction	Severe Distraction	
Undistracted	26	7	3	2	0	**38**
Mild	5	6	3	1	0	**15**
Moderate	0	3	19	3	1	**26**
Significant	0	1	1	11	2	**15**
Severe	0	1	1	2	12	**16**
Total	**31**	**18**	**27**	**19**	**15**	
Performance Metric						
Accuracy	67.27%					
Precision	0.8387	0.3333	0.7037	0.5789	0.8000	
Recall	0.6842	0.4000	0.7307	0.7333	0.7500	
F1 Score	0.7614	0.3666	0.7172	0.6561	0.7750	

5.2 Results of Random Forest

Like the panel ordered logit model, 80% of the data (N_{train} = 507) was used to train the random forest model, while 20% (N_{test} = 110) was used as a holdout sample for making predictions. A grid search was performed for tuning the model's hyperparameters using 10-fold cross-validation. The 10-folds cross-validation process involves dividing the available data into ten equal subsets. Nine of these subsets are used for training the model, while one subset is kept for testing to evaluate the model's predictive accuracy. This process is repeated ten times, each subset serving as the testing data once. The final estimation is obtained by averaging the results from all ten iterations. A range of values for the number of trees (50, 70, 80, and 100), variables for splitting the node m_{try} (3, 4, 5, and 8), minimum node size (1, 3, 5, and 7), and sample fraction (0.5, 0.6, 0.7, 0.8) were considered among which the optimal number of trees, variables for splitting the node m_{try}, minimum node size, and sample fraction were 100, 3, 1, and 0.7 respectively resulting in a minimum cross-validation error of 0.500. Table 8 presents the results of the grid search for the first ten combinations of the model hyperparameters ranked according to increasing cross-validation error. The model achieved an out-of-sample prediction accuracy of 77.27% for the test data with the optimal hyperparameters (Table 9).

The feature importance analysis indicates the individual contribution of the predictors in the model accuracy. Figure 2 presents the most influential predictors in the model with their relative importance values sorted in descending order. According to Figure 2, the CV in drivers' eye movements is the most influential predictor among the predictor variables, with a relative importance of about 68%, followed by the "Back" variable, which indicates the distance from the following vehicle, with an importance of about 48%.

Table 8: Results of Top 10 Combinations of Model Hyperparameters

Number of Trees	Variables used for splitting the node	Minimum Node Size	Sample Fraction	CV Error
100	3	1	0.7	0.500
100	4	1	0.8	0.510
100	5	3	0.8	0.512
100	4	1	0.8	0.514
100	5	1	0.8	0.515
100	5	5	0.8	0.516
100	3	5	0.7	0.517
100	8	1	0.7	0.518
100	3	3	0.7	0.519
80	4	1	0.8	0.522

Note: CV: Cross Validation

Table 9: Confusion Matrix for Test Data in Random Forest Model

Observed Outcomes	Predicted Outcomes					
	Undistracted	Mild Distraction	Moderate Distraction	Significant Distraction	Severe Distraction	**Total**
Undistracted	29	5	2	1	1	**38**
Mild	2	11	1	0	1	**15**
Moderate	0	4	19	2	1	**26**
Significant	0	2	3	10	0	**15**
Severe	0	0	0	0	16	**16**
Total	**31**	**22**	**25**	**13**	**19**	
Performance Metric						
Accuracy	77.27%					
Precision	0.9354	0.5000	0.7600	0.7692	0.8421	
Recall	0.7631	0.7333	0.7307	0.6667	1.0000	
F1 Score	0.8405	0.5946	0.7451	0.7142	0.9143	

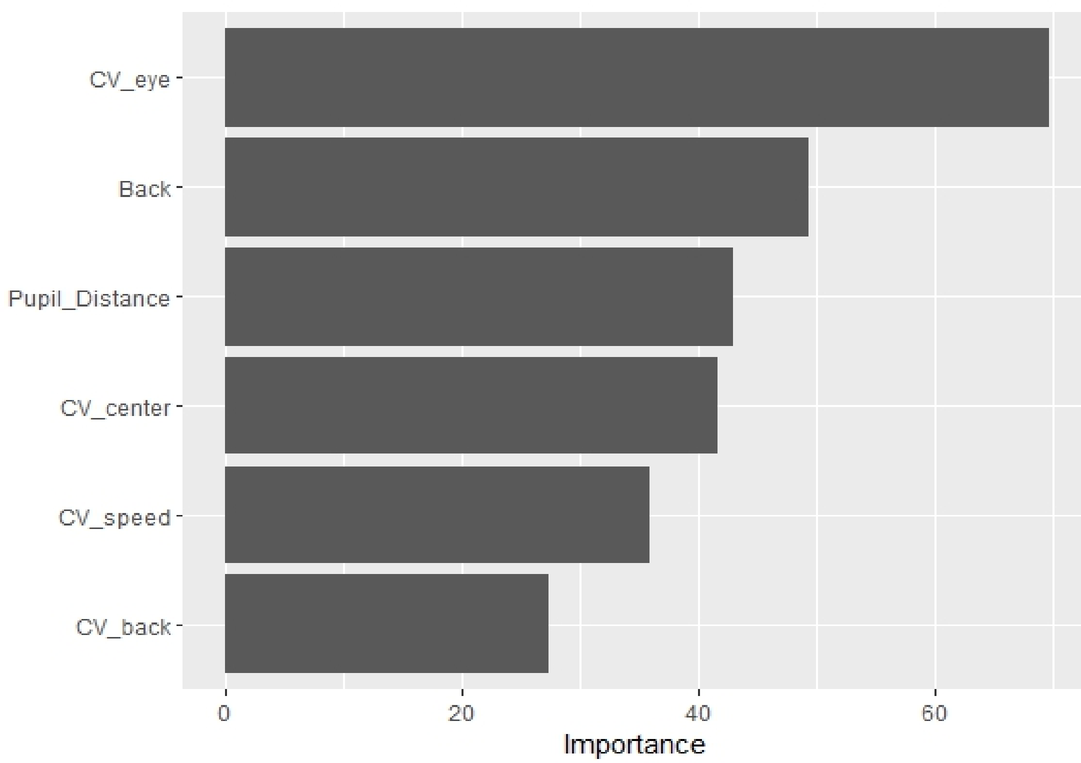

Figure 2: Relative Importance of Key Predictor Variables in Random Forest Model

5.3 Results of Artificial Neural Network

Neural networks represent a powerful and robust method in supervised ML, particularly for classification problems. They can efficiently handle large-scale data, automatically detect relevant features from the input data, capture non-linear relationships between input features and the target variable, learn complex patterns in the data, and make highly accurate predictions. The statistically significant variables in the frequentist model were selected as input features in training the neural network for consistent comparisons. Consistent with the ordered logit and random forest models, the neural network was trained on 80% of the data, while 20% of the data was allocated for making predictions by the trained model. Since the neural network requires normalized continuous input features, all the input features in the model were normalized to a unit variance by subtracting the minimum value of every input feature from each value and dividing the result by the range of each input feature. The specifications of the neural network include a single hidden layer containing 6 neurons, a logistic activation function used for smoothing the result of the cross-product of the neurons and weights, resilient backpropagation with weight backtracking as the algorithm used to train the network, the sum of squared errors as the error function to calculate the error with 5 repetitions in training the neural network. The maximum number of steps used for training the network was 1000000, with a threshold for the partial derivatives of the error function as a stopping criterion set as 1. Figure 3 presents a neural network plotted using the "NeuralNetTools" package in R software.

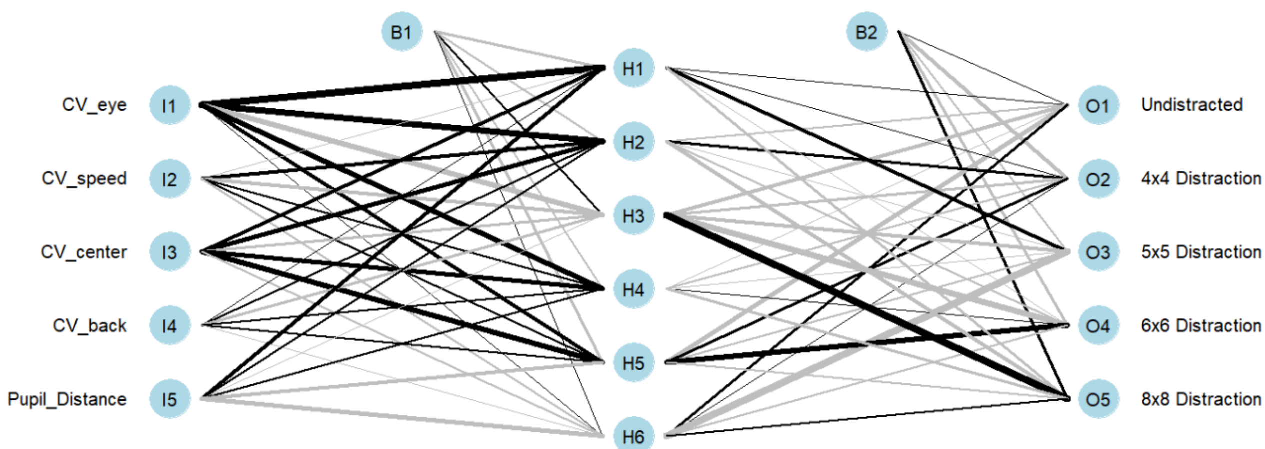

Figure 3: Artificial Neural Network Plot

Referring to Figure 3, the first layer in the neural network includes only input variables found statistically significant in the ordered logit model with nodes labeled arbitrarily as I1 through I5 for 5 input variables. Positive weights between layers are represented by black lines, and negative weights by grey lines. The line thickness proportionally represents the relative magnitude of each weight. The second layer indicates a hidden layer with 6 neurons labeled H1 through H6. The final layer represents the output layer with nodes labeled as O1 through O5, indicating the response variable categories. Bias nodes connected to the hidden and output layers are labeled as B1 and B2, respectively. Predictions were obtained for the test dataset (N_{test} = 110) from the neural network trained using the training dataset (N_{train} = 507). The model yielded an out-of-sample prediction accuracy of 75.45%. The confusion matrix indicating the neural network's predictive performance and the performance metrics for predicting each class of the response variable are presented in Table 10.

Table 10: Confusion Matrix for Test Dataset in Neural Network

Observed Outcomes	**Predicted Outcomes**					
	Undistracted	Mild Distraction	Moderate Distraction	Significant Distraction	Severe Distraction	**Total**
Undistracted	29	5	2	2	0	**38**
Mild	4	8	2	1	0	**15**
Moderate	0	2	20	3	1	**26**
Significant	0	0	1	12	2	**15**
Severe	0	0	1	1	14	**16**
Total	**33**	**15**	**26**	**19**	**17**	
Performance Metric						
Accuracy	75.45%					
Precision	0.8787	0.5333	0.7692	0.6316	0.8235	
Recall	0.7632	0.5333	0.7692	0.8000	0.8750	
F1 Score	0.8168	0.5333	0.7692	0.7058	0.8485	

6. Discussion

This study applies a panel ordered logit model and supervised ML methods (i.e., random forest and artificial neural network) to analyze a multidimensional dataset that includes dynamic information about instantaneous variations in driver biometrics, vehicle kinematics, and roadway surroundings in driving environments with varying levels of distraction. Results of the panel ordered logit model suggest that the drivers' eye movements and the CVs in drivers' eye movements, vehicle speed, vehicle distances from the lane centerline, and the following vehicle were positively associated with higher levels of driver distraction. These findings conform to the expectations of higher volatility in vehicle performance indicators associated with chaotic/irregular driving behaviors and are consistent with the results obtained in previous similar studies (Arvin et al., 2021; Mohammadnazar et al., 2021; Wali et al., 2019).

Comparing the prediction accuracy of the statistical model and the two ML methods for the holdout sample, the results indicate that the random forest classifier predicts distracted driving outcomes with an overall accuracy of 77.27% in the test sample, which is significantly higher than the corresponding out-of-sample prediction accuracy of its counterparts. The random forest classifier also shows the highest F1 score for four total distracted driving outcomes, including undistracted, mild, significant, and severe distraction levels in the test sample. To conclude, the random forest classifier was selected as the most accurate method to predict levels of distracted driving using simulated driving behavior data in this project.

7. Limitations

This study harnesses real-time driving performance data from a AV simulator at the University of Tennessee, Knoxville, to detect distracted driving behavior. Although driving simulators present a secure, relatively less expensive, and easy-to-install option for the acquisition of driving behavioral data, they cannot accurately simulate real-world roadway and traffic conditions with their true uncertainty and difficulty levels (Blana & Golias, 2002; Godley et al., 2002; Groeger & Murphy, 2020). The data collected from driving simulators can suffer from conformity bias, an issue that reflects more careful driver behavior when drivers' driving skills are being monitored (Sajid Hasan et al., 2022). Furthermore, the driving behaviors of only a limited number of participants (26 drivers) were collected and analyzed in this study. The classification accuracy of the methods used in the study would probably be higher with a higher sample size. More robust deep learning algorithms can then be used to detect complex patterns and additional features in the data.

8. Conclusions

This study attempts to detect distracted driving behavior by incorporating the variations in real-time driver biometrics, including driver gaze, eye openness, etc., with vehicle kinematics and roadway surroundings obtained from a simulated driving experiment. The study employs a frequentist panel ordered logit model, and two ML methods, namely random forest and neural network, to determine the key determinants of distracted driving and predict the instances of distracted driving with varying levels of complexity with reasonable accuracy. The instantaneous variations in the driver biometrics, vehicle, and roadway characteristics were captured through indicators of driving volatility. Results of the panel ordered logit model suggest that the CV of speed, CV of drivers' eye movements, CV of vehicular distances from the lane center line and the following vehicle, and the driver's eye movements during various distracted driving scenarios were statistically significantly associated with distracted driving. Referring to the out-of-sample prediction accuracy for the ML methods, the random forest classifier showed the highest overall out-of-sample prediction accuracy (77.27%) for the distracted driving outcomes. The study's contribution lies in incorporating real-time driver biometric characteristics and employing measures of driving volatility to detect distracted driving. The study's findings can assist in developing proactive vehicle safety features intended to detect distracted driving and warn the drivers of potential risks of SCEs to improve overall roadway safety, especially by emphasizing safe vehicles and safe users. Furthermore, real-time distracted driving detection can have practical applications in different domains. For instance, by analyzing driver behavior and variations in vehicle kinematics during distracted driving events, policymakers and traffic safety practitioners can develop tailored interventions and technologies to enhance road safety, promote eco-friendly driving, and create personalized driving experiences (Alessandrini et al., 2012; Ranacher et al., 2016; Van Mierlo et al., 2004). In summary, the findings of this study can be insightful for developing algorithms based on the results of the random forest classifier in automated vehicles, which can detect distracted driving incidents using data related to driver and vehicle performance to caution the drivers of the risk of SCEs in real-time.

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Chapter 3

How is the duration of distraction related to safety-critical events? Harnessing naturalistic driving data to explore the role of driving instability.

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This chapter presents a brief version of a refereed journal paper on the association of the duration of distraction with SCEs using naturalistic driving data. The paper was published in a transportation safety journal titled *Journal of Safety Research* and is available online.

Access the paper at: https://www.sciencedirect.com/science/article/pii/S0022437523000038

Abstract

The issue of distracted driving is a critical concern due to the variety of secondary tasks performed by drivers. This study aimed to investigate how distractions can lead to crashes and develop appropriate countermeasures strategies. The study utilized microscopic driving data and the safe systems approach to analyze a subsample of NDS data collected through the SHRP2 program. The study used rigorous path analysis to jointly model the instability in driving and event outcomes, including baseline, near-crash, and crash. The results indicated that a longer duration of distraction was positively but non-linearly associated with higher driving instability and higher chances of SCEs. The chance of a crash and near-crash was higher by 34% and 40%, respectively, with a unit increase in driving instability. Moreover, the chance of both SCEs significantly increased non-linearly with an increase in distraction duration beyond 3 seconds. For instance, the chance of a crash is 16% for a driver distracted for 3 seconds, which increases to 29% if a driver is distracted for 10 seconds. The study's findings highlight the total effects of distraction duration on SCEs, which are even higher when considering its indirect effects on SCEs through driving instability. The study discusses potential practical implications, including traditional countermeasures, such as changes in roadway environments and vehicle technologies. Overall, the study emphasizes the need for appropriate countermeasure strategies to reduce the risks of distracted driving, which is crucial in promoting road safety.

1. Introduction

Most road accidents are caused by human factors (Khattak et al., 2021; Treat et al., 1979), including distracted driving, which can lead to recognition errors and adversely affect a driver's ability to perform primary driving tasks. Researchers have used newly available microscopic NDS data to understand how distractions lead to crashes, which provide information on pre-crash driving behaviors and vehicle kinematics that are not available in police crash data. This data reveals that subject drivers are often distracted due to cellphone use, eating, interacting with other passengers, adjusting or monitoring radio and climate control, and other external sources like pedestrians and billboards (Dingus et al., 2016; Ranney, 2008; Khattak et al., 2021; Young & Regan, 2007). Studies have explored how distraction duration relates to crash risk using NDS data. However, certain research questions remain unexplored, such as whether the duration of distraction may relate to SCEs indirectly through instability in driving. This study tests this hypothesis by applying a rigorous path analysis through the joint estimation, which captures the total (direct + indirect) effects of duration of distraction on SCEs while accounting for the potential correlation between the unobserved factors that could significantly relate to both instabilities in driving and event outcome. The study uses a joint estimation framework, which is unique compared to previous studies, and captures the nonlinear effects of distraction duration on SCEs in the joint path analysis. The study harnesses newly available microscopic driving data collected through SHRP2, using the safe systems approach to explore how the distraction duration (regardless of different types of distraction or secondary tasks) may relate to SCEs. Overall, the study contributes to developing appropriate countermeasure strategies for distracted driving by providing insights into the effects of distraction duration on driving instability and SCEs.

2. Methodology

This study examines the relationship between the duration of distraction while driving and the likelihood of being involved in a crash or near-crash. The study analyzes data from the SHRP2 NDS subsample and uses the CV of speed to measure driving instability. The study also includes control variables such as maneuver judgment, relation to a junction, traffic flow conditions, and travel speed to gain insights into their relationship with instability in driving and SCEs. The conceptual framework of the study is depicted in Figure 4. The study uses Tobit and Ordered Probit models to account for the potential correlation between instability in driving and SCEs. The study contributes to the literature by accounting for unobserved factors that could affect both instabilities in driving and SCEs.

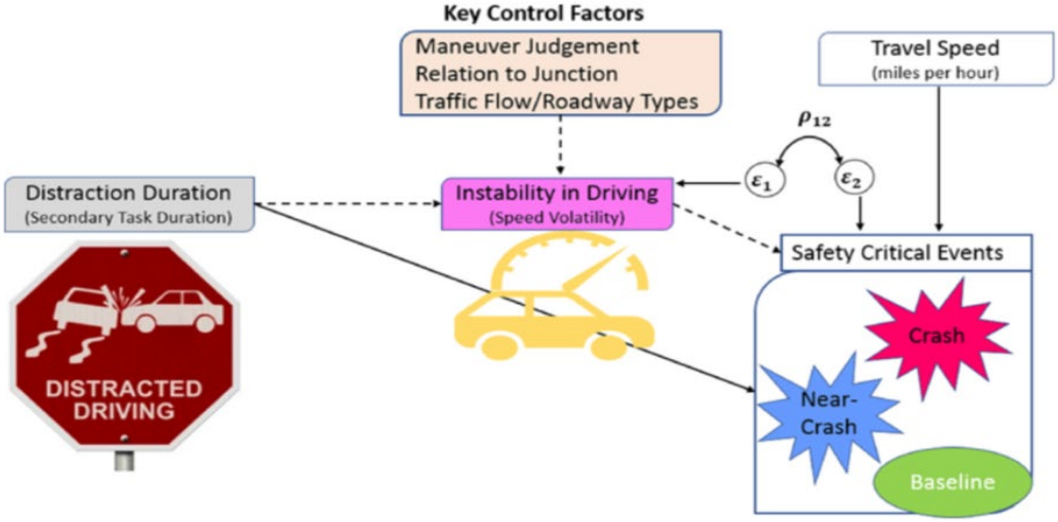

Figure 4: Conceptual Framework of the Study

The SHRP2 NDS data provide real-world data on pre-crash driving behaviors, secondary tasks, and vehicle kinematics. The data are recorded via fitted cameras and recording equipment, including data about instantaneous speed, acceleration, and deceleration, which can be used to derive various indices of instability in driving. The data also includes baselines that quantify crash risk. Baselines refer to non-event (routine) driving. Near-crash situations refer to evasive maneuvers made by the subject driver to avoid a crash, and a crash is a situation in which a subject vehicle comes in contact with either a fixed or moving vehicle or object. The data provides unique insight into driver behavior and can be used to improve road safety. CV of speed was selected to measure driving instability, and the joint path analysis framework was used to show its correlation with event outcomes.

3. Results

The study estimated the instability in driving and event outcomes independently and jointly using Tobit regression and the Ordered Probit model, respectively. Table 11 shows the results of the Tobit and Ordered Probit Model. The study found that instability in driving was higher in crash and near-crash events than in baselines. Moreover, the mean CV of speed was higher in crashes and near-crashes than in baselines. The study also found distraction duration was longer in crashes than near-crashes and baselines. The Tobit model shows that instability in driving increases non-linearly with an increase in distraction duration, reaching a value of 1 if the subject driver is distracted for 18 seconds. The Ordered Probit model indicates that the probability of a crash increases exponentially when the distraction duration exceeds 8 seconds.

Results from the joint estimation suggested that unobserved factors that increase driving instability but decrease the probability of driving events are significantly correlated. The study also found significant evidence about distraction duration's non-linear relationship with driving instability and driving events. The variance inflation factors computed for all variables included in the final models were less than 5, indicating no considerable evidence of multicollinearity. The study's findings could inform future research and policies to reduce driving events and promote safe driving practices. The study finds that as distraction duration increases, instability in driving also increases, leading to a higher probability of crashes and near-crashes. Furthermore, traffic flow conditions also affect instability in driving, with physically divided traffic conditions being safer than undivided or one-way traffic. Additionally, the study finds that the probability of crash and near-crash significantly increases with a unit increase in instability in driving. The study also conducts a path analysis to quantify the indirect effects of distraction duration on SCEs through instability in driving. The results show that the crash risk becomes twice if the indirect effects of duration of distraction on crashes through driving instability are considered. The study found that distraction duration is non-linearly associated with driving instability and the probability of SCEs. The study suggests that countermeasures such as removing external sources of distraction, educating drivers, and using hands-free and vehicle technologies can reduce distracted driving and driving instability. However, further research is needed to recommend specific strategies.

Table 11: Results of Tobit Model and Ordered Probit Model (Joint Estimation)

Independent Variables	Tobit Model (Instability in Driving)					Ordered Probit Model (Event Outcome)				
	Coeff.	p-value	ME-1	ME-2	ME-3	Coeff.	p-value	MEs		
								Baseline	Near-Crash	Crash
COV of speed	–	–	–	–	–	3.8125	< 0.001	Base	0.4016	0.3400
Secondary Task Duration (seconds)	−0.0071	0.002	−0.0055	−0.0072	−0.0041	−0.0368	0.004	Base	−0.0039	−0.0033
Secondary Task Duration * Secondary Task Duration	0.0029	< 0.001	0.0022	0.0029	0.0017	0.0087	< 0.001	Base	0.0009	0.0008
Speed (mph)	–	–	–	–	–	0.0495	< 0.001	Base	0.0052	0.0044
Speed (mph) * Speed (mph)	–	–	–	–	–	−0.0012	< 0.001	Base	−0.0001	−0.0001
Relation to Junction ***(Base Category = Intersection or intersection related)***										
Other (rail grade crossing, parking lot entrance or exit, etc.)	−0.0329	0.004	−0.0287	−0.0248	−0.0224	–	–	–	–	–
Parking lot, within boundary	−0.0177	0.477[a]	−0.0156	−0.0130	−0.0122	–	–	–	–	–
Driveway, alley access, etc.	−0.1324	< 0.001	−0.1097	−0.1203	−0.0831	–	–	–	–	–
Entrance/Exit ramp or interchange area	−0.1601	< 0.001	−0.1305	−0.1522	−0.0982	–	–	–	–	–
Non-junction	−0.1565	< 0.001	−0.1279	−0.1479	−0.0963	–	–	–	–	–
Maneuver Judgement ***(Base Category = Unsafe and illegal)***										
Unsafe but legal	0.0254	0.183[a]	0.0228	0.0162	0.0184	–	–	–	–	–
Safe but illegal	−0.1108	< 0.001	−0.0936	−0.0925	−0.0725	–	–	–	–	–
Safe and legal	−0.1332	< 0.001	−0.1112	−0.1155	−0.0856	–	–	–	–	–
Roadway Configuration ***(Base Category = Divided (median Strip or barrier)***										
No lanes	0.2210	< 0.001	0.1876	0.1796	0.1461	–	–	–	–	–
Not divided - center 2-way left turn lane	0.0241	0.018	0.0183	0.0265	0.0135	–	–	–	–	–
Not divided - simple 2-way trafficway	0.0537	< 0.001	0.0417	0.0569	0.0309	–	–	–	–	–
One-way traffic	0.1179	< 0.001	0.0952	0.1137	0.0717	–	–	–	–	–
Road Surface Condition: Wet (1/0)	0.0242	0.002	0.0190	0.0248	0.0142	0.1083	0.010	Base	0.0114	0.0097
Constant	0.3956	< 0.001	–	–	–	–	–	–	–	–
Sigma (e. Coefficient of Variation of Speed)	0.2688	< 0.001	–	–	–	–	–	–	–	–
Thresholds										
μ_1	–	–	–	–	–	2.2306	< 0.001	–	–	–
μ_2	–	–	–	–	–	3.1284	< 0.001	–	–	–
Models Summary										
Rho (Correlation between residuals of the two equations)	−0.4698 (t-stats = -12.18; p-value = <0.001)									
AIC	10375.73									
BIC	10561.14									

Note: [a] indicates that a particular variable showed insignificance. Our discussion related to Tobit regression is based on ME-1 which refers to both censored and uncensored observations. ME-2 indicates the probability of being uncensored while ME-3 is like ME-1 but is based on only uncensored observations.

4. Conclusions

The paper investigates the relationship between the duration of distraction, driving instability, and SCEs using the SHRP2 NDS subsample, which includes baselines, near-crashes, and crashes. Results indicate that drivers in crashes and near-crashes were distracted for longer than baselines. Similarly, drivers in SCEs had higher instability in driving compared to baseline drivers. Results reveal that a longer duration of distraction was positively associated with higher driving instability and higher chances of SCEs, with the chance of a crash and near-crash being higher by 34% and 40%, respectively, with a unit increase in instability in driving. The chance of both SCEs significantly increases with an increase in distraction duration beyond 3 seconds. The study used a limited sample from SHRP2 NDS which may not represent the entire United States or other areas due to differences in driving behavior, demographics, traffic, and road conditions. The subsample used in the study includes driver demographics and vehicle types which could be associated with driving instability and SCEs. Future studies could explore the relationship between driver demographics and vehicle types with driving volatility and SCEs. The report highlights potential strategies and promising measures that can reduce the duration of distraction and driving instability, such as hands-free technologies, message signs, multiple vehicle technologies (forward collision warning and adaptive cruise control), and educating drivers about the negative consequences of secondary tasks while driving.

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Chapter 4

Exploring pathways from driving errors and violations to crashes: The role of instability in driving

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This chapter presents a brief version of a refereed journal paper on the contribution of driving errors and violations to SCEs through driving instability. The paper was published in a transportation safety journal titled *Accident Analysis and Prevention* and is available online.

Access the paper at: https://www.sciencedirect.com/science/article/pii/S0001457522003116

Abstract

The study examines the impact of instability in driving speed resulting from driving errors, violations, and roadway environments on SCEs. The study analyzed a subsample of the SHRP2 NDS by employing a safe systems approach, path analysis, Tobit and Ordered Probit regressions to jointly model outcomes. The Tobit model revealed that driving errors and violations were associated with instability in the driving speed of the driver. Meanwhile, the Probit model showed that driving errors, violations, and instability in driving speed increased the chances of crashes and near-crashes. The study found that driving errors and violations directly induced crash risk and indirectly through instability in driving speed. The study also revealed significant correlations between unobserved factors in the error terms of the two models. Ignoring such correlations could lead to inefficient parameter estimates. Based on the findings, the study discussed practical implications that could lead to effective countermeasures to reduce crash risk.

1. Introduction

More than 90% of car crashes are attributed to human factors (Khattak et al., 2021; Singh, 2015; Treat et al., 1979), and there is a need to understand these factors better. Taxonomies of driving behaviors that lead to crashes have been developed in the past (Reason et al., 1990; Stanton & Salmon, 2009; Treat et al., 1979; Wierwille et al., 2002), however, these were based on police crash reports. Police crash reports may not accurately represent driving behavior due to subjectivity and underreporting (Dingus et al., 2006; Khattak et al., 2021; Yamamoto et al., 2008). To address this, a recent study used objective data from the SHRP2 NDS to develop a systematic classification of driving errors and violations called the Taxonomy of Driving Errors and Violations (TDEV). The TDEV categorizes driving errors and violations into six types: recognition errors, decision errors, performance errors, physical condition-related errors, experience errors, and violations (intentional or unintentional) (Khattak et al., 2021). The availability of high-frequency NDS data from SHRP2 provides a more realistic data source for studying driving behavior and performance (Arvin et al., 2019; Carney et al., 2015; Papazikou et al., 2017, 2019; Richard et al., 2020). The SHRP2 NDS data includes detailed information on vehicle kinematics, roadway environments, traffic conditions, and real-world microscopic data on driving parameters like speed and secondary tasks. This study uses the newly developed TDEV to categorize driving behaviors using objective SHRP2 NDS data (Khattak et al., 2021). The study aims to identify potential pathways from errors and violations in diverse roadway environments to SCEs through instability in driving speed. The study estimates models that account for potential correlations between unobserved factors associated with both epoch (video stream) outcomes (i.e., baseline, near-crash, and crash) and instability in driving speed.

2. Methodology

The study hypothesizes that drivers who make mistakes may take corrective actions that cause instability in their driving speed which may then have a significant impact on the occurrence of SCEs. The study uses a path analytic framework to explore this idea to estimate two constituent models, including the Tobit and the ordered Probit models. This method accounts for the correlation between unobserved factors that affect both the CV of speed and epoch outcome. The study's methodology is unique because it allows for efficiency gains by estimating the two models jointly. The conceptual framework of the study is presented in Figure 5.

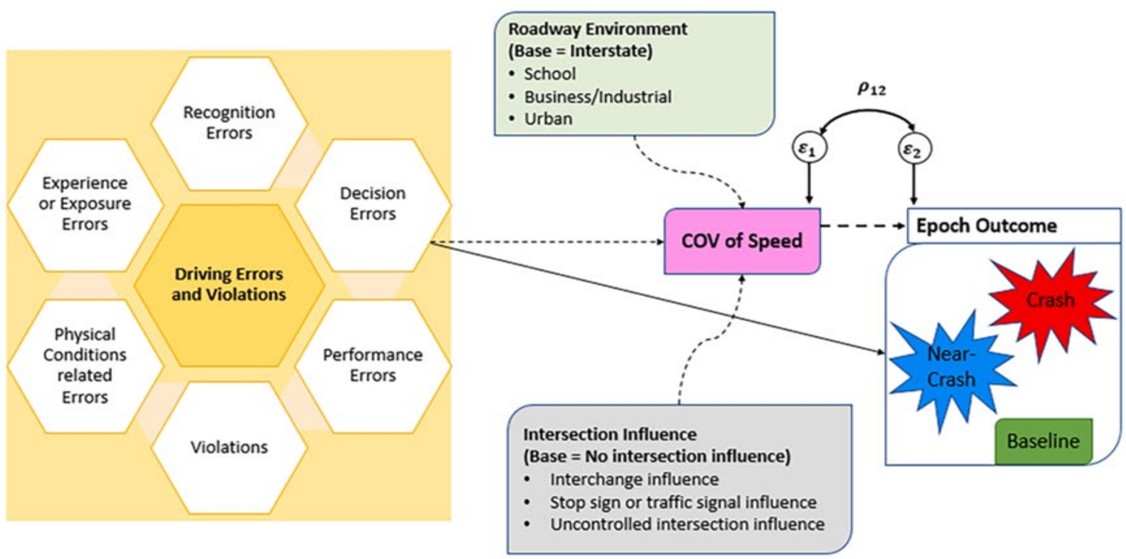

Figure 5: Study Conceptual Framework

This study uses a joint estimation method of the Tobit and the ordered Probit model to account for potential correlation between unobserved factors that could significantly affect instability in driving speed and epoch outcomes. Through path analysis, the study aims to quantify the direct, indirect, and total effects of driving errors, violations, and roadway environments on crashes and near-crashes. The SHRP2 NDS subsample is used, which includes real-world data on pre-crash driving behaviors, secondary tasks, and diverse roadway environments collected via instrumented vehicles. Data on instantaneous speed, acceleration, and deceleration is also available in the SHRP2 NDS data. This data allows for the derivation of various measures or functions of instability. One advantage of using the SHRP2 NDS data is that it includes data on near-crashes and baselines, which allows for the computation of crash risk and near-crash risk that cannot be done using police crash reports. The SHRP2 NDS sub-sample used in this study includes 9,239 events consisting of baselines, near-crashes, and crashes.

3. Results

The results of Tobit and Ordered Probit models estimated separately are presented in Table 12. The results of the Tobit model indicate that compared to no driving error and violation, all types of driving errors and violations positively influence instability in driving speed. The study finds that a recognition error and decision error increase the CV of speed by 0.2670 and 0.1596 units, respectively, compared to no driving error and violation. The CV of speed also increases in urban areas, school zones, and business/industrial locations compared to the interstate. Furthermore, the chance of both crash and near-crash increases if a driver makes an error or a violation compared to no driving error or violation.

Table 12: Results of Model for Instability in Driving Speed and Epoch Outcome Model

Independent variables	Tobit Model (COV of Speed)					Ordered Probit Model (Epoch Outcome)				
	Coeff.	*t*-stat	ME-1	ME-2	ME-3	Coeff.	*t*-stat	MEs		
								Baseline	Near-Crash	Crash
COV of Speed	—	—	—	—	—	1.7418	31.92	−0.2622	0.1620	0.1002
Drivers Errors (Base Outcome = No Driving Errors)										
Recognition Errors	0.3419	32.89	0.2670	37.59 %	0.2093	1.8758	31.52	−0.2824	0.1745	0.1079
Decision Errors	0.2044	20.04	0.1596	22.46 %	0.1251	1.8547	32.70	−0.2792	0.1726	0.1067
Performance Errors	0.3502	11.79	0.2735	38.50 %	0.2144	2.7307	15.79	−0.4111	0.2541	0.1570
Violations	0.0654	6.64	0.0511	7.19 %	0.0400	0.9983	17.25	−0.1503	0.0929	0.0574
Physical Conditions	0.0396	1.85	0.0309	4.35 %	0.0242	0.8453	6.46	−0.1272	0.0786	0.0486
Experience or Exposure	0.2367	5.20	0.1848	26.02 %	0.1449	2.3030	9.74	−0.3467	0.2143	0.1324
Roadway Locality (Base = Interstate)										
Open Country or Open Residential	0.0663	6.73	0.0518	7.28 %	0.0406	—	—	—	—	—
Moderate Residential	0.1246	16.18	0.0973	13.70 %	0.0763	—	—	—	—	—
School	0.1423	11.72	0.1111	15.64 %	0.0871	—	—	—	—	—
Business/Industrial	0.1487	20.90	0.1161	16.34 %	0.0910	—	—	—	—	—
Urban	0.2335	14.51	0.1823	25.66 %	0.1429	—	—	—	—	—
Bypass or Divided Highway with traffic signals	0.0698	4.69	0.0545	7.67 %	0.0427	—	—	—	—	—
Others (e.g., church, playground, and Campground)	0.1636	8.94	0.1278	17.98 %	0.1002	—	—	—	—	—
Intersection Influence (Base = No intersection influence)										
Interchange influence	0.0810	5.63	0.0633	8.91 %	0.0496	—	—	—	—	—
Stop sign or traffic signal influence	0.1958	26.95	0.1529	21.53 %	0.1199	—	—	—	—	—
Uncontrolled intersection influence	0.1354	9.83	0.1057	14.88 %	0.0829	—	—	—	—	—
Parking lot or driveways influence	0.2238	18.28	0.1748	24.60 %	0.1370	—	—	—	—	—
Others (e.g., crosswalk, railroad crossing, roundabouts)	0.1722	7.43	0.1345	18.93 %	0.1054	—	—	—	—	—
Secondary task duration	0.0015	1.57	0.0012	0.16 %	0.0009	0.0312	5.18	−0.0047	0.0029	0.0018
Level of Service (Base Category = C to F)										
LOS A: Free flow traffic condition	−0.1112	−12.72	−0.0868	−12.22 %	−0.0681	—	—	—	—	—
LOS B: Traffic Flow with some restriction	−0.1120	−11.68	−0.0874	−12.31 %	−0.0685	—	—	—	—	—
Constant	0.1317	14.21		—	—	—	—	—	—	—
Var (e. Coefficient of Variation of Speed)	0.0534	67.97	—	—	—	—	—	—	—	—
Thresholds										
μ_1	—	—	—	—	—	1.9485	62.92	—	—	—
μ_2	—	—	—	—	—	3.3174	67.32	—	—	—
Model Summary										
Number of observations	9,239					9,239				
AIC	−812.5798					6807.4980				
BIC	−648.5625					6878.8100				

Table 13 shows the results of the path analysis based on the joint estimation for instability in driving speeds and epoch outcomes. The joint estimation results show significant evidence that the two sets of unobserved factors contributing to both the instability in driving speed and epoch outcome are correlated. Through joint estimation, the parameter signs for all variables remain the same; however, their magnitudes vary compared to those in the separately estimated models. Based on joint-estimation results, a unit increase in instability in driving speed (CV of speed) increases the probability of crashes and near-crashes by 0.1794 and 0.2950 units, respectively. The study finds that recognition error, compared to no driving error and violation, directly increases the chance of a crash by 6.78%. It indirectly increases the chance of a crash by 4.72% through the CV of speed. Thus, the total increase in the chance of a crash due to a recognition error is 11.51%, significantly greater than the direct increase in the chance of a crash due to a recognition error. Performance error has the highest impact on crashes and near-crashes, increasing their probabilities by 0.1139 and

0.1873, respectively. Furthermore, the probability of crash increases by 0.1035, 0.0829, and 0.0678 units if a subject driver makes an experience, decision, and recognition errors, respectively. The study's key findings are presented through an infographic in Figure 6.

Table 13: Path Analysis Results (Based on Joint Estimation)

Independent variables	Direct Effects on Crash (%)	Indirect Effects on Crash through COV of Speed (%)	Total Effects (Direct + Indirect through COV of Speed) on Crash (%)	Direct Effects on Near-Crash (%)	Indirect Effects on Near-Crash through COV of Speed (%)	Total Effects (Direct + Indirect through COV of Speed) on Near-Crash (%)
COV of Speed	17.94	—	17.94	29.50	—	29.50
Drivers Errors (Base Outcome = No Driving Errors)						
Recognition Errors	6.78	4.73	11.51	11.14	7.77	18.92
Decision Errors	8.29	2.80	11.09	13.63	4.60	18.23
Performance Errors	11.39	4.84	16.23	18.73	7.96	26.68
Violations	4.82	0.91	5.73	7.93	1.49	9.42
Physical Conditions	4.57	0.55	5.12	7.51	0.90	8.42
Experience or Exposure	10.35	3.22	13.57	17.02	5.29	22.30
Roadway Locality (Base = Interstate)						
Open Country or Open Residential	—	0.93	0.93	—	1.53	1.53
Moderate Residential	—	1.62	1.62	—	2.66	2.66
School	—	1.94	1.94	—	3.19	3.19
Business/Industrial	—	1.99	1.99	—	3.26	3.26
Urban	—	3.33	3.33	—	5.47	5.47
Bypass or Divided Highway with traffic signals	—	1.01	1.01	—	1.66	1.66
Others (e.g., church, playground, and Campground)	—	2.20	2.20	—	3.62	3.62
Intersection Influence (Base = No intersection influence)						
Interchange influence	—	1.60	1.60	—	2.63	2.63
Stop signs or traffic signals influence	—	2.67	2.67	—	4.39	4.39
Uncontrolled intersection influence	—	2.31	2.31	—	3.79	3.79
Parking lot or driveways influence	—	3.41	3.41	—	5.61	5.61
Others (e.g., crosswalk, railroad crossing, roundabouts)	—	2.60	2.60	—	4.27	4.27
Secondary task duration	0.15	0.02	0.17	0.25	0.03	0.29
Level of Service (Base Category = C to F)						
LOS A: Free flow traffic condition	—	−1.58	−1.58	—	−2.60	−2.60
LOS B: Traffic Flow with some restriction	—	−1.53	−1.53	—	−2.52	−2.52

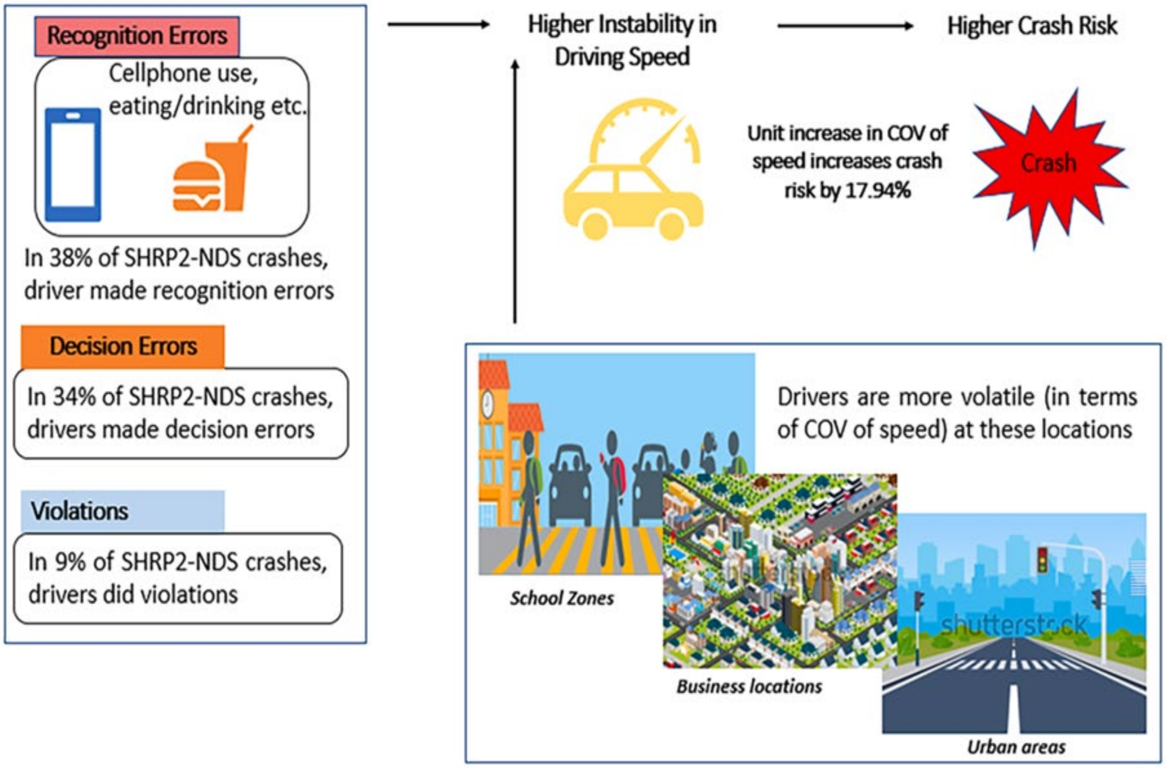

Figure 6: Key Findings Infographic

4. Conclusions

The study presents a joint estimation of models that explore the potential pathways from errors and violations in various roadway environments to SCEs through instability in driving speed (CV of Speed). The results show that the instability in driving speed increases with all five driving errors and violations, with performance errors having the strongest positive correlation with crash risk. The study also found that instability in driving speed is significantly higher in urban areas, business/industrial locations, and school zones than in driving on interstates. Path analysis results indicate that all driving errors and violations contribute to SCEs not only directly but also indirectly through instability in driving speed. The study is based on a subsample of SHRP2 NDS data and is limited to specific geographic locations, which may not represent other parts of the United States or other countries. Although SHRP2 NDS data partially satisfy research needs related to roadway environments, more detailed data on roadway and locality classifications, such as land use, activity centers, and roadway functional types, would be helpful in future studies. Additionally, the SHRP2 NDS subsample used in this research does not include important variables such as driver demographics (e.g., gender, age, and education), and it would be beneficial to investigate how these factors relate to instability in driving speed and SCEs with the availability of such data in the future. The paper concludes that various countermeasures, such as multiple vehicle technologies, roadway changes, policy interventions, and awareness campaigns, can be taken to reduce driving errors and violations, reducing the risk of SCEs. For instance, multiple vehicle technologies like forward-collision warning systems, adaptive cruise control, and lane tracking system can reduce one or more driving errors. Similarly, dilemma zone mitigation systems can reduce a significant percentage of violations. Additionally, removing sources of external distraction, such as billboards, can help reduce recognition errors. Finally, mandatory training programs for drivers can reduce performance and experience errors.

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Chapter 5

Predicting Safety-Critical Events Using Driver Behaviors and Performance: Application of Machine Learning

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This chapter presents a brief version of a technical paper presented at the 2023 Transportation Research Board Annual Meeting.

Abstract

This study attempts to bridge the research gap in predicting safety-critical events (SCEs) caused by human factors. The study utilizes Naturalistic Driving Study (NDS) data, which offers dynamic pre-crash information about driving behavior and performance. A subsample of the SHRP2 NDS dataset, consisting of 9,237 observations, is split into training (70%) and test (30%) samples. An Ordered Probit model is employed as a frequentist method to predict different levels of severity: baseline, near-crashes, and crashes. The study employed Dominance Analysis to determine the most important predictor variables in the statistical model. The dominance analysis evaluates 262,143 different models for 18 predictors, identifying the most influential predictors for predicting SCEs. Three non-parametric supervised ML methods, including naive Bayes (NB), k-nearest neighbors (KNN), and gradient boosting tree (GBT) classifiers, are then used to predict SCEs. The GBT classifier exhibits the highest out-of-sample prediction accuracy at 91.23%, outperforming the Ordered Probit model (85.75%). The study highlights the significance of naturalistic data, particularly the CV of speed, deceleration, jerk, driving errors, and secondary task duration, in improving the prediction accuracy of SCEs. The study's findings can prove insightful for developing more proactive collision warning systems, resulting in safer road users.

1. Introduction

Human factors give rise to more than 90% of road traffic crashes (Sabey & Staughton, 1975; Singh, 2015; Treat et al., 1979). Various studies have attempted to develop comprehensive frameworks to identify driving mistakes and transgressions to help adopt suitable safety countermeasures (Reason et al., 1990; Stanton & Salmon, 2009; Treat et al., 1979; Wierwille et al., 2002). However, most of these studies have one common issue: utilizing police-reported crash data, which could be biased or highly under-reported. With the recent advancements in ML and the availability of detailed pre-crash driver behavior and performance in SCEs in the form of NDS data collected through the SHRP2 program, new avenues for predicting SCEs can be explored. The NDS data collected through the SHRP2 program provides detailed information about pre-crash driver behavior and performance, including near-crashes and baseline driving. It also includes data on speed, acceleration, deceleration, and jerk, allowing the assessment of driving instability (Dingus et al., 2006; Hankey et al., 2016). Secondary task duration and details about the roadway and environment are also available, making the SHRP2 NDS data a comprehensive and reliable source for investigating human factors in diverse contexts.

Recent studies utilizing the SHRP2 NDS data have found that human factors contribute to around 93% of road crashes (Khattak et al., 2021). A systematic taxonomy of naturalistic driving errors and violations (TDEV) was developed to understand the nature and role of these factors. Recognition and decision errors were the primary driving errors contributing to road crashes. Previous studies have examined the pathways linking different roadway environments to SCEs through driving errors. The studies provide insights into how various roadway environments relate to driving errors and violations (Ahmad et al., 2021). Additionally, statistical evidence supports a positive correlation between driving instability and SCEs using the SHRP2 NDS data (Wali et al., 2019; Wali & Khattak, 2020). The mentioned studies utilizing SHRP2 NDS data offer valuable insights into the impact of different human factors on SCEs. However, there are still research gaps to address. Firstly, while statistical models were used to explore the relationships between human factors (e.g., driving errors, violations, distraction duration, driving instability) and SCEs, none of the studies focused on real-time prediction of SCEs using these factors. Secondly, none of the studies integrated all relevant human factors into a single model for accurate prediction of SCEs, including both crashes and near-crashes.

Consequently, this study aims to enhance predictive accuracy by leveraging the unique SHRP2 NDS data, which provides dynamic pre-crash information on driving behavior and performance. The study utilizes frequentist statistical models and ML methods, including KNN, NB, and GBT classification techniques. These ML methods were chosen for their promising prediction performance and cost-effectiveness. This study seeks to deepen the understanding of the connection between pre-crash driving behavior, performance, and SCEs. It also aims to identify the most accurate model or method for real-time prediction of SCEs. By incorporating all available key human factors, such as driving errors, violations, distraction duration, and various measures of driving instability, within a real-world naturalistic driving context, this study stands out as a unique attempt to predict SCEs using more precise ML-based methods. The anticipated findings from this study are expected to contribute valuable knowledge, particularly in the context of partially automated vehicles. This knowledge can inform efforts to improve roadway safety by prioritizing safer roadway users and safer vehicles.

2. Methodology

This study evaluates the out-of-sample prediction accuracy of a statistical model and ML methods for SCEs. It also employs dominance analysis to compare the importance of variables in predicting SCEs between the statistical model and ML methods, providing a more effective and consistent comparison. The study framework is depicted in Figure 7.

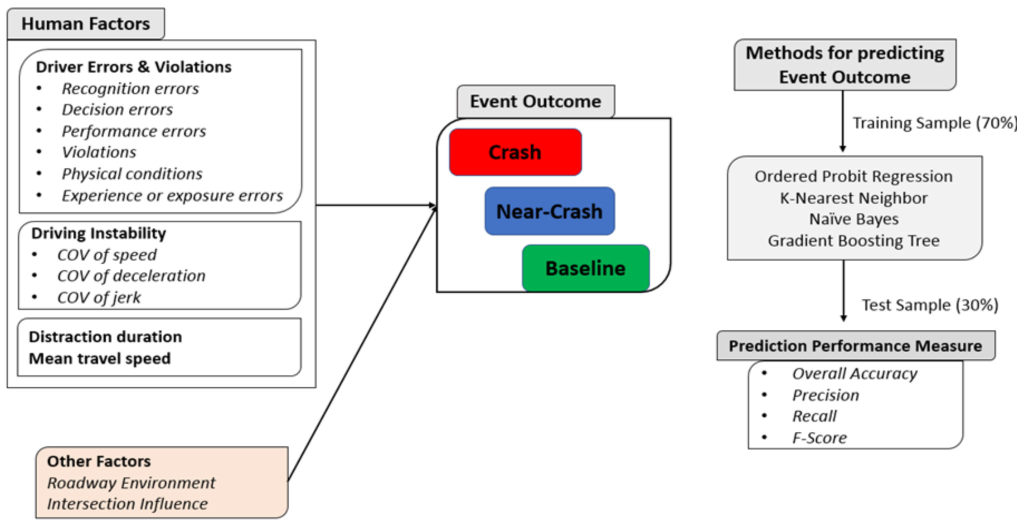

Figure 7: Study Framework

This study analyzes a subsample of SHRP2 NDS data, providing reliable dynamic pre-crash information about driving behavior and performance. The data includes vehicle kinematics used to assess driving instability by analyzing instantaneous speed, acceleration, and deceleration. Detailed information about roadway and environmental variables is also recorded through video cameras, radar, and other recording equipment in the subject vehicles. A data reductionist team carefully coded the NDS videos' variables to define baselines, near-crashes, and crashes. Baselines represent non-event driving periods selected for comparison purposes, while near-crashes refer to situations where evasive maneuvers were required to avoid collisions. Crashes involve any contact with fixed or moving objects that could lead to kinetic energy dissipation. The study considers various human factors, including driving errors, violations, measures of driving instability, and duration of distraction. The driving error and violation coding relies on the driver's behavior and secondary task variables, which indicate their potential contribution to SCEs. Various indices, such as the CV of speed, deceleration, acceleration, and jerk, are computed to assess driving instability. Acceleration/deceleration represents the first derivative of travel speed, while jerk corresponds to the second derivative. Negative jerk indicates the derivative of deceleration, while positive jerk relates to the second derivative of travel speed during acceleration. The duration of distraction is determined by calculating the difference between the secondary task's end time and start time, as provided in the SHRP2 NDS data for each specific secondary task. The study aims to bridge research gaps by analyzing both statistical models and ML methods to predict SCEs using the SHRP2 NDS data. By comparing the out-of-sample prediction accuracy of different models and conducting dominance analysis, the study seeks to determine the importance of variables in predicting SCEs. The ML methods employed include KNN, NB, and GBT classification techniques, selected for their promising prediction performance and cost-effectiveness. The study's unique approach aims to enhance understanding of the relationship between pre-crash driving behavior, performance, and SCEs while aiding the selection of accurate prediction models for real-time applications.

3. Findings

The data set of 9,237 observations was randomly divided into a training sample (6,466 observations) and a test sample (2,771 observations) with a 70:30 ratio. Descriptive statistics in Table 14 show that baselines have a significantly lower mean CV of speed, deceleration, and negative jerk compared to near-crashes and crashes. For example, the mean CV of speed is 0.142 in baselines, significantly lower than in near-crashes (0.556) and crashes (0.642). The mean duration of distraction is significantly higher in crashes (3.814 seconds) and near-crashes (3.333 seconds) compared to baselines (1.745 seconds). Regarding driving errors and violations, baseline drivers, who were not involved in any SCEs, still made around 10% of errors and violations that could lead to SCEs. Subject drivers committed errors and violations in 61.26% and 92.74% of near-crashes and crashes, respectively.

Table 14: Descriptive Statistics of Explanatory Variables

Explanatory Variables	Baselines (N = 5,195)				Near-Crashes (N = 844)				Crashes (N = 427)			
	μ	SD	Min	Max	μ	SD	Min	Max	μ	SD	Min	Max
Measures of Volatility												
CV of Speed	0.14	0.16	0.001	1.92	0.55	0.42	0.02	3.04	0.64	0.38	0.01	2.42
CV of Deceleration	0.75	0.23	0.000	2.11	1.24	0.40	0.17	2.66	1.04	0.35	0.00	2.58
CV of Negative Jerk	0.79	0.23	0.000	2.78	1.29	0.45	0.48	3.00	1.07	0.41	0.41	2.77
Secondary Task Duration (seconds)	1.74	2.14	0.000	8.96	3.33	3.88	0.00	15.68	3.81	4.18	0.00	18.3
Mean Travel Speed (miles per hour)	17.7	8.2	0.002	40.9	11.5	7.44	0.16	42.7	8.20	5.99	0.15	34.4
	Frequency		**%**		**Frequency**		**%**		**Frequency**		**%**	
Driving Errors												
No error	4,676		90.01		327		38.74		31		7.26	
Recognition Error	13		0.25		279		33.06		171		40.05	
Decision Error	138		2.66		120		14.22		144		33.72	
Performance Error	4		0.08		7		0.83		29		6.79	
Violation	297		5.72		89		10.55		39		9.13	
Physical Condition-related Error	63		1.21		17		2.01		7		1.64	
Experience or Exposure Error	4		0.08		5		0.59		6		1.41	
Intersection Influence												
No Intersection Influence	4,229		81.41		267		31.64		176		41.22	
Interchange Influence	112		2.16		79		9.36		15		3.51	
Stop Sign or Traffic Signal Influence	626		12.05		275		32.58		105		24.59	
Uncontrolled Intersection Influence	104		2		91		10.78		34		7.96	
Parking Lot or Driveway Entrance/Exit	99		1.91		98		11.61		87		20.37	

Other Intersection Influence	25	0.48	34	4.03	10	2.34
Roadway Environment						
Urban area indicator (1/0)	80	1.54	69	8.18	32	7.49
Moderate Residential (1/0)	1,165	22.43	124	14.69	89	20.84

Note: μ: Mean; SD: Standard Deviation

The results of the ordered Probit model presented in Table 15 indicate that an increase in the CV of speed, CV of deceleration, and CV of negative jerk leads to a higher chance of a crash by 5.17%, 5.98%, and 1.16%, respectively. These findings suggest that drivers with more volatile driving behaviors are at a greater risk of crashes. Similar trends are observed for near-crashes. The model also highlights the significance of driving errors and violations in increasing the likelihood of SCEs. Performance errors have the highest impact, increasing crash risk by 13.75%, followed by decision errors (10.09%) and recognition errors (9.08%). The duration of distraction contributes to crash risk, with a 0.17% increase for each unit increase in distraction duration while other variables are held constant. To compare the importance of variables between the statistical model and ML methods, a dominance analysis (DA) was performed (Table 16). The DA analysis sampled and evaluated 262,143 different models, considering 18 predictor variables. The results reveal that recognition error, CV of speed, decision error, CV of deceleration, and CV of negative jerk are the top five most important predictors, explaining 17.5%, 17.4%, 14.4%, 13.8%, and 8.8%, respectively of the overall McFadden R^2 (0.493). These findings indicate that approximately 72% (0.354 out of 0.493) of the McFadden R^2 is accounted for by these top five predictor variables, all of which relate to human factors. Comparing the predictive performance of the statistical model and ML methods reveals that the GBT classifier outperforms the others (Table 17). The GBT classifier accurately predicts the event outcome for 91.23% of observations in the test sample, demonstrating higher prediction accuracy than the other models. It also exhibits the highest precision, recall, and F1 score for crashes and near-crashes in the test sample. Consequently, the GBT classifier is the most accurate method for predicting SCEs using the SHRP2 NDS data.

The key insights from the GBT classifier highlight the top five most important features for predicting SCEs: CV of speed, CV of deceleration, duration of distraction, recognition errors, and CV of a negative vehicular jerk, shown in Figure 8. These findings align with the earlier dominance analysis and emphasize human factors' significance in predicting SCEs. Additionally, both the ordered Probit model and GBT classifier identify driver behavior and performance as the most influential predictor variables. The intersection influence and roadway variables are less important in predicting SCEs using the SHRP2 NDS data.

Table 15: Estimation Results of the Ordered Probit Model

Key Explanatory Variables	Coeff	t-stats	Chance in % (Marginal Effects*100)		
Measures of Volatility			**Baseline**	**Near-Crash**	**Crash**
CV of Speed	0.956	9.97	-11.74	6.57	5.17
CV of Deceleration	1.107	13.25	-13.59	7.61	5.98
CV of Negative Jerk	0.214	2.76	-2.63	1.47	1.16
Secondary Task Duration (seconds)	0.032	4.18	-0.39	0.22	0.17
Mean Travel Speed (miles per hour)	-0.022	-4.96	0.26	-0.15	-0.12
Driving Errors (Base = no driving error)					
Recognition Error	1.681	22.49	-20.64	11.55	9.08
Decision Error	1.867	26.13	-22.93	12.84	10.09
Performance Error	2.544	11.91	-31.24	17.49	13.75
Violation	1.009	13.29	-12.39	6.94	5.45
Physical Condition-related Error	0.978	6.19	-12.01	6.72	5.29
Experience or Exposure Error	1.781	5.87	-21.86	12.24	9.62
Intersection Influence (Base = no intersection influence)					
Interchange Influence	0.785	7.76	-9.64	5.39	4.24
Stop Sign or Traffic Signal Influence	0.247	4.03	-3.03	1.70	1.33
Uncontrolled Intersection Influence	0.593	6.38	-7.28	4.07	3.20
Parking Lot or Driveway Entrance/Exit	0.755	8.80	-9.27	5.19	4.08
Other Intersection Influence	0.560	3.59	-6.87	3.85	3.02
Roadway Environment					
Urban area indicator (1/0)	0.319	3.08	-3.92	2.20	1.73
Moderate Residential (1/0)	-0.203	-3.32	2.50	-1.40	-1.10
Threshold parameters					
μ_1	2.801	27.92	---	---	---
μ_2	4.292	37.42	---	---	---
Summary Statistics					
N	6,464				
Pseudo R^2	0.493				
Loglikelihood (null)	-4013.632				
Loglikelihood (convergence)	-2036.74				
AIC	4113.479				
BIC	4248.959				

Table 16: Importance of Predictors on SCEs: Ordered Probit Regressions

Explanatory Variables	Dominance Statistic	Standardized Dominance Statistic	Ranking
Measures of Volatility			
CV of Speed	0.086	0.174	2
CV of Deceleration	0.068	0.138	4
CV of Negative Jerk	0.043	0.088	5
Secondary Task Duration (seconds)	0.017	0.034	8
Mean Travel Speed (miles per hour)	0.040	0.081	6
Driving Errors (Base = no driving error)			
Recognition Error	0.086	0.175	1
Decision Error	0.071	0.144	3
Performance Error	0.016	0.033	9
Violation	0.011	0.022	10
Physical Condition-related Error	0.002	0.004	18
Experience or Exposure Error	0.003	0.006	15
Intersection Influence (Base = no intersection influence)			
Interchange Influence	0.007	0.015	12
Stop Sign or Traffic Signal Influence	0.007	0.015	13
Uncontrolled Intersection Influence	0.008	0.016	11
Parking Lot or Driveway Entrance/Exit	0.019	0.039	7
Other Intersection Influence	0.003	0.006	16
Roadway Environment			
Urban area indicator (1/0)	0.002	0.004	17
Moderate Residential (1/0)	0.004	0.009	14
Total	0.493	1.000	---

Table 17: Comparing Overall and Class-level Out-of-Sample Prediction Accuracy

Performance Measure	Ordered Probit	NB	KNN	GBT
Overall Accuracy (%)	85.75	89.75	88.70	91.23
Baseline				
Recall (%)	98.32	96.95	97.13	98.27
Precision (%)	92.07	95.65	94.39	96.21
F1 Score (%)	95.09	96.29	95.74	97.23
Near-Crash				
Recall (%)	38.93	68.70	61.83	71.50
Precision (%)	56.04	71.43	65.50	74.54
F1 Score (%)	45.95	70.04	63.61	72.99
Crash				
Recall (%)	34.44	47.78	44.44	48.33
Precision (%)	41.06	52.12	57.97	58.39
F1 Score (%)	37.46	49.86	50.31	52.89

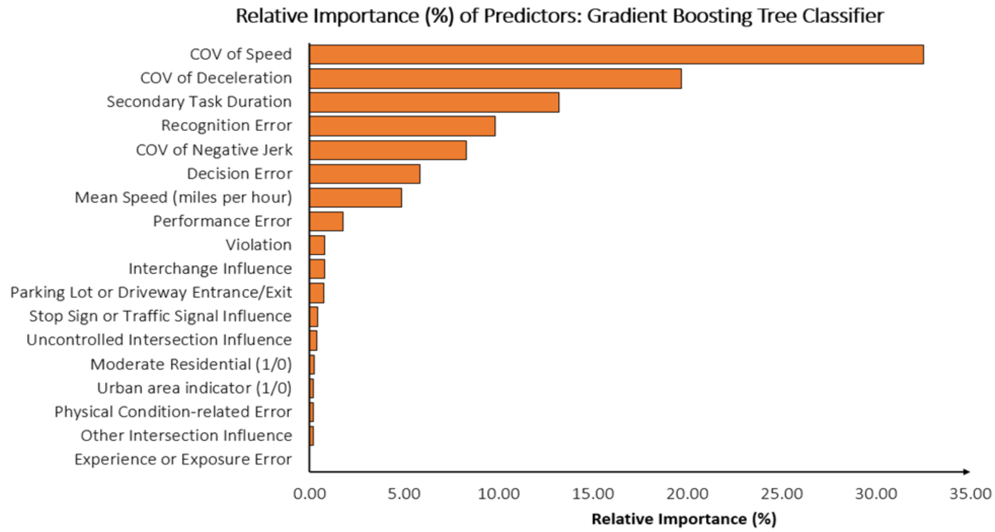

Figure 8: Feature Importance Plot for the GBT Classifier

4. Conclusions

This study utilizes the unique SHRP2 NDS data to improve predictive accuracy for SCEs by considering driving behavior and performance. Statistical and ML models were employed and evaluated using training and test samples. Dominance analysis determines the most important predictor variables for SCEs. The Ordered Probit model and the GBT classifier identified human factors as the top predictors, including CV of speed, deceleration, duration of distraction, recognition errors, and CV of a negative vehicular jerk. The findings indicate that leveraging naturalistic data, particularly the mentioned human factors, significantly enhances the accuracy of SCE prediction. The cumulative importance of predictor variables related to human factors in the GBT classifier is approximately 94%. Out-of-sample prediction accuracy showed that the GBT classifier outperformed other models, achieving an overall accuracy of 91.23% for event outcomes (baselines, near-crashes, and crashes). This study contributes to the field by utilizing comprehensive human factor data and accurate ML techniques in real-world driving environments.

Based on the results, the study suggests potential applications to improve roadway safety. Proactive ML algorithms can provide real-time warnings to drivers about potential SCE risks based on their behaviors and performance. Furthermore, designing automated vehicle features, such as braking systems or cruise control, could take control from drivers after receiving warnings about hazardous behaviors.

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Appendix A:

Driver Impairment Detection and Safety Enhancement through Unified Analysis of Driver, Vehicle and Traffic Volatilities

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Abstract
Vehicles are generating more data than ever, and this study seeks to find a way to leverage rich vehicle kinematics data in combination with driver biometrics and information about the surrounding traffic environment to create a tool for reliable estimation of the driver's state of distraction while operating a vehicle. The tests were conducted in a safe and immersive VR environment where participants driving a simulated vehicle (using a head-mounted display and natural controls, such as accelerator, brake pedals, and steering wheel) were visually distracted by an increasingly complex task. The visual distraction was meant to emulate the use of cell phones or operating a touchscreen interface and was achieved by having the driver repeatedly find the randomized location of a differently oriented arrow in a grid of otherwise similarly directed arrows. Environmental data (such as the relative distance and the relative speed of traffic around the subject vehicle, deviation from the lane centerline), vehicle kinematics data (such as speed, acceleration, steering input, accelerator, and brake effort), as well as driver-biometric data (such as the gaze direction, pulse rate), were collected in real-time and synchronized. This combined time-series data was then used to train a multivariate time-series feature extractor (WEASEL+MUSE) and a logistic regression classifier. The relative importance of the features in the dataset was examined by permuting through and quantifying the classification accuracy of combinations of features. Most importantly, the data shows that combining the different modalities can give higher predictive accuracy than when using any modality.

1. Introduction

Cognitive issues like stress, inattentiveness, distraction, fatigue, and sleep deprivation are the major contributors to crashes (NHTSA, 2017) and are a prime area of R&D among fleet operators and long-haul trucking companies. Moreover, it is argued that there is no pathway to full autonomy in driving without a robust and infallible driver monitoring system which has led Tesla, Cadillac, and open-source platforms such as the Comma.ai to develop driver monitoring systems to complement their Autopilot and OpenDrive systems. Impaired driving is a key contributing factor leading to 10,497 fatalities (28% of all transportation crash-related deaths) in 2016 (FHWA, 2018). Various studies have investigated the impacts of driver error and behavior on the outcome of a crash, such as distracted driving (Neyens and Boyle, 2008; Donmez and Liu, 2015), aggressive driving (Paleti et al., 2010; Lambert-Be´langer et al., 2012), impaired driving (Behnood and Mannering, 2017; Behnood et al., 2014), etc. In the United States, aggressive driving (speeding, failure to yield the right of way, and reckless driving) contributes to more than 50 percent of fatal crashes (AA Association, 2009). The impact of distracted and aggressive driving on driving stability performance is also explored by different studies (Horberry et al., 2006; Beede and Kass, 2006; Stavrinos et al., 2013; Hamdar et al., 2008). Various measurements are incorporated to explain the stability performance of driving, such as speed (Ghasemzadeh et al., 2018), speed variability (Rakauskas et al., 2004), lane position maintenance (Rakauskas et al., 2004), lateral control (Beede and Kass, 2006), time to collision (Papazikou et al., 2017). A validated model for driver behavior can positively benefit the automotive sector. As autonomous driving looms ever ahead, there must be a way to quantify the driver's participation in the event of and to prevent an accident. A driver behavior model can be a valuable resource to impose a more honest discourse in the upcoming era of human-machine fusion. By integrating and fusing multiple data sources such as driver biometrics, vehicle kinematics, and environmental conditions in real-time, this paper aims to identify the relative importance of data modality when classifying whether the driver is distracted or not. In the event the vehicle detects the driver is distracted, it would be able to take control of the vehicle and bring it to a stop in a safe manner. This allows the driver and the machine to operate synchronously and provides a trade-off between vehicle automation and unsafe driver behavior.

Researchers have made significant progress in developing algorithms and models that analyze driver behavior using various data sources. Some approaches focus on analyzing vehicle kinematics, such as acceleration, deceleration, and steering behavior, to detect driving patterns indicative of distraction or impairment (Ali et al., 2021; Yarlagadda et al., 2021). Other methods involve analyzing driver biometrics, such as eye movement, facial expressions, and physiological measures (e.g., heart rate, skin conductance) to assess the driver’s cognitive and emotional state (Dang et al., 2021; Aghaei et al., 2016). In addition, studies have considered the surrounding traffic environment to determine the impact of external factors on driving performance (Liu et al., 2022; Kashevnik et al., 2021).

However, most of these studies have focused on analyzing individual data sources in isolation, potentially missing the opportunity to exploit the complementary information in different data modalities. Integrating and fusing multiple data sources can provide a more comprehensive and accurate representation of the driver’s state and facilitate the development of more effective safety enhancement systems (Wang et al., 2020; Yang et al., 2021a). Additionally, understanding the relative importance of different data modalities can help optimize the design of these systems, ensuring that they are effective while minimizing the burden on the driver and the vehicle.

In this paper, we present a unified analysis of driver, vehicle, and traffic volatilities in a simulated driving environment, which allows for the safe and controlled study of the impacts of visual distraction on driving performance. Our approach involves collecting real-time, synchronized data from multiple sources, including driver biometrics, vehicle kinematics, and environmental conditions. We then employ a multivariate time series feature extractor (WEASEL+MUSE) and a logistic regression classifier to analyze the combined data and estimate the driver's state of distraction. By permuting through and quantifying the classification accuracy of combinations of features, we explore the relative importance of different data modalities in predicting driver distraction.

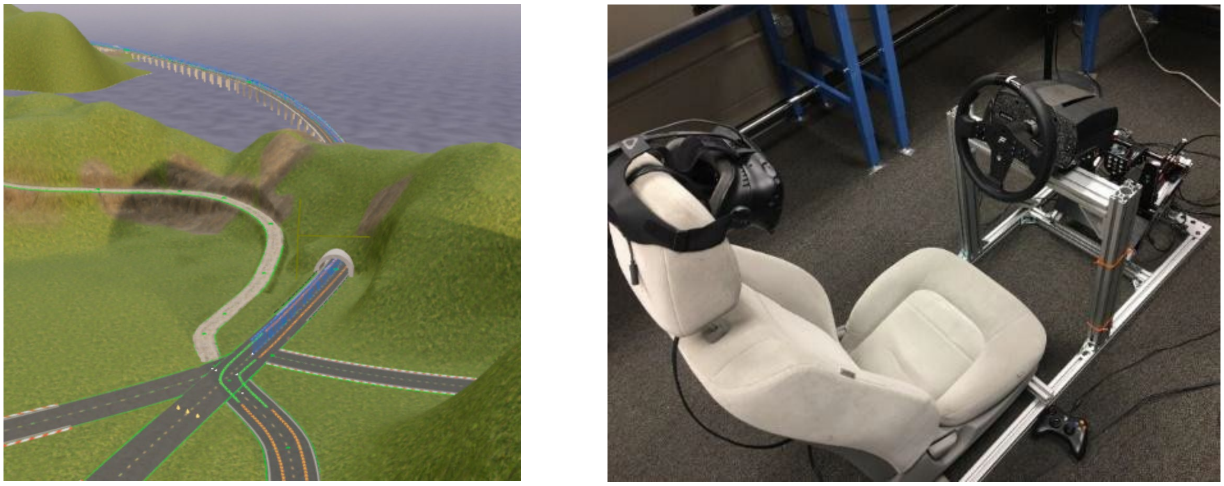
Our results demonstrate that combining multiple data sources can achieve a higher predictive accuracy can be achieved than when using any single modality alone. This finding has significant implications for the design of future driver monitoring and safety enhancement systems, as it suggests that a more comprehensive and effective approach may involve the integration of multiple data modalities. Ultimately, our work contributes to the growing body of research aimed at improving road safety by better understanding and detecting driver impairment and distraction, paving the way for the development of more advanced and effective systems that can help reduce the risk of accidents and save lives.

2. Related Works

Research in distracted driving is diverse, and with the rising popularity of self-driving cars, it has never been a more important topic. Many use simulators to safely conduct the research (Ahangari, 2019). The use of VR to provide a safe environment for testing driver distraction while preserving realism has also been explored (Lin et al., 2008). There is also a distinction in the type of distraction applied: manual, visual, or cognitive. Different types of distractions manifest themselves in varied ways, namely different changes in speed and steering volatility (Engstrom, 2005). The sensors used for this study can each individually be found in many studies (Kashevnik et al., 2021), but none have conglomerated the array of sensors that we have. Many papers use EEG data as a biometric indicator (Fan et al., 2021), which we did not explore due to logistical complications with a VR headset. One paper used gaze zone estimation to infer what the driver was looking at (Yang et al., 2021b), which accomplishes the same thing our virtual processing does. Similarly, another team used gaze data to predict how situationally aware the driver was (Zhou et al., 2022). More generally, ML has shown strong performance in classifying time series data (Fawaz et al., 2019).

In recent years, researchers have investigated the role of smartphones as a major source of distraction in driving. Some studies have focused on understanding the effects of smartphone while driving (Khan et al., 2021), on driving performance, and crash risk (Gliklich et al., 2016). Others have examined the potential of using smartphones themselves as a source of data for detecting distracted driving behavior, exploiting the embedded sensors, such as accelerometers and gyroscopes, to capture information about the vehicle's motion and the driver's interaction with the phone (Ahmed et al., 2018). Another line of research has focused on the development ADAS that can support drivers in maintaining safe and attentive driving behavior. These systems often rely on various sensing technologies, such as cameras, lidars, and radars to monitor the vehicle's surroundings and provide real-time feedback or intervention to help drivers avoid potential hazards (Ziebinski et al., 2017). Some studies have explored the potential of integrating ADAS with driver monitoring systems to create more holistic solutions for detecting and mitigating the effects of driver distraction and impairment (Simic´ et al., 2016).

Our work builds on this rich body of research by investigating the potential of combining multiple data sources, including driver biometrics, vehicle kinematics, and environmental conditions, to create a more comprehensive and accurate assessment of driver distraction. By collecting data across 3 different modalities, we could quantify the relative importance of features in classifying the driver's state of attention and establish that predictive accuracy increases when using all modalities. We also investigated sensor importance within each modality, a depth of analysis not missing so far, specifically with the variety of sensor features analyzed in this paper (Koay et al., 2022).



(a) (b)

Figure A-1: (a) Driving environment for participants, (b) Driving simulator hardware consisting of aluminum frame, steering, brake and accelerator setup and HTC Vive Pro head-mounted display.

3. Methods

3.1 Virtual Environment

The VR simulation was designed in Unreal Engine 4 with a two-way road around an island as the setting for data collection. The environment was populated with other vehicles controlled with logic to simulate realistic driving behavior. Drivers were spawned in the simulation on the road shown on the right side of Figure 1a. The participants were asked to turn right onto the road as traffic flowed in both directions. Once established on the roadway with normal driving behavior, data collection was started.

The other cars populating the simulation were controlled by an AI controller that operated based on distances to the cars in front of them. This was designed to emulate realistic traffic behavior where the AI-controlled cars would rubber band when traffic was congested. This also required the participants to be vigilant about braking or risk rear-ending the car in front of them. For the conducted experiments, we omitted all trials where the participant crashed or deviated from the designed procedure. This was done so that we could create a dataset containing distraction predictors without requiring a negative outcome, such as a crash, to be a strongly correlated predictor.

1) Biometric Sensors: The seat from a real car and a steering wheel and pedals designed for gaming were attached to aluminum framing to create the custom simulator.

An HTC VIVE Pro VR headset was used to immerse the driver in the environment and elicit more natural reactions to the traffic and distraction stimuli. This headset was selected for its ability to track pupil position and eye openness. The raw pupil position and eye openness data were augmented with a derived feature related to the driver's awareness of the environment, which we call "objects." Objects were a categorical feature describing what the driver was looking at out of a small subset of tracked objects, such as the front windshield or the source of visual distraction. This was accomplished by using the pupil position sensors inside of Unreal Engine 4 to create a ray trace from the in-game camera origin to a fixed distance away in the direction of the driver's gaze and calculating possible intersections of the gaze ray with each tracked object. 4 possible focal points (front windshield, arrows, other, and none) were tracked with ”other” and ”none,” corresponding to when the driver was looking at an un-tracked object or when the sensor could not locate the driver's pupil with confidence.

2) *Kinematic Sensors:* We also tracked the car's speed and acceleration as scalars in addition to controller inputs such as steering angle, throttle activation, and brake activation. The core additional complexity for multivariate time series data is that discriminatory features may be in the interactions between dimensions, not just in the autocorrelation within an individual series. Features like throttle and brake have a high correlation to features like acceleration. The implications of this inter-modal correlation are discussed using a "Leave-one-out" strategy discussed in the Results section.

3) *Environmental Sensors:* Environmental sensors encompass all data collected from outside the vehicle within the simulation. This includes metrics such as distances to cars in front and behind the driver as well as the distance to the center of the lane.

TABLE 1: Feature Aliases, Descriptions, and Units

Feature Alias	Description	Units
Acceleration	Vehicle acceleration	m/s^2
Speed	Vehicle speed	m/s
Steering	Steering wheel activation	degrees
Throttle	Throttle pedal activation	%
Brake	Brake pedal activation	%
Distance to Car in Front	Distance to the car in front	m
Distance to Car Behind	Distance to the car behind	m
Distance to Center Line	Distance from left wheel to centerline	m
Openness	How open is eye	%
PupilX	Left pupil X-coordinate	-
PupilY	Left pupil Y-coordinate	-
Front (Gaze)	Is the driver looking through the front windshield	Binary
Arrows (Gaze)	Is the driver looking at arrows	Binary
Other (Gaze)	Is the driver looking elsewhere	Binary
Undetected (Gaze)	Is the driver's eye undetected	Binary

4) Data Collection: Because of the multi-modal nature of the time series data collected from different sensors, some physical and some virtual, it was important to synchronize the data streams. This was accomplished with Lab Streaming Layer, an open-source networked middleware ecosystem to stream, receive, synchronize, and record data streams acquired from diverse sensor hardware. The setup allowed for virtual sensors to be accessed in Unreal Engine 4 and physical sensors such as galvanic skin response sensors and blood pressure (not used in this work). The sensors and UE4 simulation communicated with a local server that unified the data into an extensible data format (XDF) file, which was later read using PyXDF package in Python.

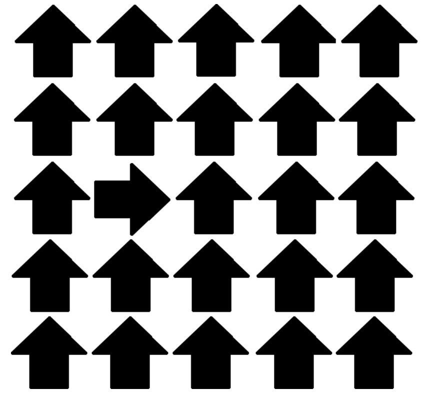
B. Distraction

The causes of driver distraction are diverse and pose large risk factors—more than half of the crashes that involve inattention were caused by driver distraction (Ranney et al., 2001; Regan et al., 2008). Thirteen types of potentially distracting activities listed in Stutts et al., 2001 include eating or drinking, looking outside of the vehicle, talking or listening on a cell phone, dialing a cell phone, using in-vehicle-technologies, and so on. Because the distracting activities take many forms, the NHTSA classifies distractions into the following four categories from the viewpoint of the driver's functionality (Ranney et al., 2001):

- Visual distraction, e.g., looking away from the roadway,
- Biomechanical distraction, e.g., manually adjusting the radio volume,
- Cognitive distraction, e.g., being lost in thought, and
- Auditory distraction, e.g., responding to a ringing mobile phone.

In this work, we have followed precedence in literature to design and perform experiments designed for visually distract the drivers while asking them to drive realistically. Using a head-mounted display to simulate an environment limits the ability to accurately model external distractions, such as using a cell phone or interacting with the radio or air conditioning. To provide a visual distraction, analogous to visual distractions in daily life but quantifiable, a grid of arrows was positioned on a virtual screen where the entertainment center would normally be in regular vehicles. The participants were asked to name the grid position of the arrow facing differently from the others, and after each answer, the challenge was repeated with a different random arrangement of arrows. In total, we tested 5 different grid sizes starting from 4x4 grids all the way up to 8x8 grids. The motivation was to create an easily scalable, bias-resistant metric for inducing a particular level of visual distraction.

(a)



(b)

Figure A-2: (a) View from the driver's perspective inside the vehicle, (b) Sample distraction grid - the driver is instructed to identify the location (row 3, column 2 in this case) of the "different" arrow

The assumption was that as the grid size increases, the reaction time of drivers to identify the grid position of the indicated arrow will increase. For our purpose, we define the entire time the participant is actively identifying where the arrows are as distracted, even though the driver's gaze and attention moves back and forth from the distraction task to the driving task. The assumption follows our informal categorization of a driver as distracted until any activity (visual, cognitive, or auditory) competes with the task of controlling the vehicle.

4. Procedure

A total of 26 drivers (14 male and 12 female) participated in the study. All the drivers were above 18 years and had a valid U.S. driving license. Every participant in the study was given a prompt explaining that they were to be distracted and asked to drive along a road with increasingly demanding distractions (based on the arrow grid size). Because of uncontrollable variability in factors like the participant's driving style and familiarity with VR, some participants required multiple attempts at submitting a regimented dataset. If a participant crashed or deviated from the verbal instruction, the sample was discarded, and the participant was retested. The step-by-step protocol followed during these tests is as follows:

- The participants were asked to acquaint themselves with the environment and controls by driving on the road until they felt comfortable. (several minutes)
- The participant was asked to bring the vehicle to a stop, and their vehicle position was reset (teleported) to the starting point.
- The participants were instructed to turn right onto the road and drive without distraction. (≈ 30 seconds)
- Stop and reset the position.
- The participants were instructed to turn right onto the road and drive in the presence of a specific level of distraction. (≈ 15 − 30 seconds)
- Stop and reset the position.
- The participants were instructed to turn right onto the road and drive with a more intensive distraction. (≈ 15 −30 seconds)
- After these steps, the data collection was stopped and saved to a file.

The dataset consists of 15 features, listed in Table 1, each collected from a specific distraction condition - undistracted or distracted with a 4 × 4, 5 × 5, 6 × 6 or 8 × 8 grid of arrows. Often during the analysis, data corresponding to 4 × 4 and 5 × 5 grids of arrows are grouped together as “small distraction,” while the datasets pertaining to the 6 × 6 and 8 × 8 grids of arrows are grouped together as “large distraction.” The multivariate time series data corresponding to these 16 features are then analyzed with a multivariate time series feature extractor called WEASEL+MUSE. Both binary classification (distracted-vs-undistracted) and ternary classification (distracted-vs-small-vs-large distraction) accuracy are studied and reported.

A. *Classifier Model*

A multivariate time series feature extractor was trained using WEASEL + MUSE (Patrick Schafer, 2018) along with a logistic regression classifier. The model works under the bag-of-words paradigm, finding patterns within the data with a sliding window and categorizing each pattern with a letter. WEASEL-MUSE takes the derivatives of each input feature which is windowed, transformed to the frequency domain, and binned using a bag-of-words approach. The output of WEASEL + MUSE is a matrix of size n by m where n represents the number of samples and m represents the output dimension. Effectively, the model outputs a matrix of feature vectors that can be efficiently classified with a linear classifier. The outputs of WEASEL + MUSE have no physical signal counterparts, as each output feature is a linear combination of input features that maximizes the variance of the input features.

B. *Feature Importance*

Because WEASEL+MUSE works as a time series feature extractor, the model outputs make it difficult to discern the relative importance of features. To work around this, we use a method of feature permutation, training the model on multiple subsets of features to determine which has the largest impact on accuracy. We first mask each feature in the input and compare the resultant accuracy on the dataset to the baseline accuracy with all features. This is repeated for each slice of the dataset (4x4 & 5x5, 6x6 & 8x8, and a combined dataset). We also test a pairwise feature masking where each possible combination of 2 features is masked, the model is trained, and the resultant difference in accuracy from the baseline with all features is recorded. This was done to see if the interplay between two features was more important for model accuracy rather than one single feature being most important. It was also considered because of the low variance between some features, such as throttle and acceleration, meaning that masking one removes very little information in the feature space.

5. Results

Classification is done on the data with two distinct sets of labels. One set of labels formats the dataset into a binary classification task where participants are classified as either distracted or undistracted without differentiating between the level of distraction. We also consider a second set of labels where we divide participants into 3 categories: undistracted, distracted, and very distracted. On the binary classification task, we achieve 93% accuracy; on the ternary classification task, we achieve 85% accuracy.

Importantly, the distributions of the data collected are distinct across all different levels of distraction, indicating that more challenging distraction induces observable differences in the driver's biometrics and control over the vehicle.

This fact can be seen in Figure 3. As the grid size of the distraction increases, the time spent looking at the arrows increases while the time spent looking through the front windshield (front) decreases. The label "Other" corresponds to the driver looking at an untracked object (such as a side window or the rear-view mirror or in transit between the windshield and the arrows), and "None" corresponds to the HTC Vive Pro sensor not detecting the driver's gaze. Some drivers would look down at the grid of arrows on the center console with their eyes rather than moving their heads away from the road, which caused the sensors not to be able to detect a major portion of their eyes. This explains the increase in the "None" category with increasing distraction.

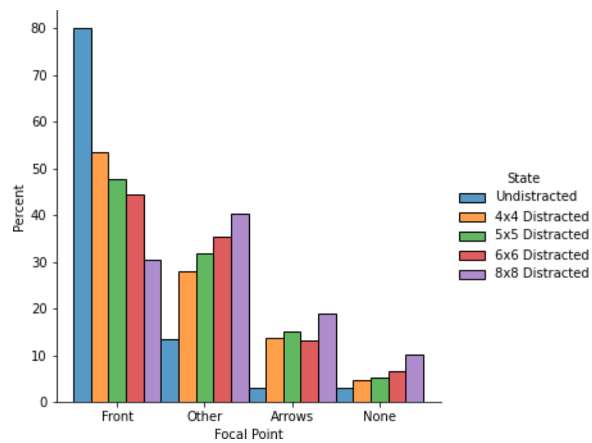
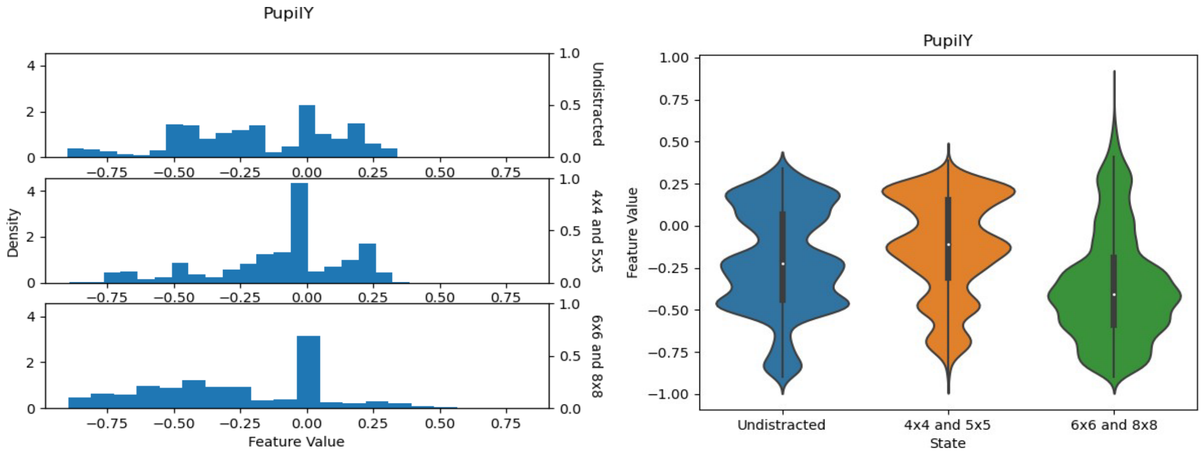


Figure A-3: Object focal point distribution across 5 levels of distraction

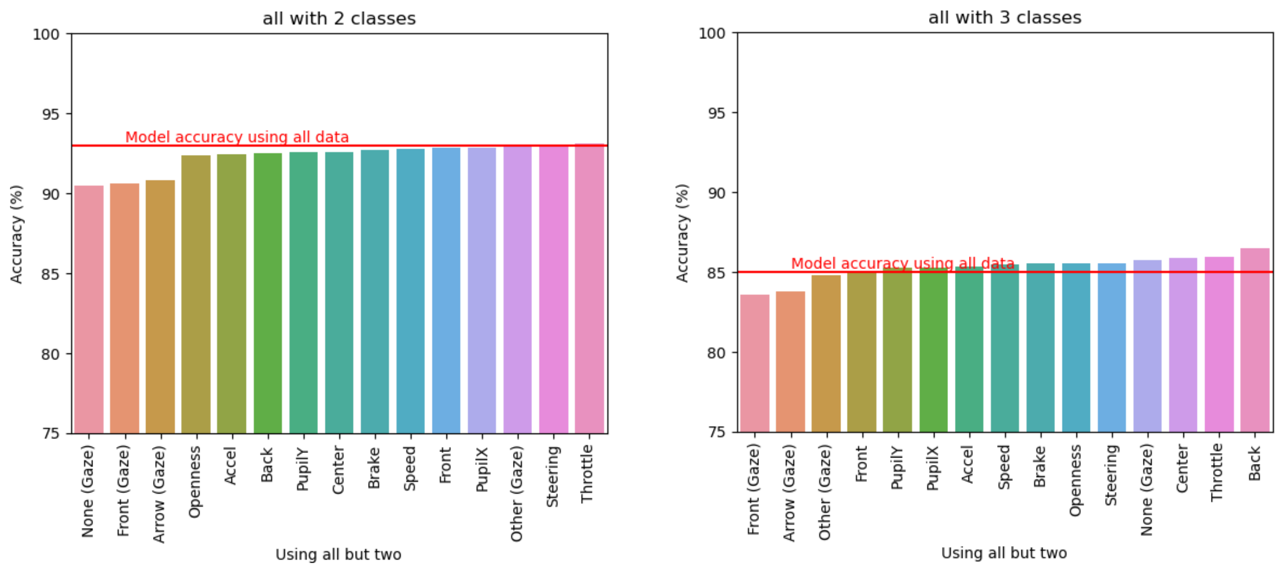
We also plot the vertical pupil position distributions with histograms and violin plots to observe how distraction level affects driver behavior from an empirical visual inspection of the graphs. In Fig 4a and Fig. 4b, as the distraction level increases, the pupils of drivers behave in vastly different ways. The mean pupil height is indistinguishable from the undistracted case for medium-level distraction. In contrast, in the case of the highest level of distraction, drivers have their pupils positioned downward far more, indicating there is some consistent behavior across drivers with varying levels of distraction. This may also point to the important fact that there is a threshold in the complexity of the distraction-inducing task the drivers are trying to accomplish. If the task is too complex, the drivers commit too much of their visual bandwidth to the distraction.



(a) (b)

Figure A-4: (a) Histogram of pupil vertical position, stratified by distraction level, (b) Violin plot of pupil vertical position, stratified by distraction level

We establish feature importance by masking unique pairs of features resulting in 102 unique pairs. For each masked pair of features, the model is trained on the remaining features and the difference in accuracy to the baseline is recorded for each feature in the pair. After training and evaluation with all unique masked pairs, we aggregate and find the average accuracy when masking a feature in combination with each of the other features. For example, the accuracy drop is quite prominent for the “Front (Gaze)” category, as seen in both Fig. 5a and Fig. 5b. Fourteen accuracy values are calculated by leaving out pairs of features with “Front (Gaze)” being common to each pair of features. Each of these 14 accuracy values are then averaged and reported to find the relative importance of the feature “Front (Gaze)” when combined with another feature. This procedure is then repeated for each feature. It was considered important to train the model on pairs of masked features rather than masking individual features to account for the interplay between features that influence the model's accuracy. We found tracking what the driver was looking at to be the most important feature, which can be attributed to the signal's inherent information and the fact that those features are completely uncorrelated with any other features, meaning that when masking them, we lose significant information. The same could not be said for features that have lower variance between them, like acceleration, speed, throttle, brake, etc., where masking only two features removes comparatively little information.



(a) (b)

Figure A-5: (a) Average classification accuracy when masking a pair of features on a binary classification task, (b) Average classification accuracy when masking a pair of features on a ternary classification task

While we only mask features in pairs of 2 due to computational limits, masking more features is not expected to drastically change the feature importance measured. A smoothing of the graph would be expected as the number of accuracies being averaged for each feature would increase dramatically. Notably, the variance of accuracies reported before averaging would be expected to increase as there are certain feature combinations that remove lots of important information. To observe this effect, we instead mask modalities of features as a whole rather than attempting to mask each possible group of features, as seen in Fig. 6a and Fig. 6b. Within these plots, we see how removing any of the three modalities leads to a significant reduction in classification accuracy that is comparable for each modality. This was surprising compared to earlier findings when masking only one or two features, indicating that there are non-trivial feature interplay dynamics that affect accuracy. Counter to what is seen in masking pairs of features, when we mask an entire modality of data, regardless of which modality, the accuracies drop significantly more, even when masking modalities containing features that seemed unimportant in Fig. 5a and Fig. 5b. This is because the complete removal of a modality of data removes information that cannot be recovered otherwise. Said another way, the variance within modalities is small, while the variance between modalities is large. We also test the unimodal classification accuracy, reporting results in Fig. 7a and Fig. 7b. We observe comparable performance when masking only one modality, with the exception being biometric features reaching almost the same classification accuracy as obtained by using all modalities in the ternary classification task.

While the accuracy differences when masking one modality is slightly different, this can be attributed to noise and an effect of a relatively small dataset. The main takeaway, and the hypothesis we formed, is that using all 3 modalities improves accuracy when compared to using a subset of these modalities.

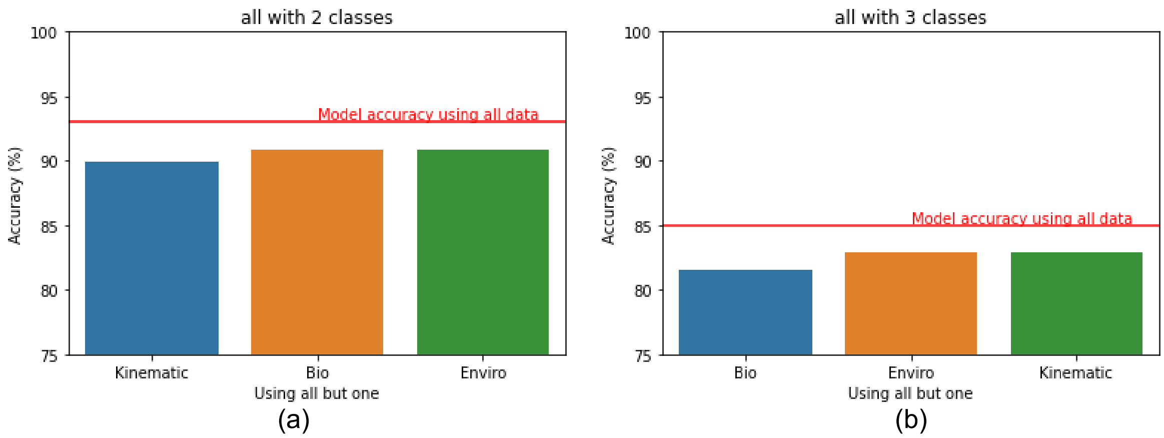


Figure A-6: (a) Average classification accuracy when masking features belonging to a modality on binary classification task, (b) Average classification accuracy when masking features belonging to a modality on ternary classification task

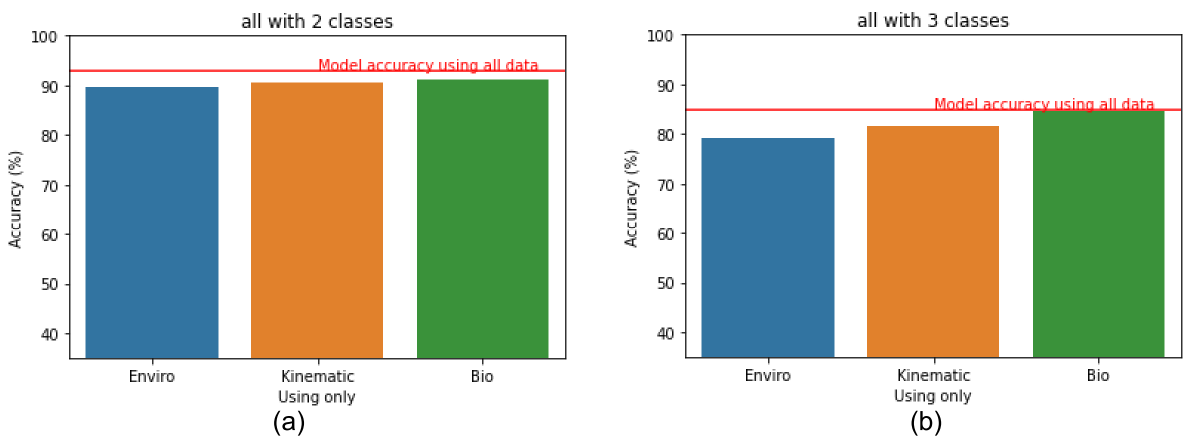


Figure A-7: (a) Average classification accuracy when using a single modality on the binary classification task, (b) Average classification accuracy when using a single modality on a ternary classification task

6. Conclusion

This study has shown the importance of a multi-modal approach to driver monitoring. Limitations of the experiment are mainly related to the required use of VR. Extensions of this research should observe the changes when collecting more authentic vehicular kinematic data. The biometric data proved extremely valuable in classification, but few biometric features were chosen for analysis. Further surveys could find more valuable biometric features for further use.

Moreover, the study showcases the potential for developing ADAS that seamlessly integrate driver monitoring systems, vehicle kinematics, and environmental data to detect and mitigate driver impairment effectively. This comprehensive approach holds promise for improving road safety by allowing the vehicle to assume appropriate control when the driver is identified as distracted or impaired, subsequently reducing the likelihood of accidents. Future research could expand the dataset and examine supplementary data sources and modalities, such as auditory distractions or physiological data, to augment the model's predictive accuracy. Furthermore, assessing the real-world applicability of the proposed approach through experiments involving actual vehicles and drivers on the road under diverse driving conditions and scenarios would be valuable. Integrating the proposed approach with other safety features and systems, such as collision avoidance systems, lane departure warnings, and adaptive cruise control, could yield a comprehensive safety solution for contemporary vehicles.

This study substantiates the feasibility and advantages of a multi-modal approach to driver impairment detection and safety enhancement. By capitalizing on the wealth of information available from driver biometrics, vehicle kinematics, and environmental data, it is feasible to develop more precise and dependable systems for detecting and mitigating driver distraction and impairment. This ultimately contributes to a safer and more efficient transportation system, benefiting drivers and society.

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