Collaborative Sciences Center for ROAD SAFETY

FINAL REPORT

Driver impairment detection and safety enhancement through comprehensive volatility analysis

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2. Arvin, R., & Khattak, A. J. Driving Impairments and Duration of Distractions: Assessing Crash Risk by Harnessing Microscopic Naturalistic Driving Data. Forthcoming in *Accident Analysis & Prevention*, 2020.
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16. Abstract

The ubiquity of sensors and increasing computational resources has enabled monitoring driver, vehicle, and roadway surroundings. A key objective of this research is to extract useful information from multi-dimensional data streams coming in from sensors. The has developed a framework for obtaining, processing, and analyzing high-frequency multi-dimensional large-scale data using vehicle-based sensors that monitor the driver, vehicle, and roadways. The framework harnesses the data and quantify variations in driver biometrics and behavior, vehicle kinematics, and roadway/environmental conditions utilizing the concept of volatility. The naturalistic driving study data from Strategic Highway Research Program (SHRP-2) are utilized for in-depth analysis on impairment and distracted driving. The associated risks with engagement in such behaviors in terms of occurrence of safety critical events are quantified and discussed. A real-time artificial intelligence framework is developed to harness multi-dimensional data and quantify instantaneous crash risk by monitoring driver biometrics (in terms of distraction), vehicular movements, and instability in driving. Furthermore, steps were taken to review the literature on driver monitoring, as well as conducting driving experimentation in simulated and naturalistic settings, which will contribute to future research.

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1. Introduction

Human behaviors such as distracted driving, alcohol or drug impairment, fatigued driving, and speeding that can cause driving errors are commonly known as the main contributing factors for crashes (Pietrasik 2018). In particular, distracted and impaired driving typically contribute to about 35% of all transportation-related deaths. For example, 10,497 fatalities in 2016 had distracted and impaired driving as main contributors, based on US Traffic Safety Facts (NHTSA 2017). While the driving task requires the execution of several cognitive, sensory, and psychomotor skills (Young *et al.* 2007), it is common to observe drivers under impairment (Fan *et al.* 2019) and engaged in various non-driving tasks such as using a cellphone, interacting with other passengers, listening to music, and even writing and reading (Stutts *et al.* 2005, Dingus *et al.* 2016, Kamrani *et al.* 2019). Impaired and distracted drivers allocate fewer available attentional resources to driving tasks such as controlling vehicle position and maintaining speed (Martin *et al.* 2013, Verstraete *et al.* 2014, Paolo Busardo *et al.* 2018).

Distracted driving can be defined as "a diversion of attention from driving because the driver is temporarily focusing on an object, person, task or event not related to driving, which reduces driver's awareness, decision making ability and/or performance, leading to an increased risk of corrective actions, near-crashes, or crashes" (Regan *et al.* 2008). It is a prominent contributing factor in traffic crashes (Lee *et al.* 2008). It is estimated that driver inattention contributes to around 23 percent of police-reported crashes (Klauer *et al.* 2006). In addition, the introduction of cellphones worsened the situation as they have widely diffused among the population (Anon 2011, Engelberg *et al.* 2015, Arvin *et al.* 2017, Nasr Esfahani *et al.* 2019), especially among young drivers (Anon 2011). While a majority of drivers are aware of the associated risks with distracted driving, more than 25 percent still frequently use their cellphone while driving (Motamedi and Wang 2016). Cellphone distracted driving is one of the great challenges in the transportation field, as it contributes to 18 percent of fatal and 5 percent of injury crashes across the U.S. based on the police-reported crash data (Overton *et al.* 2015). However, these crash databases are deficient due to unreported crashes (around 50% of no-injury and 25% of minor-injury crashes were not reported to the police (NHTSA 2009)). Such datasets under-report the prevalence of distracted driving and do not have information on distraction duration. Therefore, the problem may be more widespread than suggested by current reporting, which typically leaves out important crash details.

Impaired driving, resulting from alcohol/drug impairment, fatigue, or emotional state, is also widely common among drivers. Although the share of alcohol-related traffic fatalities significantly dropped in last decades (from 48 percent in 1982 to 28% in 2016), still it remains the main contributing factor in fatal crashes. It is estimated that individuals 16 years and older who drove with alcohol-related impairment is about 11.6 percent (Lipari *et al.* 2016). Impairment substantially affects drivers' ability to control a vehicle and increases driver-risk taking (Laude and Fillmore 2015). In terms of driver performance, impaired driving significantly increases the number of errors (Verster *et al.* 2009) and driver reaction time (Deery and Love 1996, Verster *et al.* 2009) and worsens lateral (Hartman *et al.* 2015), and longitudinal vehicle control (Hartman *et al.* 2016). Impaired driving is a significant risk factors in vehicle crashes, since it can slow the brain's information processing speed and delay its normal function, leading to deterioration in hand and eye coordination (Berning *et al.* 2015). Therefore, it is important to quantify association of impaired driving on crash risk.

While aforementioned studies mainly investigated the correlation of distracted and impaired driving with driving performance using a driving simulator (Rumschlag *et al.* 2015, Saifuzzaman

et al. 2015, Li *et al.* 2016), the absence or paucity of realism and driving simulator sickness may affect the validity and reliability of results (Nickkar *et al.* 2019). Crash datasets suffer from unreported crashes and near-crashes, and lack of detailed information on pre-crash driver state and behavior. While the crash only databases can only be used for frequency and prevalence of specific factors with crashes (Shinar and Gurion 2019), Naturalistic Driving Study (NDS) data provides an opportunity to analyze the associated risk with these factors. The emergence of high-resolution microscopic NDS data compensates for these limitations by collecting real data on real-world conditions. The second Strategic Highway Research Program (SHRP-2), sponsored by the National Academy of Sciences, is the largest naturalistic driving data collection by collecting data on more than 3500 drivers (Dingus *et al.* 2015). It provides an opportunity for researchers to gain insight into factors leading to a crash/near-crash (CNC) event, especially actual driver state, behavior, and performance (Dingus 2003, Dingus *et al.* 2011). Such a dataset helps researchers to overcome limitations of traditional datasets and explore not only minor crashes but also pre-crash driver state and behavior, specifically impairment and distraction profile.

In recent years, with the ubiquity of sensors and increasing computational resources had enabled monitoring drivers, vehicles, and roadways/environments to extract useful information from multi-dimensional data streams coming in from diverse sources. Through a National Science Foundation study, which the team has already completed, the team has developed the concept of *driving volatility*, which quantifies instability in driving. Variations in vehicle kinematics are captured, which are strong movements (e.g., hard braking) in the lateral and longitudinal directions. Using the concept, this study explores how to quantify crash risk by integrating and fusing data from multiple sources in real time.

A key focus is driver biometrics data, accompanied by data on vehicle kinematics as well as roadway/surrounding conditions. In this project driver biometrics is defined as any measurement related to human physical conditions or movements while they are driving (e.g., gaze, heart rate, galvanic skin response, and brain activity). The risk level can be communicated to the driver in the form of useful feedback and also warnings to surrounding vehicles regarding hazards. The objectives of this research are to:

1. Develop a framework for obtaining, processing, and analyzing high-frequency multi-dimensional large-scale data using sensors that monitor the driver, vehicle, and roadways. The framework is meant to harness the data and explore volatility in driver biometrics and behavior, vehicle kinematics, and roadway/environmental conditions.
2. Analyze the naturalistic driving study data from the SHRP-2 program for in-depth analysis on impairment and distracted driving. The associated risks with engagement in non-driving tasks in terms of occurrence of safety critical events are quantified and discussed. A real-time artificial intelligence method is applied to harness multi-dimensional data and quantify instantaneous crash risk by monitoring driver biometrics (in terms of distraction), vehicular movements, and instability in driving. The predictions of driver behavior can be used to provide feedback and warnings to drivers.
3. Use experimentation in simulated and naturalistic settings, demonstrate collection and processing of driver biometric, vehicle, and roadway surroundings data. This effort includes a review of the literature on driver monitoring, as well as setting up the experimentation procedures, which will contribute to future research in driver biometric monitoring and impairment detection.

This report summarizes the activities conducted in this project during the first year.

2. Current State-of-the-Art

The first step toward developing a framework is performing a comprehensive literature review to identify the gaps in previous studies and how we can address the gaps. The knowledge will be synthesized for a deeper understanding of studies. We performed the literature review on three main topics: 1- Impaired and distracted driving; 2- Instability in driving; and 3- Real-time anomaly detection.

2.1 Impaired and distracted driving

The impact of impaired and distracted driving on driving performance has been widely studied in the literature (Shinar 2017). It has been shown that deviation of attention from the driving task can delay reaction time (Drews *et al.* 2009, Choudhary and Velaga 2017, Gao and Davis 2017), deteriorate vehicle control (Shinar *et al.* 2005, Choi *et al.* 2013, Tractinsky *et al.* 2013, Young *et al.* 2014), and lead to missed events (Hosking *et al.* 2009). The availability of microscopic naturalistic driving data has enabled research that studies driving behavior prior to critical events and their associations. In the literature, several papers have investigated the association of distraction on crash risk (Dingus *et al.* 2011, Dingus *et al.* 2016, Guo *et al.* 2017, Kamrani *et al.* 2019) and crash severity (Beanland *et al.* 2013, Arvin *et al.* 2019a). Since drivers are receiving almost all information through their eyes (Shinar 2008), recent studies have focused on secondary tasks that remove the driver's eyes from the roadway, and have established a relationship between eye-off-road and crash risk (Klauer *et al.* 2006, Simons-Morton *et al.* 2014, Victor *et al.* 2015). Glance location can be utilized to infer whether the driver is fully engaged in the driving task or not (Wickens *et al.* 2003, Taylor *et al.* 2013). It has been shown that drivers do not tend to hold their glances away from the roadway for more than 1.6-2 seconds (Sodhi *et al.* 2002, Liang *et al.* 2014); instead, drivers increase the number of times that they look away from the road (Victor *et al.* 2005). Several studies have leveraged these results to develop driver distraction warning systems that generate feedback to drivers and reduce crash risk (Ahlstrom *et al.* 2013).

In terms of impaired driving, several studies have investigated the association of alcohol/drug impairment on driving behavior using police-reported crashes (Romano and Voas 2011, Liu *et al.* 2016, Valen *et al.* 2019), and driving simulator (Creaser *et al.* 2011, Dingus *et al.* 2016, Helland *et al.* 2016, McCartney *et al.* 2017). One of the few studies exploring the association of alcohol/drug-impaired driving on real-world crash and near-crash events using NDS data is performed by Dingus et al. (Dingus *et al.* 2016). Several driving behavioral factors are explored using a binary logistic regression model to quantify the association of the presence of distraction and impairment on crash risk.

With regards to fatigue impairment, several studies have explored the contribution of fatigue driving on driver performance (Philip *et al.* 2005, Meng *et al.* 2019) and safety (Williamson *et al.* 2011, Zhang *et al.* 2016), and tried to develop a framework to predict fatigue driving (Morales *et al.* 2017, Mollicone *et al.* 2019). It is worth noting that along with distracted and impaired driving, the literature suggests that roadway and environmental factors such as weather condition (Ghasemzadeh and Ahmed 2016, Haghighi *et al.* 2018), road characteristics (Manan *et al.* 2017), surface condition (Wang and Zhang 2017), and traffic flow (Theofilatos and Yannis 2014, Kamrani *et al.* 2019) are associated with crash risk and need to be considered in the analysis. Notably, in the studies mentioned above, the association of duration of distraction on crash risk remains unknown. Furthermore, the risks of impaired emotional state, drowsy or fatigued driving, and alcohol or drug impairments can be quantified using deeper analysis.

2.2 Instability in driving

Studies available in the literature have focused on the investigation of speed, driver behavior, roadway, and environmental factors, which are mainly based on police crash reports, which might not be precise or truly represent the crash circumstances. The availability of NDS data has enabled researchers to perform in-depth analysis of contributing factors just before a crash.

Studies have investigated the severity of outcomes in crashes related to human-errors and the impact of driver behaviors, such as distracted driving (Neyens and Boyle 2008, Donmez and Liu 2015), aggressive driving (Paleti *et al.* 2010, Lambert-Bélanger *et al.* 2012), and impaired driving (Behnood *et al.* 2014, Behnood and Mannering 2017). In the United States, aggressive driving (such as speeding, failure to yield the right of way, and reckless) is accounted as a contributing factor in more than 50 percent of fatal crashes (AAA 2009). On the other hand, the impact of distracted and aggressive driving on the driving stability performance is explored by different studies (Beede and Kass 2006, Horberry *et al.* 2006, Hamdar *et al.* 2008, Stavrinos *et al.* 2013). Various measurements are incorporated to explain stability performance of driving such as speed (Beede and Kass 2006, Ghasemzadeh *et al.* 2018), speed variability (Rakauskas *et al.* 2004, Beede and Kass 2006), lane position maintenance (Rakauskas *et al.* 2004), lateral control (Beede and Kass 2006), time to collision (Papazikou *et al.* 2017), reaction time (Rakauskas *et al.* 2004, Sheng *et al.* 2019), etc.

In this study, the concept of “driving volatility” is utilized as an indicator for driving stability performance prior to a crash occurrence. In order to define driving volatility, various measures are applied to kinematics of vehicles such as speed (Kamrani *et al.* 2018b, a, Arvin *et al.* 2019b), acceleration and deceleration (Kamrani *et al.* 2018b, Arvin *et al.* 2019b), and vehicular jerk (Kamrani *et al.* 2018b). In addition, analysis has shown that driving volatility is highly correlated with the frequency of crashes at intersections (Kamrani *et al.* 2017, Kamrani *et al.* 2018b, Arvin *et al.* 2019b).

The association of roadway/environmental factors on the severity outcome of crashes were investigated in several studies. As an illustration, the impact of traffic flow (Theofilatos and Yannis 2014), weather conditions (Ghasemzadeh and Ahmed 2018a, Jalayer *et al.* 2018), surface conditions (Wang and Zhang 2017), roadway alignment (Wang and Zhang 2017, Haghighi *et al.* 2018) on the crash severity have studied. Furthermore, researchers have investigated the impact of these factors on driving stability such as traffic density (Shakouri *et al.* 2014, Teh *et al.* 2014), road geometry (Wang *et al.* 2015, Hamdar *et al.* 2016), work zone (Shakouri *et al.* 2014, Mokhtarimousavi *et al.* 2019), adverse weather (Ghasemzadeh and Ahmed 2017, 2018b), surface condition (Kircher and Thorslund 2009), vehicle type (Rahimi *et al.*), etc.

2.3 Real-time anomaly detection

Several studies have explored the contribution of driver behavior, vehicle factors, roadway, and environmental characteristics on the probability of crash using statistical methods (Dingus *et al.* 2011, Arvin *et al.* 2019a, Kamrani *et al.* 2019). Although most of this research relies on police-reported data, they provide insightful inferences regarding the association of driving behavior and crash risk. The emergence of naturalistic driving data and high-resolution driving actions has allowed for the exploration of microscopic driving behavior prior to crash occurrence. In our previous research (Arvin *et al.* 2019a, Kamrani *et al.* 2019), we have shown that instability in driving not only increases the likelihood of a crash involvement but also the severity of a crash.

Deep learning methods have recently received attention due to the emergence of big data, which is generated by multiple sources and rapid increases in computational power (Goodfellow *et al.*

2016). Referring to the transportation field, deep learning and reinforcement has applied to several areas including demand prediction (Lin *et al.* 2018, Xu *et al.* 2018a, Bao *et al.* 2019), network assignment (Xu *et al.* 2019), transportation maintenance (Wei *et al.* 2019), travel time prediction and reliability (Ghanim and Abu-Lebdeh 2015, Tang *et al.* 2019), driver behavior prediction (Liu and Shi 2019, Osman *et al.* 2019, Elassad *et al.* 2020), signal control (Jeon *et al.* 2018, Xu *et al.* 2018b, Aragon-Gómez and Clempner 2020), driver impairment detection (Ye *et al.* 2017, de Naurois *et al.* 2018), and vehicle classification (Nezafat *et al.* 2019). The main advantage of deep learning architecture over traditional statistical methods is the ability to model complex non-linear relations between associated factors and a dependent variable by incorporating distributed and hierarchical features (Ma *et al.* 2015).

Referring to the micro-level analysis of crash risk, few studies have attempted to identify crash risk level in a real-time manner. Shi et al. (Shi *et al.* 2019) performed a discrete Fourier transform and performed XGBoost and K-mean to detect critical events. Kluger et al. (Kluger *et al.* 2016) performed a Discrete Fourier Transform and K-means clustering on longitudinal acceleration to detect critical events on a sample of 49 crashes and 42 near-crashes. Perez et al. (Perez *et al.* 2017) utilized thresholds to identify boundaries for the detection of crash/near-crash events. Gao et al. (Gao *et al.* 2018) predict the longitudinal conflicts between vehicles with Convolutional Neural Net (CNN) using vehicle kinematics and front-camera videos. However, their analysis only captures a commercial truck fleet, and the results might not be generalizable to other drivers and vehicle types. Osman et al. (Osman *et al.* 2018) attempted to predict safety-critical events based on vehicle kinematics information using multiple machine learning approaches. From a methodological standpoint, the framework proposed in this study can capture the complexity embedded in the data, which can improve safety.

2.4 Gaps in the literature

After reviewing the current state-of-the-art, several gaps can be identified. First, the association of duration of secondary tasks and driving impairment on crash risk remains unknown. Second, the correlation of distraction and impairment on instability in driving and the overall association with crash risk and severity has not been explored in the literature. Finally, the real-time prediction of crash risk using leading indicators embedded in driver biometrics (i.e., distractions due to performance of secondary tasks over time) has not been studied. In this regard, a key goal and contribution of this project is to untangle associations of distraction duration on probability of crash and near crash occurrence. Overall, this project aims to address the gaps mentioned above by utilizing the largest naturalistic driving data collection known as NDS SHRP-2, focusing on distracted driving and impairment.

3. Model development

The team developed a framework to model association of driver impairment, distraction, and instability in driving on safety-critical events by analyzing the streams of biometric, vehicle kinematic, and built environment data coming from sensors that are now becoming widely available. Such data have been collected in the SHRP 2 NDS database described below. The basic idea is to identify any abnormality in driver's biometrics, vehicle kinematics, and surrounding environment for early detection of hazard.

3.1 Data

3.1.1 Data description

This study utilized the NDS SHRP-2 data. More than four petabytes of data was collected in the original study, which makes the SHRP-2 the most comprehensive naturalistic driving study. Drivers' gaze and actions/decisions information is available in the dataset, which is based on monitoring of drivers' biometrics. Notably, the NDS data contains drivers' physical condition and their decisions to engage in secondary tasks, which can be inferred from their movements while they are driving. However, the data collection effort did not include collecting information on drivers' heartrate, brainwaves, galvanic skin response, or other such biometrics. The high-quality and high-resolution data was captured from 2010 to 2013 via multiple sensors, including a camera, accelerometer, alcohol sensor, forward sensor, and a data acquisition system (DAS) with a 10 Hz frequency (Hankey et al. 2016). In the SHRP-2 study, the DAS with the main components of radar unit, head unit, and the main unit is utilized to instrument the vehicles and collect data (Hankey et al. 2016). The radar unit was aimed to collect data on the surrounding environment and was mounted on the front bumper. The head unit, mounted on the rear-view mirror, contained four cameras that collected data on the driver's face, driver's hands, vehicle cabin, and front windshield. Furthermore, the head unit was equipped with an ambient atmospheric analyzer to detect the presence of alcohol. All considered cameras continuously collected data except the cabin camera, which periodically took a photograph to monitor the presence of passengers in the vehicle. Finally, all the collected data were transmitted to the main unit, or hard drive, to store the data (Fraser and Jovanis 2013). The NDS SHRP-2 data has information on more than 3500 drivers from six states (Washington, New York, Pennsylvania, North Carolina, Florida, and Indiana) across the U.S., with more than five million trips covering more than 50 million miles traveled (Hankey et al. 2016). The NDS data includes vehicular movement data (e.g., speed, acceleration), along with information regarding the drivers' behavior, roadway factors, and environmental factors from the videos coded by the data reductionist using the appropriate protocols to ensure consistency and high quality.

Although more than 5M trips are recorded in the raw SHRP-2 NDS data, a subset of data is used in the data reduction process by the Virginia Tech Transportation Institute (VTTI). In this process, all the crashes and near-crash events are recorded in the final SHRP-2 dataset. However, in order to study crash risk, baseline events are necessary to provide crucial comparative information on normal driving and typical driving behavior and conduct analysis (Antin *et al.* 2019). Therefore, more than 7.5K baseline events were selected via case-cohort and case-crossover random sampling methods, which was stratified by drivers and driving time (Hankey *et al.* 2016). A significant effort was taken by the VTTI data reduction team to manually code crash, near-crash, and baseline events characteristics to collect the sequence of states, decisions, and actions prior to CNC events, which were not automatically recorded. It is worth noting that the same information was collected for the baseline events to maintain a form similar to CNC events. Further information on data reduction can be found in (Hankey *et al.* 2016). This study considers a subset of original NDS SHRP-2 data, containing 9,239 trips taken by 1,546 drivers with 7394 baseline events, 1228 near-crashes, and 617 crashes. In the data, the definition of a crash is "any contact that the subject vehicle has with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated." Even though near-crashes did not result in a severe outcome, the data for crash events and near-crash events were combined in this study and defined as CNC events. To be clear, crashes are events where a subject vehicle has contact with other objects such as another vehicle, pedestrian, bicycle, animal, or roadway curbs. Near-crashes are events that required an instant evasive action by the driver to avoid a crash. These were coded

by trained professionals. For each CNC event, 30 seconds of vehicular movement data are available. It is worth noting that the data contains time in which the driver uses evasive maneuvers to avoid the CNC event and also the seconds after the occurrence of a CNC event. Since this paper examines the association of distracted driving before CNC event occurrence, the seconds after the crash should be excluded, which will be further discussed. Moreover, since we are investigating the association of distraction duration with crash risk, the information on driver distraction needs to be linked with vehicle kinematics.

3.1.2 Data processing

The SHRP-2 NDS data contains detailed information on baseline and CNC events coded as categorical variables. The subset of data available in this study consist of three main files:

1- Event summary: Detailed information on each event including
   a) Event details: factors used to establish the CNC event characteristics and sequence of events prior to and throughout its occurrence, such as event type (i.e., baseline, crash, near-crash), event severity, time of reaction, impact time.
   b) Driver state: a systematic description of the driver prior to and during an event, such as driver distraction, impairment, start and end of distraction, driver behavior.
   c) Roadway and weather conditions: the roadway/environmental conditions, such as traffic flow, locality, weather, and surface condition.
2- Timeseries data: timeseries information (between 20 to 30 seconds) for each event (i.e., baseline and CNC), such as recording time information, video frame related to each time, and vehicle kinematics.
3- Video data: the front camera video of each event.

This study utilized the first two files to extract evasive maneuver time and duration of distraction, and link this information with vehicular movements, driver behavior, and roadway/environmental factors. The workflow of data processing is provided in Figure 1. The input is the event summary and event timeseries data. The first step removes the errors and outliers, recodes distractions, and identifies distraction themes. The next step identifies distraction type, distraction start and end time, and labels the distraction seconds for each event. Following this, evasive maneuvers were removed from the analysis. It is vital to consider only the seconds of driving that contain typical driver behavior instead of the seconds that drivers are reacting to a crash stimulus. In other words, we need to exclude the seconds that the driver is reacted to the crash and the time after the crash occurrence. First, the time that the driver started to react, and the time of impact are extracted from the trip summary. The minimum of these two values is selected as the start of evasive maneuver, and the trajectories after the evasive maneuver initiation are removed. To further demonstrate the time exclusion used, a speed profile, an acceleration profile, and a distraction profile of a random crash event are provided at the bottom of Figure 1. In this event, the crash happened at the 24th second of the data stream, while the driver reacted to the stimulus at the 23rd second of the data. Therefore, the observations after the second 23 need to be excluded for the purpose of this study. In other words, only the seconds of the data up to the second that the driver starts to react to the CNC event were considered in this study. Finally, in order to be consistent in all the events (both baselines and CNC events), we subset 15 seconds of data prior to the evasive maneuver and calculate the duration of distraction and vehicular movements during the 15 seconds time frame.

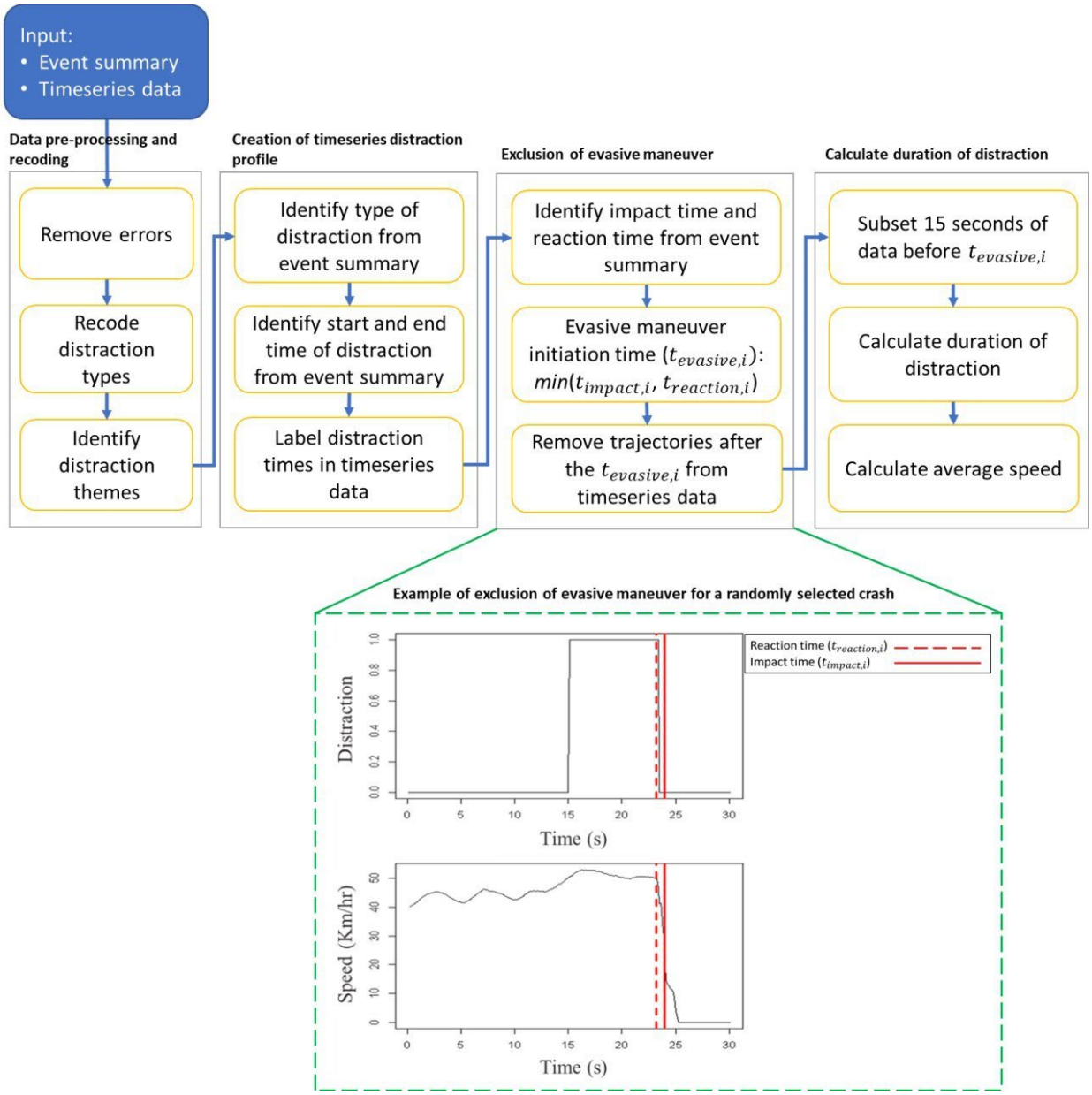


Figure 1 Data processing framework

3.1.3 Coding distraction

As mentioned earlier, the NDS data contains rich and detailed information on driver behavior, roadway condition, and environmental condition, etc. Distraction is measured using the variable "secondary task," which was coded into 62 different groups in the NDS data. However, in some groups, there are similarities that allow the data to be clustered into intuitive and cleaner constructs. As illustrated in Figure 2, three themes of distractions are identified in the NDS SHRP-2 data: cellphone-oriented tasks, object-oriented tasks, and activity-oriented secondary tasks. In summary, cellphone-oriented distractions involve cellphone use while driving, such as reaching, dialing, talking, texting, and other uses. The object-oriented group focuses on distractions with objects other than a cellphone, either inside or outside the vehicle's cabin. This group includes distractions with the vehicle's radio, climate control, objects inside the vehicle, and objects outside the cabin. Finally, the activity-oriented group is focused on activities and tasks that drivers were involved in during driving, such as reaching for an object, eating, drinking, smoking, interacting with other passengers, singing and talking by him/herself, hygiene, and atypical activities. It is worth noting that Figure 2 also provides the common secondary tasks in the SHRP-2 dataset and methodology for recoding and grouping these distractions into three main groups. The thicknesses of the recorded secondary task in the dataset represent the approximate proportion of the grouped category.

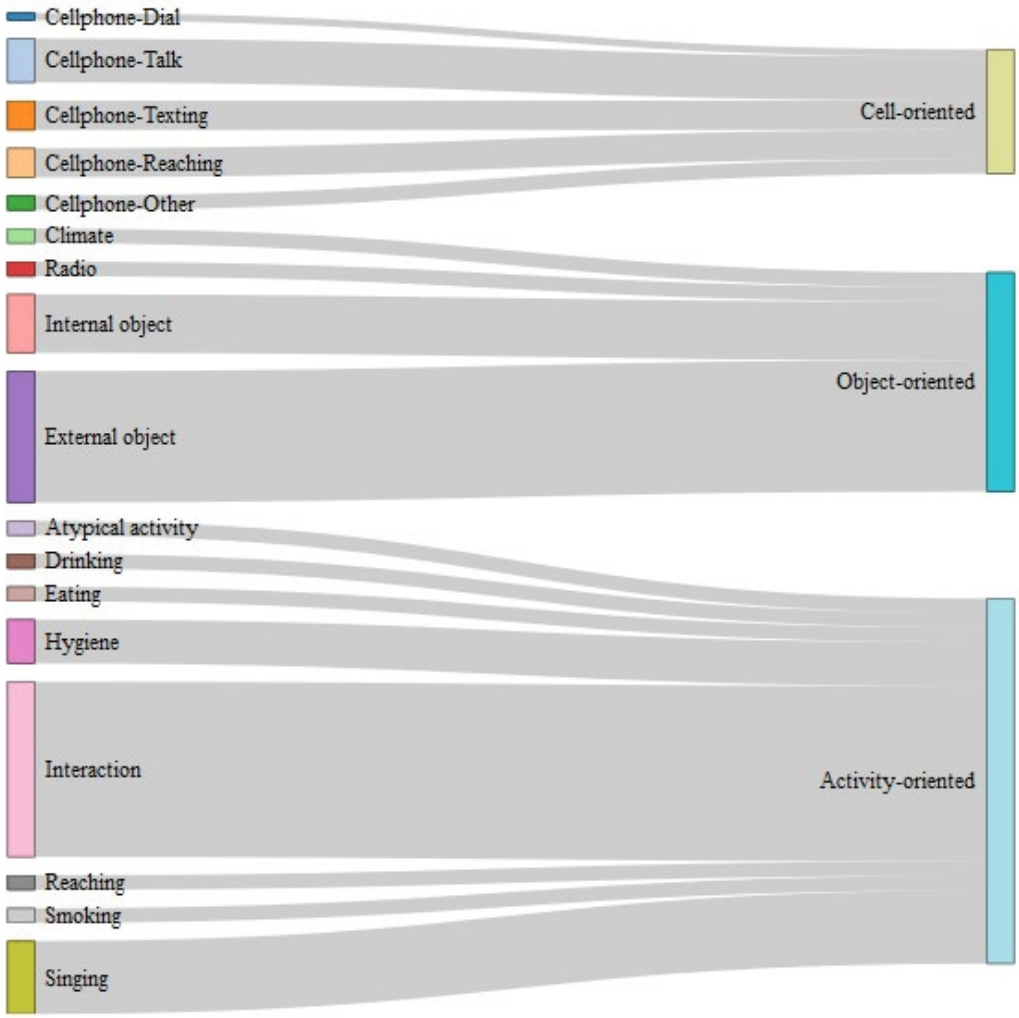


Figure 2 Categorization of secondary tasks

3.2 Quantifying instability and anomaly in driving

To identify abnormal behavior, we need to identify and define a baseline threshold and what constitutes abnormality. Anomaly can occur in biometrics (e.g., heart rate) or vehicle kinematics (e.g., speed and acceleration). They can be analyzed using volatility functions, which are applied to vehicle speed, acceleration, and deceleration in this study. Further details are available in (Kamrani *et al.* 2018b). In the following, the applied functions on vehicle kinematics are discussed.

Standard deviation: The first function is the standard deviation, which is desirable for capturing the data variations. We can write:

$$S_{dev} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{1}$$

where x_i is the observed value *i*, $\bar{x}$ is the mean of observations, and *n* is the total number of observations. This function is applied to speed and acceleration/deceleration.

Time-varying stochastic volatility: The time-varying stochastic volatility measure is widely used in the econometric field, which can be written as (Figlewski 1994):

$$V_f = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})} \qquad \text{from } t = 1 \text{ to } n \tag{2}$$

where

$$r_i = \ln\left(\frac{x_t}{x_{t-1}}\right) \tag{3}$$

where x_t and x_{t-1} are the observations at time t and $t-1$, respectively, and *ln* is the natural logarithm. Since this measure needs timeseries observations with positive values, only vehicle speed is used (acceleration/deceleration have negative values).

Coefficient of Variation: This measure obtained by dividing the standard deviation by the mean (Everitt and Skrondal 2002), which applied to speed, acceleration, and deceleration, and can be written as:

$$C_v = \frac{S_{dev}}{|\bar{x}|} \tag{4}$$

Quartile Coefficient of Variation: This measure is desirable when the data is not following a normal distribution (Zwillinger and Kokoska 2000), which can be defined as (Bonett 2006):

$$Q_{CV} = \frac{Q_3 - Q_1}{Q_3 + Q_1} \tag{5}$$

where Q_1 and Q_3 are the 25th and 75th percentiles of data, respectively.

3.3 Analyzing data streams

In this analysis, the NDS SHRP-2 data was analyzed, focusing on the role of distractions and impairments. The biometric data was based on observations of drivers' gaze and secondary tasks

performed by the driver. (A more complete set of biometric data collection will be included in future work.) This analysis attempts to quantify risk based on biometrics-based distractions and driver impairments. Since the driving style, biometrics, and vehicle performance characteristics of each person can be somewhat unique, drivers' instantaneous behavior will be compared with their historical data from previous trips. In other words, we will baseline the instantaneous driving behavior based on the drivers' own style. Drivers will be classified as calm or aggressive based on their volatility (see below). While some behaviors might be normal for aggressive drivers, they may be abnormal behavior for calm drivers. The objective is to develop a method to personalize thresholds based on streams of biometric and vehicle kinematics data for each driver.

3.3.1 Impaired and distracted driving

Table 1 provides the descriptive statistics of the key variables, focusing on the ones found to be statistically significant in modeling. The table consists of three sections, driver related variables, roadway/environmental factors, and vehicular movements. The driver variables include distraction type and impairment. The impairments further include emotional state (such as anger or agitation), drowsy or fatigued driving, and alcohol or drug impairments. The considered roadway/environmental factors include weather conditions, density of traffic, road alignment, construction zone, intersection influence, and roadway type. The results are also separated for the baseline and CNC events. Descriptive statistics for the baseline and CNC events can be observed to have a substantial difference, especially in terms of driver performance. This indicates that further analysis is needed to explore the association of these factors on the probability of a CNC event.

Table 1 Descriptive statistics of the driver, vehicle, and roadway/environmental factors

Variable	Category	Total (N = 9239)		Baseline (N = 7394)		CNC (N = 1845)	
		%	Freq.	%	Freq.	%	Freq.
Distraction	Cellphone oriented						
	Reaching	2.50%	231	2.11%	156	4.07%	75
	Dialing	0.18%	17	0.11%	8	0.49%	9
	Talking	3.56%	329	3.38%	250	4.28%	79
	Texting	2.24%	207	1.51%	112	5.15%	95
	Other	0.80%	74	0.73%	54	1.08%	20
	Object-oriented						
	Climate	1.21%	112	1.12%	83	1.57%	29
	Radio	1.71%	158	1.65%	122	1.95%	36
	Internal	4.32%	399	3.90%	288	6.02%	111
	External	9.43%	871	9.44%	698	9.38%	173
	Activity oriented						
	Drinking	0.71%	66	0.76%	56	0.54%	10
	Eating	1.17%	108	1.20%	89	1.03%	19
	Smoking	0.80%	74	0.76%	56	0.98%	18
	Reaching	0.88%	81	0.57%	42	2.11%	39
	Interacting	12.88%	1190	13.23%	978	11.49%	212
	Atypical	1.79%	165	1.39%	103	3.36%	62
	Talking/singing	5.89%	544	5.88%	435	5.91%	109
	Hygiene	3.16%	292	3.02%	223	3.74%	69
	None (no distraction)	46.77%	4321	49.24%	3641	36.86%	680
Impairment	Emotional state	0.50%	46	0.28%	21	1.36%	25
	Drowsy/Fatigue	1.40%	129	1.23%	91	2.06%	38
	Alcohol/Drug	0.24%	22	0.05%	4	0.98%	18

	No impairment	97.60%	9016	98.24%	7264	94.96%	1752
	Other	0.28%	26	0.19%	14	0.65%	12
Weather	Adverse Conditions	6.13%	567	5.91%	437	7.05%	130
	Mist/Light Rain	4.09%	378	3.85%	285	5.04%	93
	No Adverse Conditions	89.77%	8294	90.24%	6,672	87.91%	1622
Density (Level-of-service)	A1	40.23%	3717	42.51%	3,143	31.11%	574
	A2	30.15%	2786	32.31%	2,389	21.52%	397
	B	20.16%	1863	18.49%	1,367	26.88%	496
	C	6.07%	561	4.56%	337	12.14%	224
	D	2.10%	194	1.27%	94	5.42%	100
	E	1.02%	94	0.72%	53	2.22%	41
	F	0.25%	23	0.14%	10	0.70%	13
	Unknown	0.01%	1	0.01%	1	0.0%	0
Road Alignment	Curve	13.60%	1256	13.97%	1034	12.03%	222
	Straight	86.40%	7983	86.03%	6,360	87.97%	1623

Figure 3 provides the frequency of impaired driving in CNC and baseline events. It can be inferred that the emotional state (such as agitation, anger, sadness, or crying), drowsy/fatigue, alcohol/drug, and other impairments are substantially higher in CNC events than baseline, which highlights the correlation of impaired driving on crash risk. As an illustration, drowsy and fatigued driving occurred in 2.06% CNC events, while it was present in only 1.23% of baseline events. Referring to alcohol and drugs, it was present in 0.05% of baseline events, while its prevalence in CNC events was 0.98%. Although these statistics provide insightful information regarding the contribution of impaired driving on crash risk, it should be quantified by developing a statistical model, which will be discussed in section 3.4.1.

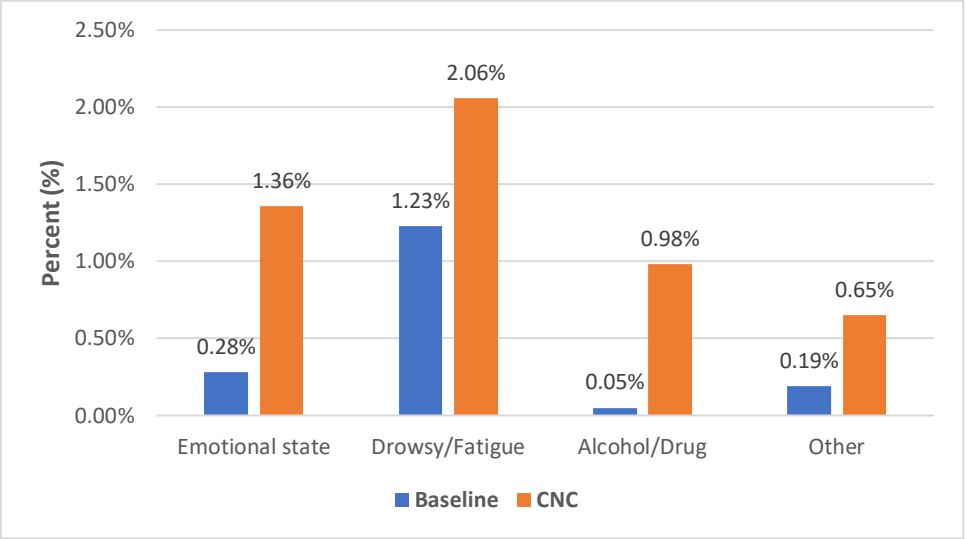
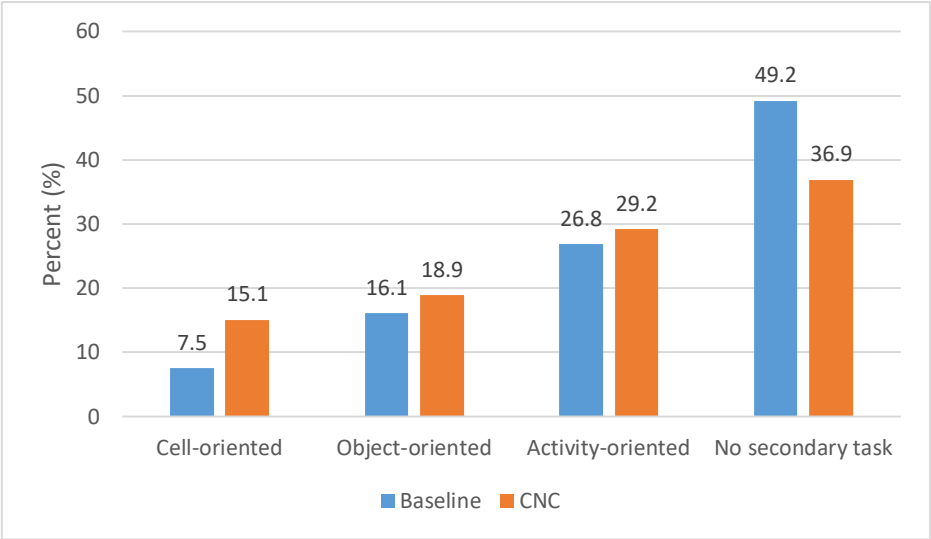


Figure 3 Prevalence of impaired driving in baseline and crash/near-crash events

As discussed, the secondary tasks associated with distracted driving are grouped into three main categories, i.e., cellphone-oriented distraction, object-oriented distraction, and activity-oriented distraction. Figure 4 (top) provides the prevalence of different categories among baseline and CNC events. Based on the results, it can be observed that in 50.8% of baselines, distracted driving was present, while in CNC events, this number is 63.1%. In addition, the prevalence of all distraction categories is higher in CNC events compared to the baseline. Figure 4 (bottom) illustrates the presence of different distraction types in baseline and CNC events. Based on the

results, the prevalence of most of the distraction types was substantially higher in CNC events comparing to the baselines. As an illustration, texting while driving was present in 1.51% and 5.15% of baseline and CNC events, respectively. It is worth noting that literature has widely discussed the association of the presence of secondary tasks on crash risk (Dingus *et al.* 2016, Gao and Davis 2017, Arvin *et al.* 2019a). However, a key goal and contribution of this project is to untangle association of their duration on probability of CNC occurrence.



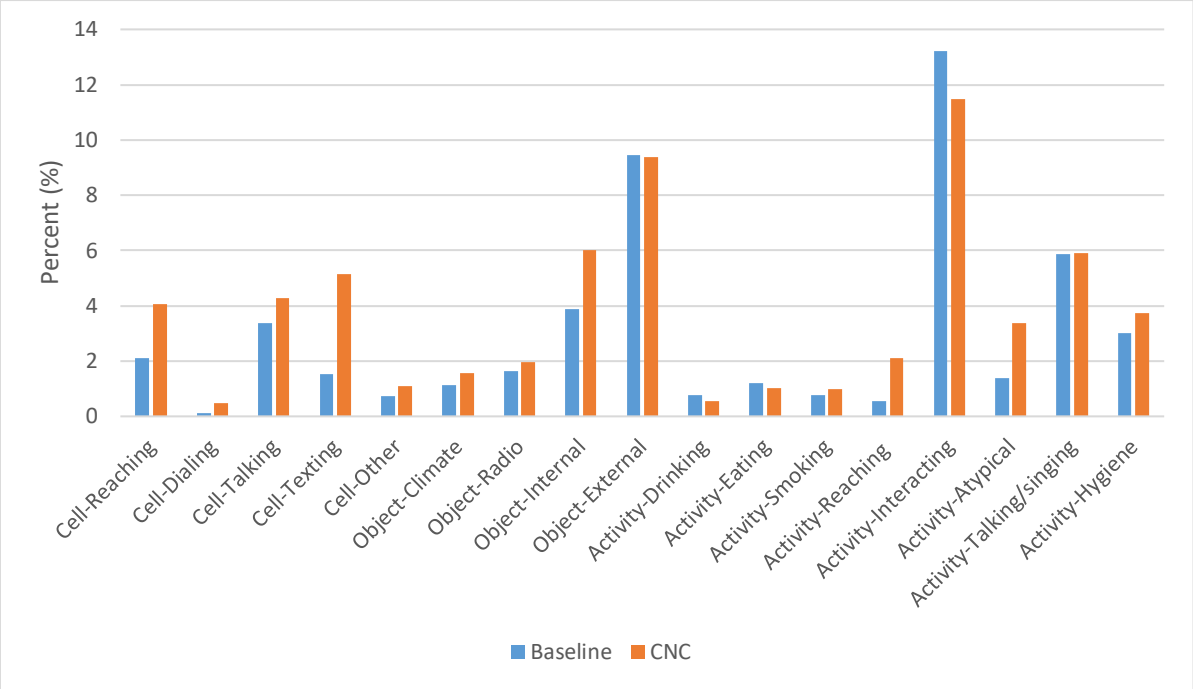
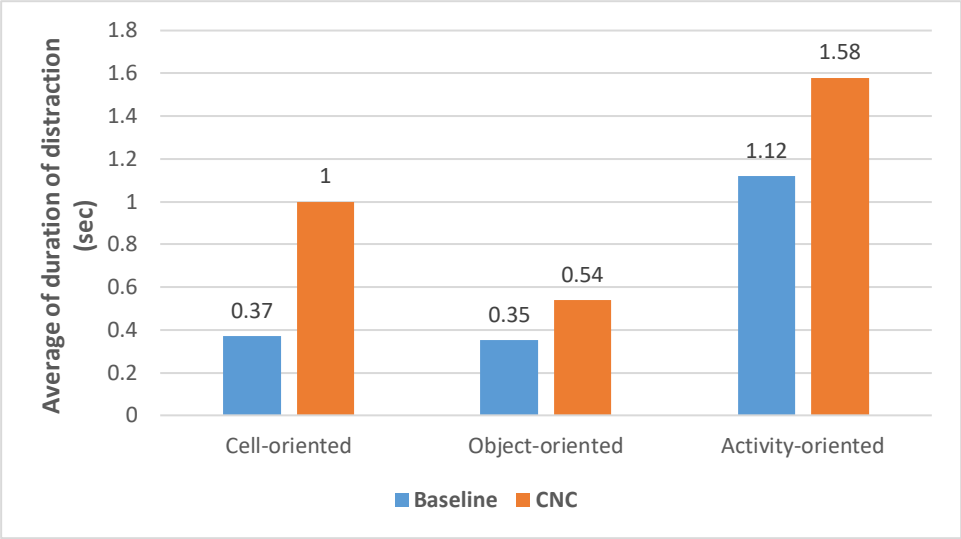


Figure 4 Prevalence of three groups of distractions (a) and different distraction types (b) in baseline and CNC events

3.3.2 Duration of distracted driving

This study utilized a unique method to investigate the effect of the duration of distracted driving on the probability of crash occurrence by analyzing the time that drivers were disengaged from driving and performing tasks other than driving. While section 3.3.1 presents descriptive statistics on the prevalence and presence of distraction among baseline and CNC events, the correlation of each distraction duration with the resulting crash risk is discussed here. Figure 5 provides the average of distraction duration for each distraction type within the 15 seconds of data. Figure 5 (top) shows the average distraction duration for three distraction categories for both baseline and CNC events. Comparing the two groups, there is a substantial difference between the duration of distraction in CNC events compared to baseline events. On average, the duration of distraction in cellphone-oriented group is 0.37 and 1.01 seconds in baseline and CNC events, respectively. The duration of the secondary task in the object-oriented group is 0.35 and 0.54 seconds for baseline and CNC events. Finally, distraction duration in activity-oriented distractions is 1.12 and 1.58 seconds in baseline and CNC events. These time differences imply that the prevalence of distraction is higher, and the duration of the distraction is longer in CNC events. A similar pattern can be observed in all the distraction types. Figure 5 (bottom) provides an average of distraction duration in different secondary task categories. As an illustration, when considering texting while driving distraction, drivers were distracted on average for 0.07 seconds within baseline events, while in the CNC events, the distraction duration was 0.35 seconds. Drivers were distracted by an external object for 0.18 seconds on average in baseline events, with an average duration of 0.27 seconds in CNC events. Distraction by objects inside the vehicle follows a similar pattern, indicating that, on average, drivers were distracted for longer compared to baselines (0.14 vs. 0.08 seconds). Additionally, the duration of interaction with other passengers is slightly higher in CNC events. Furthermore, the distraction duration of the category “atypical” is substantially higher in CNC events compared to baseline events (0.08 vs. 0.03 seconds).



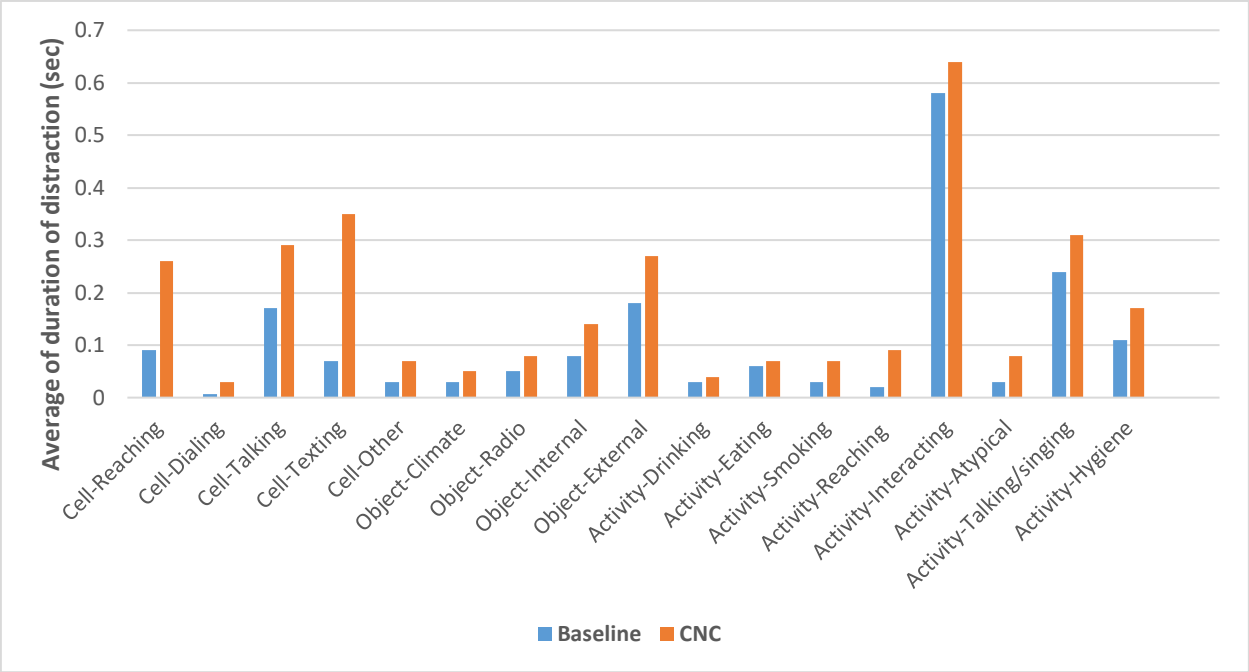


Figure 5 Average of the duration of distraction for different distraction groups (top) and distraction types (bottom) for baseline and CNC

3.3.3 Instability in driving

A deep learning framework that integrates multiple data streams, including vehicular kinematics (i.e., of speed, longitudinal and lateral accelerations), driving stability (i.e., several measures of driving volatility), and driver behavior (i.e., impairment and distraction) was developed to predict the occurrence of a crash/near-crash.

This section provides some statistical analysis to illustrate the positive association of driving volatility and distracted driving on crash risk. The previous sections have discussed the procedure for calculating event-based and temporal driving volatility for speed and longitudinal and lateral acceleration. Here, the contribution of the volatility on the crash risk is shown using a boxplot analysis, provided in Figure 6. It can be noted that there is a substantial difference between these two groups. In CNC events, drivers were more distracted and volatile compared to the baseline events.

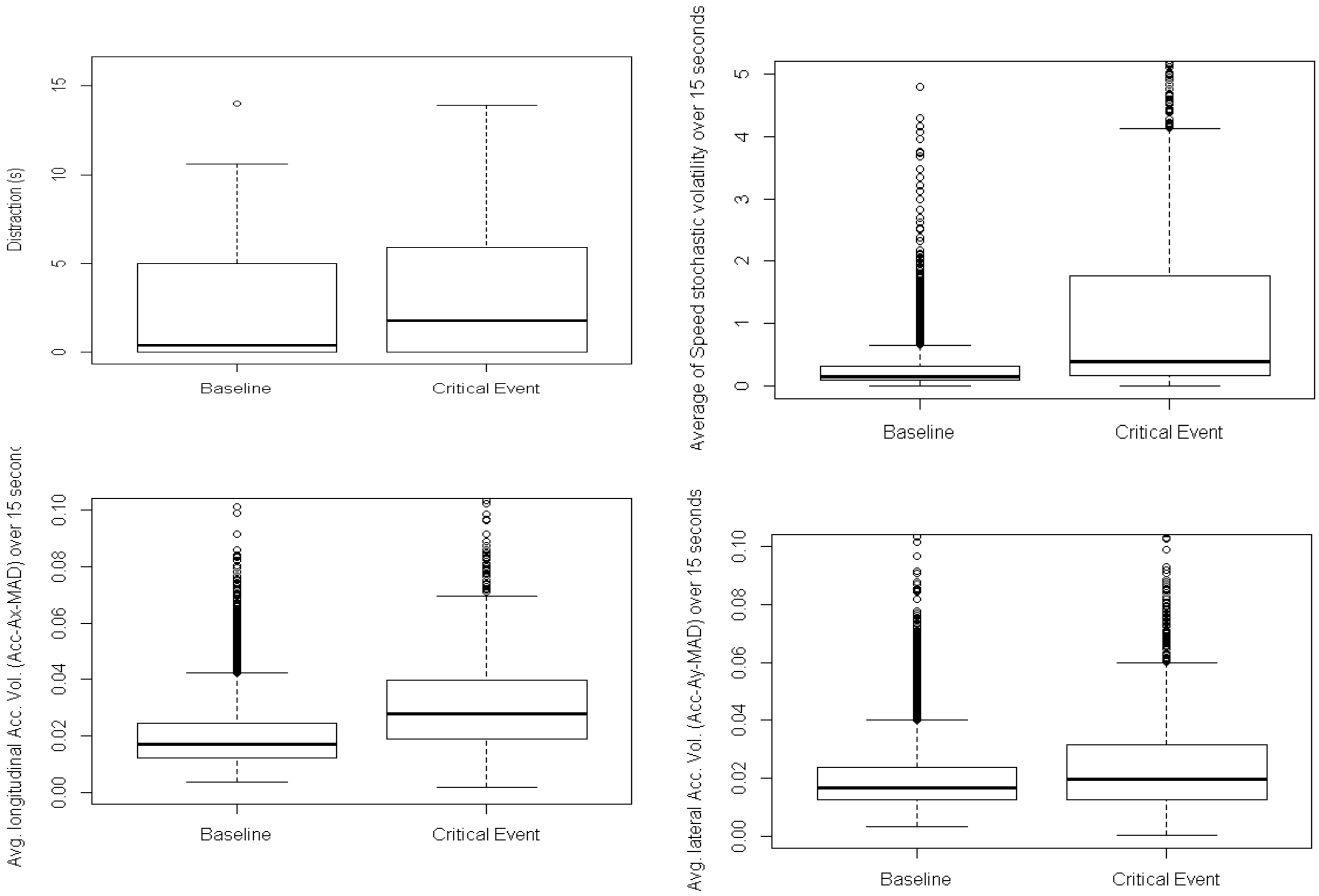


Figure 6 Boxplot of distracted driving, speed, longitudinal and lateral volatilities for the baseline and critical events

The descriptive statistics of the variables are provided in Table 2. The feature space contains information on three dimensions of vehicular movements: seconds that the driver was distracted with a secondary task, event-based and temporal driving volatility indices for speed, longitudinal, and lateral accelerations. It can be observed that the seconds of distraction and the driving volatility are substantially higher in the critical events compared with baselines.

Table 2 Descriptive statistics of the baseline and critical events

Variable (feature)	Baseline events (N=7566)				Critical events (N=1925)			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Speed (mph)	62.36	31.22	0	125.81	41.23	30.12	0	116.74
$Acceleration_x\ (m/s^2)$	-0.01	0.04	-0.23	0.25	-0.01	0.06	-0.87	0.26
$Acceleration_x\ (m/s^2)$	0	0.04	-0.2	0.33	0	0.04	-0.2	0.24
Seconds of distraction	1.852	2.19	0	14.00	3.11	3.26	0	13.90
L1-Speed-S_{dev}	1.51	1.46	0	31.88	2.2	1.76	0	12.12
L1-Speed-D_{mean}	1.28	1.27	0	27.05	1.88	1.58	0	11.6
L1-$Accleration_x$-S_{dev}	0.05	0.03	0.01	0.2	0.08	0.04	0.01	0.28
L1-$Accleration_x$-D_{mean}	0.04	0.03	0	0.18	0.06	0.03	0	0.22
L1-$Accleration_y$-S_{dev}	0.04	0.04	0.01	0.24	0.06	0.05	0	0.4
L1-$Accleration_y$-D_{mean}	0.03	0.03	0	0.21	0.04	0.04	0	0.31
L2-Speed-V_f	0.01	0.04	0	0.68	0.03	0.06	0	0.6
L2-Speed-S_{dev}	2.68	2.32	0	96.22	3.72	2.52	0	20.06
L2-Speed-D_{mean}	2.28	1.98	0	81.91	3.16	2.15	0	16.89
L2-Speed-C_v	0.04	0.07	0	1.15	0.13	0.17	0	1.16
L2-Speed-*EWMA*	0.01	0.04	0	0.68	0.03	0.06	0	0.6
L2-$Accleration_x$-S_{dev}	0.02	0.01	0	0.12	0.04	0.02	0	0.15
L2-$Accleration_x$-D_{mean}	0.02	0.01	0	0.1	0.03	0.02	0	0.13
L2-$Accleration_y$-S_{dev}	0.03	0.01	0	0.15	0.03	0.02	0	0.23
L2-$Accleration_y$-D_{mean}	0.02	0.01	0	0.13	0.02	0.02	0	0.19

*L1: Event-based volatility measure; L2: Temporal volatility measure; S_{dev}: Standard deviation; V_f: Time-varying stochastic volatility; C_v: coefficient of variation; D_{mean}: mean absolute deviation; $Acceleration_x$: longitudinal acceleration; $AccDec_x$:both longitudinal acceleration and deceleration; $Accleration_y$: lateral acceleration; EWMA: Exponentially Weighted Moving Average Volatility

Note: The sample size is different from Table 1. This is because some of the information was not available in the summary data linked to this dataset. Therefore, number of observations is lower for the analysis presented in the previous section.

3.4 Quantifying association of impaired and duration of distraction on crash risk

3.4.1 Impact of impairment and distraction on crash risk

The descriptive statistics of the data presented in the previous section suggest meaningful relationships between the duration of distraction and crash risk. However, without controlling for other factors such as driving behavior and roadway/environmental factors, these relations might not be generalizable or conclusive. This study utilized a fixed and random parameter binary logistic regression model to explore the association of the duration of distracted driving and impairment with the probability of crash and near crash occurrence. The random parameter model addresses unobserved heterogeneity, and a parameter is considered to be random in two different conditions: first, only standard deviation is significant; second, both mean and standard deviation are significant. Along with the duration of distraction and impaired driving factors, driver behavior and roadway environmental variables are considered in the model as the control variables. To perform the model selection, intuition, variable significance, and model parsimony were considered, and Akaike Information Criteria or AIC was used to score model performance. The full dataset of 9239 events is used for this analysis, including no-distraction events and all secondary tasks. Similar to the previous models, the random-parameter model performs better in terms of goodness of fit, and all the variables are significant at the 95% CI, except the duration of drinking while driving, which is significant at the 90% CI (Table 3).

Table 3 Logistic regression to quantify association of impairment/distraction on CNC probability

Variable	Fixed parameter				Random parameter			
	β	Std. Err.	P-value	ME	β	Std. Err.	P-value	ME
Intercept	-1.117	0.070	<0.001	-	-0.709	0.049	<0.001	-
Cell Oriented								
Reaching	0.251	0.029	<0.001	3.3%	0.189	0.023	<0.001	3.0%
Dialing	0.503	0.116	<0.001	6.6%	0.381	0.094	<0.001	6.1%
Talking	0.173	0.025	<0.001	2.3%	0.130	0.019	<0.001	2.1%
Texting	0.322	0.030	<0.001	4.2%	0.251	0.027	<0.001	4.0%
Other	0.199	0.051	<0.001	2.6%	0.145	0.041	<0.001	2.3%
Object-Oriented								
Climate	0.203	0.064	0.001	2.7%	0.147	0.051	0.004	2.4%
Radio	0.183	0.049	<0.001	2.4%	0.137	0.038	<0.001	2.2%
Internal	0.217	0.040	<0.001	2.9%	0.163	0.033	<0.001	2.6%
External	0.198	0.031	<0.001	2.6%	0.147	0.024	<0.001	2.4%
Activity oriented								
Drinking	0.115	0.064	0.072	1.5%	0.083	0.045	0.064	1.3%
Eating	0.113	0.046	0.014	1.5%	0.083	0.035	0.016	1.3%
Smoking	0.161	0.053	0.002	2.1%	0.122	0.039	0.002	2.0%
Reaching	0.328	0.068	<0.001	4.3%	0.247	0.055	<0.001	4.0%
Interacting	0.110	0.017	<0.001	1.4%	0.072	0.013	<0.001	1.2%
Std. Interaction	-	-	-	-	0.089	0.017	<0.001	-
Atypical	0.300	0.037	<0.001	4.0%	0.235	0.030	<0.001	3.8%
Talking/singing	0.163	0.024	<0.001	2.1%	0.092	0.019	<0.001	1.5%
Std Talk/sing	-	-	-	-	0.179	0.029	<0.001	-
Hygiene	0.210	0.034	<0.001	2.8%	0.155	0.026	<0.001	2.5%
Driving impairment								
Emotional state	1.442	0.326	<0.001	24.7%	1.154	0.233	<0.001	18.5%
Drowsy/Fatigue	0.960	0.221	<0.001	15.3%	0.721	0.159	<0.001	11.6%
Other	1.567	0.427	<0.001	27.2%	1.308	0.306	<0.001	21.0%
Alcohol/Drug	2.560	0.599	<0.001	46.9%	2.122	0.496	<0.001	34.0%
Traffic density								
A1	0.286	0.077	<0.001	3.9%	0.218	0.057	<0.001	3.5%
A2	1.000	0.077	<0.001	14.9%	0.768	0.058	<0.001	12.3%
B	1.441	0.108	<0.001	24.3%	1.101	0.080	<0.001	17.7%
C	1.676	0.163	<0.001	29.4%	1.243	0.111	<0.001	19.9%
D	0.965	0.230	<0.001	15.4%	0.712	0.161	<0.001	11.4%
E	1.109	0.470	0.018	18.1%	0.758	0.366	0.039	12.2%
Vehicular movement								
Average Speed over 15 seconds	-0.024	0.001	<0.001	-0.3%	-0.022	0.001	<0.001	-0.4%
Speed Std	-	-	-	-	0.014	0.001	<0.001	-
Model Summary								
Number of observations	9239				9239			
Null Deviance	-4619.3				-4619.3			
Model Deviance	-3872.2				-3866.6			
McFadden R-Squared	0.162				0.163			
AIC	7802.4				7797.7			

Distracted driving

This study identified three main groups of distraction and quantified the duration of distraction by different types to study their association with crash risk, including cellphone-oriented, object-oriented, and activity-oriented distractions. Three specific models for each group of distraction are developed. The most notable finding is that duration of all types of distracted driving are positively and significantly associated with the probability of the occurrence of a safety critical event (i.e. near-crash and crash events). The results suggest that the association of duration of distraction with crash risk is non-linear and with increased engagement with a secondary task, the risk of crash increases following a sigmoid function. In order to perform a comparison of between different distraction groups, the marginal effect plots of the three developed models are integrated and provided in the Figure 7. The figure suggests that there is a substantial variation among different secondary tasks. The riskiest distraction types are Dialing with a cellphone, reaching for an object, and texting with cellphone while driving. These distractions require not only visual attention of drivers, but also disengage drivers' manual, and cognitive capabilities. As an illustration, the marginal effect analysis revealed that 9 seconds distraction with texting while driving on average is associated with a 0.57 probability of getting involved in an CNC event, controlling for other variables. Furthermore, by comparing the groups of distractions, it can be inferred that duration of cellphone-oriented distractions are substantially higher comparing to the activity-oriented and object-oriented distractions, which implies the importance of prohibition of using cellphone while driving. On the other hand, there are some distraction types that their duration have lower risk comparing to other secondary tasks, however, their risk is significant and substantial. Based on the results, interacting with other passengers, drinking, and eating has the lowest risk comparing to other distraction types. Duration of interaction with passengers has a less negative effect on driving performance, and this could be due to the fact that responsibility of monitoring environment could be shared with passengers (Overton *et al.* 2015).

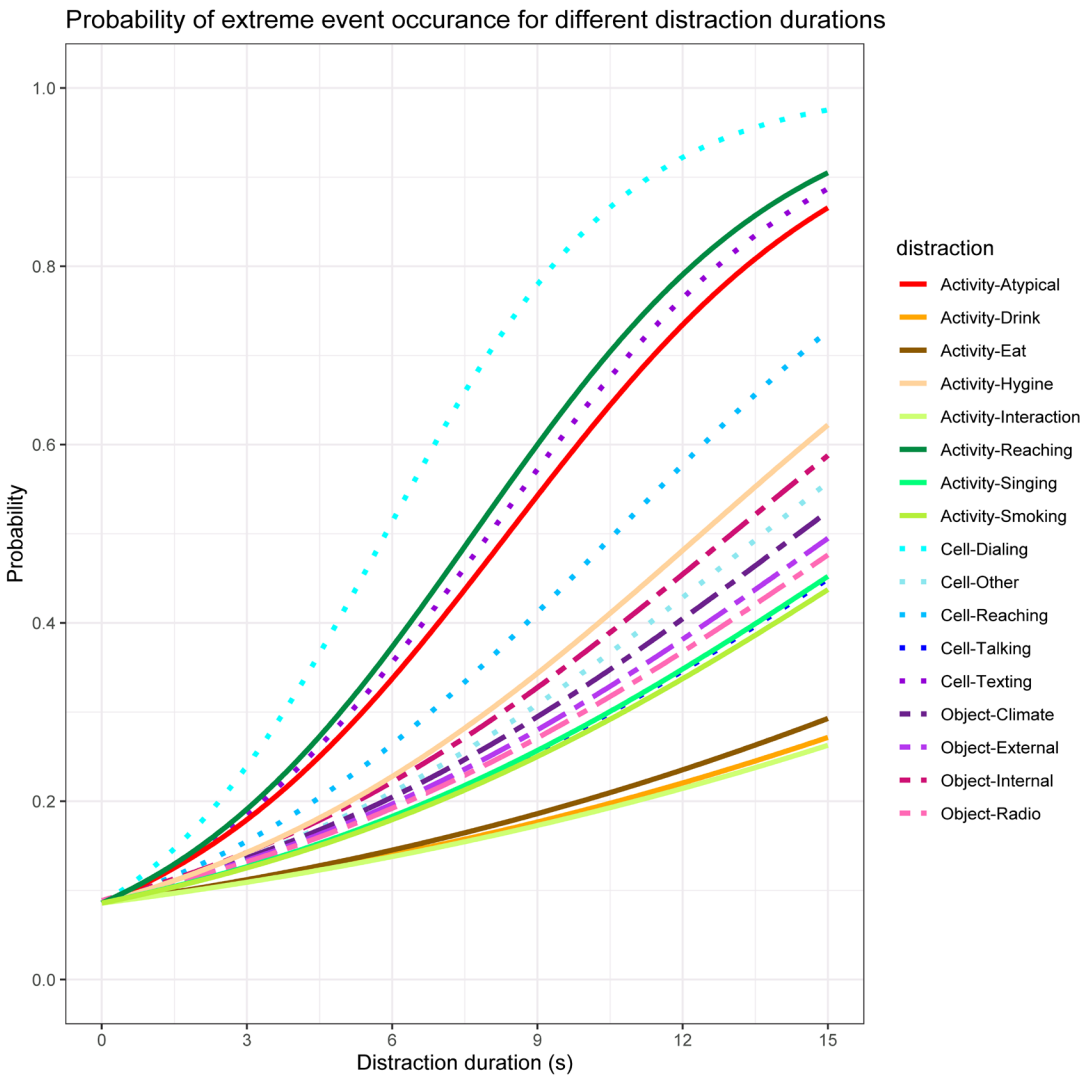


Figure 7 Probability of CNC event occurrence with increasing duration of distraction for all types of secondary tasks

Driver impairment

As mentioned before, impaired driving is known as one of the significant risk factors in vehicle crashes, since it can slow the brain's information processing speed and delay its normal function, leading to deterioration in hand and eye coordination (Berning *et al.* 2015). Therefore, it is crucial to quantify association of impaired driving on crash risk. The modeling results (Table 3) reveal that all types of impairment increase the likelihood of CNC events, controlling for other variables. Specifically, (and confirming earlier results) alcohol and drug related impairments are associated with a 34 percent increase in the probability of crash/near-crash involvement. The results are consistent with the findings of Dingus et al (Dingus *et al.* 2016) who found that alcohol and drug impairment increases the crash risk 35.9 times. Furthermore, drowsy and fatigued driving are associated with increased probability of CNC event by 11.6 percent, which is in line with the literature (Klauer *et al.* 2006, Lee *et al.* 2016). In line with previous studies (Dingus *et al.* 2016), emotional driving (i.e. sadness/crying, anger, other emotional states) increased the probability of involvement in an CNC event by 18.5 percent. Other impairment types are associated with 21 percent higher crash risk.

3.4.2 Impact of distraction on driving instability and crash severity

The conceptual framework of this chapter is shown in Figure 8. There are several factors that can be directly associated with the safety outcome, i.e., crash intensity. Such associated factors can include driver behavior, roadway/environmental factors, and vehicle-specific factors. Furthermore, these factors can indirectly affect crash intensity through driving instability. Although the vehicle-specific factors can also potentially affect crash intensity, due to unavailability of such information in the available subset of SHRP2 NDS data, relevant variables could not be included in the analysis. The structure of the path analysis model can be written as:

$$Instability\ in\ speed: Y_{1,1} = F_{speed\ volatility}(\alpha_{1,1} + \beta_{1,1}X_1) \quad (6)$$

$$Instability\ in\ acceleration: Y_{1,2} = F_{acceleration\ volatility}(\alpha_{1,2} + \beta_{1,2}X_1) \quad (7)$$

$$Crash\ intensity: Y_2 = F_{intensity}(\alpha_2 + \beta_2 X_2 + \gamma_1 Y_{1,1} + \gamma_2 Y_{1,2} + \beta_3 V) \quad (8)$$

where $Y_{1,1}$ is speed volatility that captures driving instability which for speed volatility varies from 0.15 (stable) to 12.43 (unstable) and $Y_{1,2}$ is acceleration volatility which captures variations in acceleration and varies from 0 (stable) to 2.72 (unstable), and Y_2 is an ordinal variable with four levels of severity including Low-risk Tire Strike, Minor Crash, Moderate Crash, Severe Crash. Additionally, $F_{volatility}$ is the driving volatility function, $F_{intensity}$ is the crash severity model, α_1 and α_2 are the model intercept, β_1 is the vector of estimated coefficients, X_1 is the matrix of covariates including driver behavior and roadway/environmental factors, β_2 represent the estimated coefficients for explanatory variables X_2, γ is the association of driving instability on crash intensity, V is the vehicle speed just before the crash, β_3 are the estimated coefficients for speed.

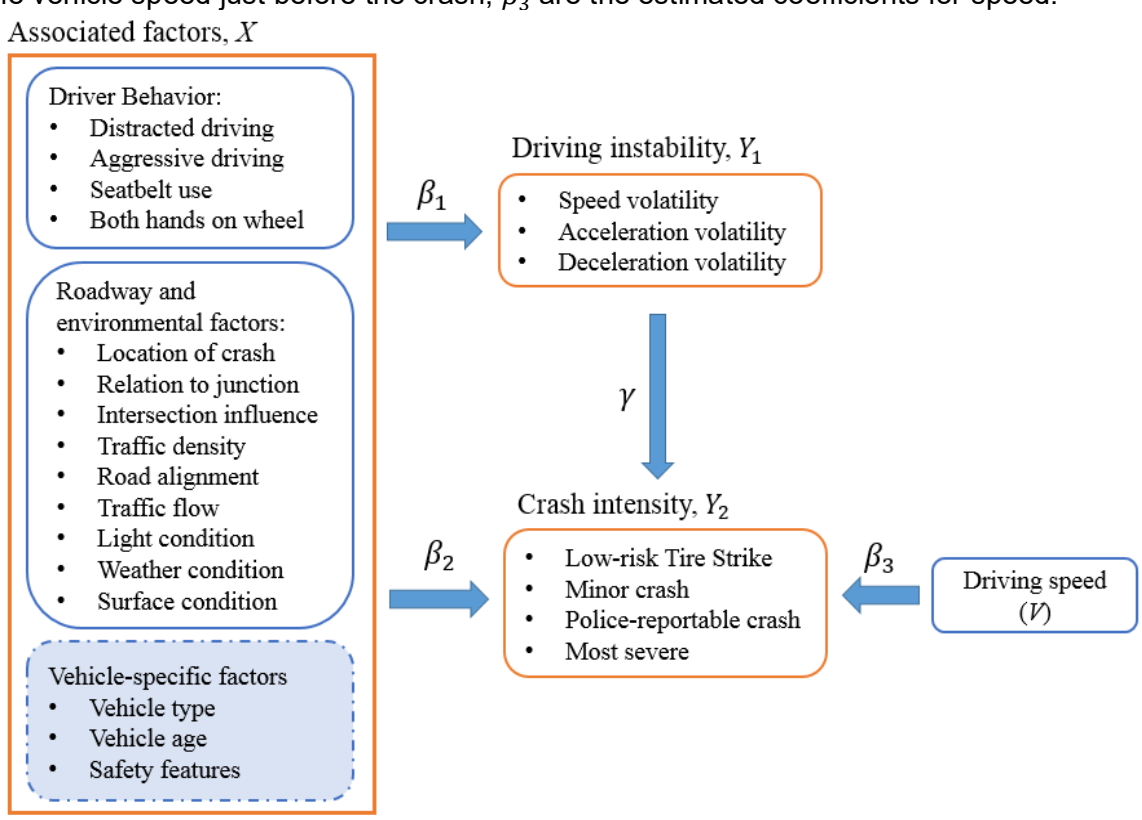


Figure 8 Conceptual framework for the pathways modeled

While driver distractions and roadway/environmental factors can affect the driving speed of vehicles, which several studies have investigated these associations (Gargoum and El-Basyouny

2016, Huang *et al.* 2018, Sadia *et al.* 2018, Wang *et al.* 2019), this study focuses on the investigation of these factors on driving instability and crash intensity."

Table 4 provides the descriptive statistics of the dependent variables (crash intensity, speed volatility and acceleration volatility), and independent variables (impairment/distraction, driving behavior, roadway and environmental factors).

Table 4 Descriptive statistics of the dependent and independent variables (N=617)

Variable	Description	Mean/ Percent	S.D./ frequency	Min	Max
Crash intensity (Y2)					
	Low-risk Tire Strike	40.19%	248	0	1
	Minor Crash	36.79%	227	0	1
	Moderate Crash	13.61%	84	0	1
	Severe Crash	9.4%	58	0	1
Instablity in driving (Y1)					
$Speed - S_{dev}$ (m/s)	*Standard deviation of speed*	3.9	2.35	0.15	12.43
$Decel - C_v$ (m/s^2)	*Coefficient of variation of deceleration*	1.04	0.37	0	2.72
Driving behavior					
Hand on wheel	*Two hands on wheel*	46.52%	287	0	1
	Other	53.48%	330	0	1
Aggressive	*Aggressive driving*	9.72%	60	0	1
	None	90.28%	557	0	1
Distracted	*Distracted driving*	64.67%	399	0	1
	None	35.33%	218	0	1
Seatbelt	*Seatbelt used*	90.6%	559	0	1
	No	9.4%	58	0	1
Legal Maneuver	*Yes*	82.82%	511	0	1
	No	17.18%	106	0	1
Roadway/Environmental factors					
Locality	*Business/Industrial*	46.84%	289	0	1
	Bypass/Divided Highway with traffic signals	2.59%	16	0	1
	Church	2.11%	13	0	1
	Bypass/Divided Highway with no traffic signal	6.65%	41	0	1
	Moderate residential	19.77%	122	0	1
	Open country	1.13%	7	0	1
	Open residential	5.19%	32	0	1
	Playground	0.81%	5	0	1
	School	7.78%	48	0	1
	Urban	7.13%	44	0	1
Relation to Junction	*Relation to junction (base: non-junction)*	27.07%	167	0	1
	Driveway, alley access, etc.	5.67%	35	0	1
	Entrance/Exit ramp	2.11%	13	0	1
	Interchange area	3.4%	21	0	1
	Intersection	19.77%	122	0	1
	Intersection-related	11.35%	70	0	1
	Other	0.49%	3	0	1
	Parking lot entrance/exit	13.94%	86	0	1
	Parking lot, within boundary	16.21%	100	0	1
Density	*Traffic density (base: LOS A)*	73.42%	453	0	1
	LOS B	18.31%	113	0	1
	LOS C and Below	8.27%	51	0	1
Road Alignment	*Straight*	85.74%	529	0	1
	Curve	14.26%	88	0	1
Roadway type	*Divided (median strip or barrier)*	22.69%	140	0	1
	No lanes	17.18%	106	0	1

	Not divided - center 2-way left turn	5.51%	34	0	1
	Not divided - simple 2-way traffic way	48.30%	298	0	1
Surface condition	*One-way traffic*	6.32%	39	0	1
	Dry	74.39%	459	0	1
	Ice/snow	3.24%	20	0	1
	Other	0.32%	2	0	1
	Wet	22.04%	136	0	1
Weather	*Weather (base: no adverse condition)*	85.58%	528	0	1
	Adverse Conditions	8.59%	53	0	1
	Mist/Light Rain	5.83%	36	0	1

As shown in Figure 9, instability in driving (in terms of speed and deceleration volatilities) is highly associated with an increase in the probability of severe crashes. On the other hand, impaired driving in terms of distraction is associated with the instability in driving and indirectly associated with the intensity outcome of the crash. Furthermore, it directly increases the likelihood of a severe crash. Referring to volatility measures, results revealed that a one-unit increase in the speed volatility is associated with a 0.4 percent chance of severe crashes. Considering a wide range of speed volatility, its impact can be substantial. Furthermore, higher deceleration volatility positively and significantly associates with an increase in the probability of a severe crash. A one-unit increase in deceleration volatility is associated with an increase in the chance of severe crash for 10.9 percent. In addition, the vehicle speed is directly associated with the crash intensity, and 1 m/s increase in the speed of the vehicle is associated with a 0.3 percent increase in the chance of a severe crash, which is in line with previous studies (O'donnell and Connor 1996, Yasmin *et al.* 2014).

Previous studies investigated the association of distracted driving on the crash intensity, and it was shown that distracted driving increases the probability of a severe crash (Neyens and Boyle 2008, Donmez and Liu 2015). Modeling results revealed that distracted driving increases the probability of severe crash by 11.1 percent. On the other hand, although aggressive driving is not significant in the crash intensity model, the indirect association through speed and deceleration volatilities increase the probability of a severe crash by 1.3 percent.

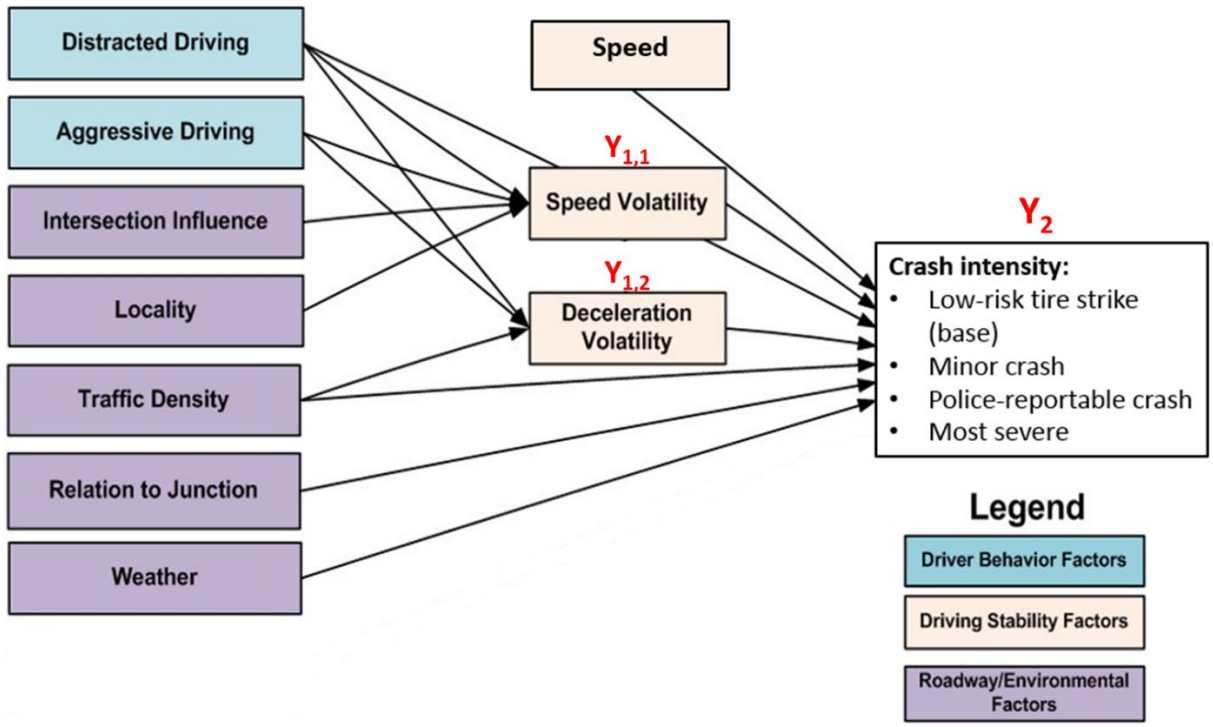


Figure 9 Pathway diagram of the model

Based on the analysis, speed and deceleration volatilities are highly associated with an increase in the probability of severe crashes. The marginal effect is provided in Table 5, which illustrates the effect of driving volatilities on crash intensity. The contributing factors that are associated with the speed and deceleration volatilities are indirectly associated with the intensity outcome of the crash. Although some factors are not significant in the intensity model, they are significantly associated with driving volatilities and indirectly correlated with the intensity outcome. As an illustration, aggressive driving is not significant in the severity model, and one might conclude that it is not correlated with crash intensity, while it is significant in volatility models and indirectly increase the likelihood of a severe crash. In the following, the marginal effect analysis for severe crashes is discussed, and the results for other severity categories can be found in Table 5.

As discussed in the previous section, instability in driving prior to a crash occurrence significantly increases the probability of a severe crash. Referring to volatility measures, results revealed that one-unit increase in the volatility is associated with a 0.4 percent chance of severe crashes. Considering a wide range of volatility, its impact can be substantial. Furthermore, higher volatility positively and significantly associates with an increase the probability of a severe crash. A one-unit increase in volatility is associated with an increase in the chance of severe crash for 10.9 percent. In addition, the vehicle speed is directly associated with the crash intensity and 1 m/s increase in the speed of the vehicle is associated with a 0.3 percent increase the chance of a severe crash, which is in line with previous studies (O'donnell and Connor 1996, Yasmin *et al.* 2014).

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volatilities increase the probability of a severe crash by 1.3 percent. Referring to the crash location, comparing to the non-junction, entrance/exit ramps and interchange areas increase the likelihood of a severe crash by 9 and 8.3 percent, respectively. On the other hand, parking lot crashes are less severe than at non-junction areas. Volatility at intersections is higher than non-intersections, indirectly increasing the probability of a severe crash.

Table 5 Total marginal effect of random parameter model on crash intensity (in percent)

Variable	Direct Marginal Effect			Indirect Marginal Effect via volatility			Total Marginal Effect		
	Minor	Moderate*	Severe**	Minor	Mod.	Severe	Minor	Mod.	Severe
Speed	0.3	0.3	0.3				0.3	0.3	0.3
Speed volatility	0.5	0.4	0.4				0.5	0.4	0.4
Deceleration volatility	11.7	11.1	10.9				11.7	11.1	10.9
Aggressive driving *(Yes=1, No=0)*				1.0	1.0	1.3	1.0	1.0	1.3
Distracted with secondary task *(Yes=1, No=0)*	2.2	8.6	9.9	0.0	0.8	1.2	2.2	9.4	11.1
Traffic density *(base: LOS A)*									
LOS B	1.6	4.7	6.9	1.1	1.5	1.6	2.7	6.2	8.5
LOS C and Below	0.0	11.6	15.8	2.1	3.6	3.2	2.1	15.2	19.0
Relation to junction (base: segment)									
Driveway, alley access, etc.	-3.8	-2.7	-2.4				-3.8	-2.7	-2.3
Entrance/Exit ramp	2.5	8	9				2.5	8	9
Interchange area	2.7	7.5	8.3				2.7	7.5	8.3
Intersection	-4.9	-3.3	-2.9				-4.9	-3.3	-2.9
Intersection-related	-4.9	-3.4	-3.0				-4.9	-3.4	-3.0
Other	-4.7	-3.2	-2.9				-4.7	-3.2	-2.9
Parking lot entrance/exit	-13.1	-6.9	-5.7				-13.1	-6.9	-5.7
Parking lot, within boundary	-9.7	-5.6	-4.7				-9.7	-5.6	-4.7
Weather (base: clear)									
Adverse Conditions	2.7	4.1	4.2				2.7	4.1	4.2
Mist/Light Rain	1.6	1.8	1.8				1.6	1.8	1.8
Number of the lanes				0.0	0.8	1.8	0.0	0.8	1.8
Intersection influence *(Yes=1, No=0)*				0.1	0.2	0.3	0.1	0.2	0.3
Locality (base: business area)									
Bypass/Divided highway with traffic signals				0.3	0.9	1.2	0.3	0.9	1.2
Bypass/Divided highway with no traffic signal				0.3	0.7	1.0	0.3	0.7	1.0
Moderate residential				0.0	0.2	0.3	0.0	0.2	0.3
Open residential				0.2	0.6	0.7	0.2	0.6	0.7
School				0.0	-0.1	-0.1	0.0	-0.1	-0.1
Urban				0.0	-0.1	-0.1	0.0	-0.1	-0.1
Other				0.0	0.0	0.0	0.0	0.0	0.0

* Police reportable crash (base is tire-strike)
** Most severe crash

3.5 Anomaly detection by developing complex event-stream processing and deep learning model

3.5.1 Conceptual Framework

The goal of this chapter is to illustrate the development of a deep learning framework that integrates multiple data streams representing vehicular kinematics (in terms of speed, longitudinal and lateral accelerations, driving stability) and driver behavior to predict in real-time unsafe driving situations. The framework can process micro-level driving data, extract volatility features and learn driving patterns and behavior to quantify crash or near-crash (CNC) risk, which can have a substantial impact on safety. The developed framework has several advantages:

a. The architecture configuration of the estimated model is compact, making the model easy to implement for real-time safety performance monitoring and safety-critical event prediction.
b. The framework has the ability to capture temporal variations in the input data, which is generated from multiple sensors in a vehicle.
c. The capability of the model to be efficiently trained with a limited training dataset, while utilizing back-propagation iterations.

With the emergence of new data sources in automated vehicles, this study is timely and original as it harnesses streaming (big) data and incorporates the data in instantaneous driving behavior analysis. This is done by developing a deep learning framework, which can predict unsafe driving situations and in such cases warn drivers regarding the heightened risk of crash involvement. The compact configuration of the developed model enhances ease of implementation for car companies in real-time applications.

Figure 10 provides the framework used to apply the deep learning methods. It has three main phases. The first phase is sensing, which collects driver information (i.e., in terms of distraction) and vehicular movements (i.e., speed, longitudinal and lateral acceleration). As discussed in the previous section, the data is preprocessed and cleaned by excluding the evasive maneuvers of CNC events and considering 15 seconds for each event. In the second phase, the raw data is fed to the feature extraction phase to obtain volatility indices at the event and temporal levels. Seventeen volatility indices are extracted to quantify speed and longitudinal and lateral acceleration variations. Finally, the raw data and extracted features are fed to the deep-learning phase. Deep Neural Net (NN), one dimensional Convolutional Neural Net (1D-CNN), Long Short-Term Memory Recurrent Neural Net (LSTM RNN), and 1DCNN-LSTM models are developed to classify events as either baseline or critical events and evaluate the performance of the models.

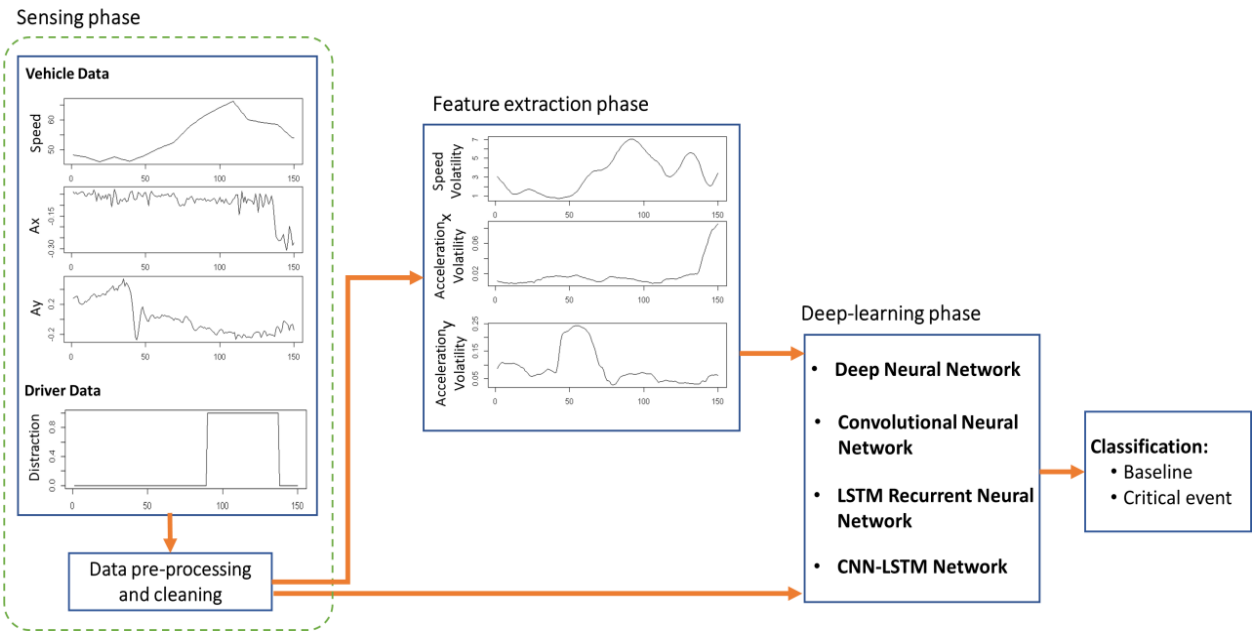


Figure 10 Conceptual framework of the study

3.5.2 Problem formulation

Three deep-learning methods are utilized to predict the occurrence of an anomaly in terms of a crash and near-crash: Deep Neural Network, 1D-Convolutional Neural Network (1D-CNN), Long Short-Term Memory (LSTM), and 1DCNN-LSTM model. While the multi-layer deep neural network processes the input data and information through interconnected neurons, it suffers from the limitation of the base assumption that all inputs are independent of each other, which is not the case in different fields, such as image classification, language processing, and timeseries problems. Therefore, several methods are proposed to address the dependency in the input of the network (in this paper time dependency) by including local information (temporal information) in the input data. The main contribution of our approach is the development of a deep learning framework that integrates multiple data streams, including vehicular kinematics in terms of speed, longitudinal and lateral accelerations, driving stability, and driver impairment to predict the occurrence of a crash/near-crash. The framework can process micro-level driving data, extract volatility features, and learn driving patterns and behavior to quantify crash risk, which can have a substantial impact on the field.

This project utilized one of the most novel approaches in AI, 1DCNN-LSTM, which can capture time dependency between times series data and vehicle trajectories, and also extract addition features using convolutional layers. The structure of the 1DCNN-LSTM model is shown in Figure 11.

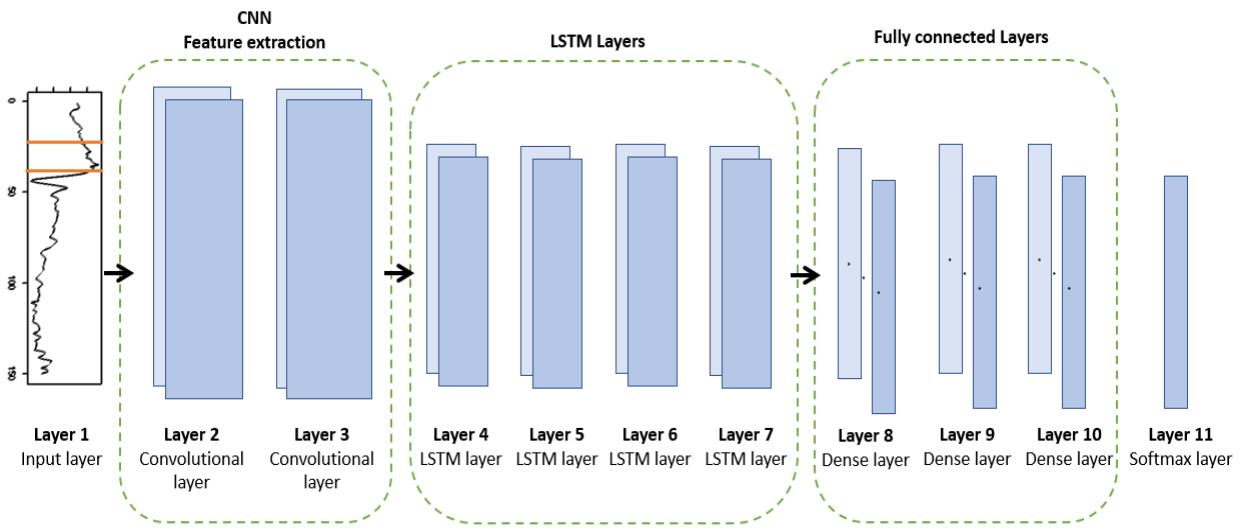


Figure 11 – Structure of the 1DCNN-LSTM model

Figure 12 illustrates the accuracy and loss for the training and validation data compared to the training epoch for each model. Based on the results, the performance of the 1DCNN-LSTM model in terms of training and validation accuracy and loss is better at predicting outcomes than other models (the measures used are defined formally in the following section). Further details are provided in the following section.

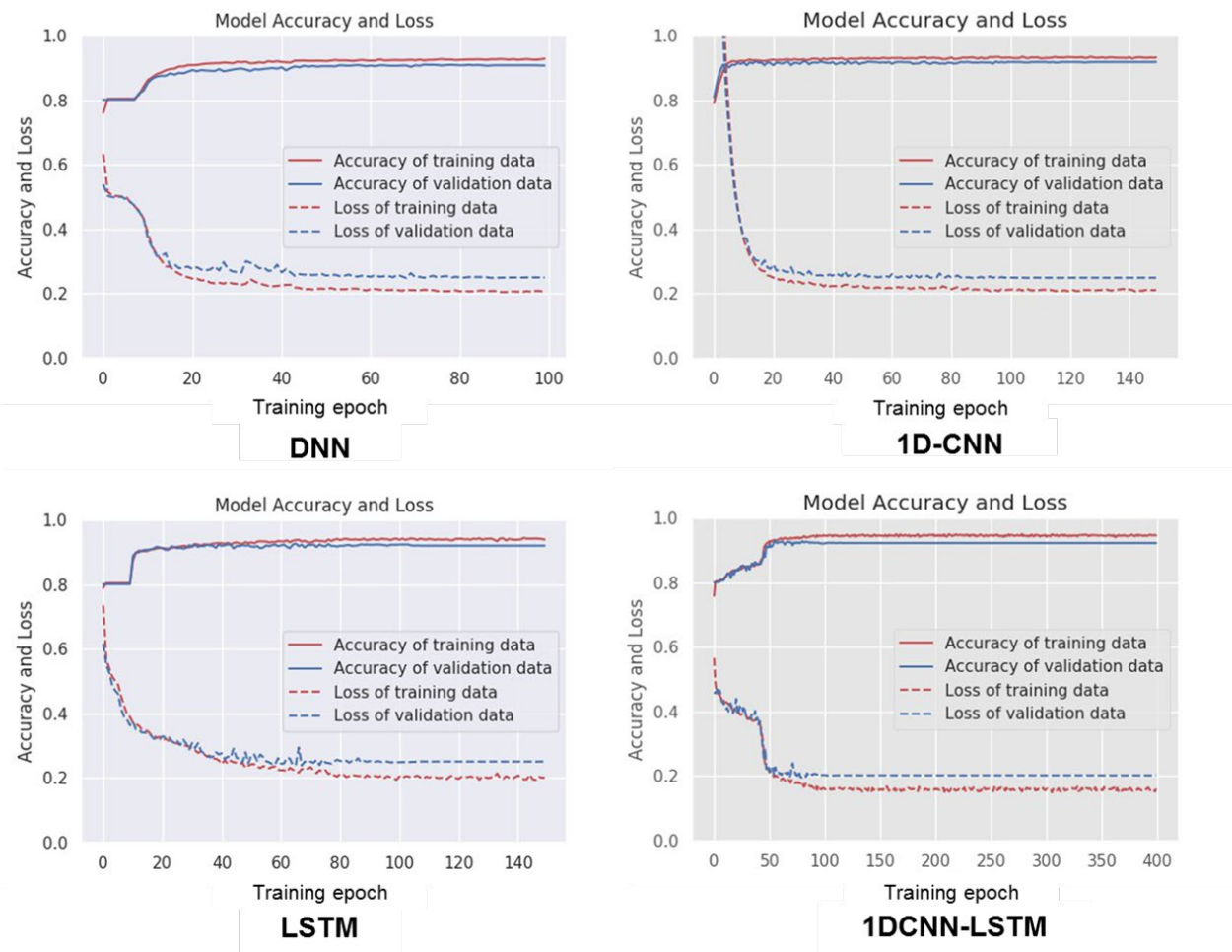


Figure 12 – Accuracy and loss for the training and validation datasets

In order to evaluate the performance of different AI techniques, four specific metrics are used: accuracy, precision, recall, and F-measure (F_1). We can write:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

$$Precision_c = \frac{TP_a}{TP_a + FP_a} \tag{10}$$

$$Recall = \frac{TP_a}{TP_a + FN_a} \tag{11}$$

$$F_1 = \sum_i 2 * w_i \frac{Precision_i * Recall_i}{Precision_i + Recall_i} \tag{12}$$

where TP, TN, FP, and FN are the total true-positive, true-negative, false-positive, and false-negative predictions, P_a, FP_a and FN_a are the number of true-positive, false-positive, and false-negative of class *a*.

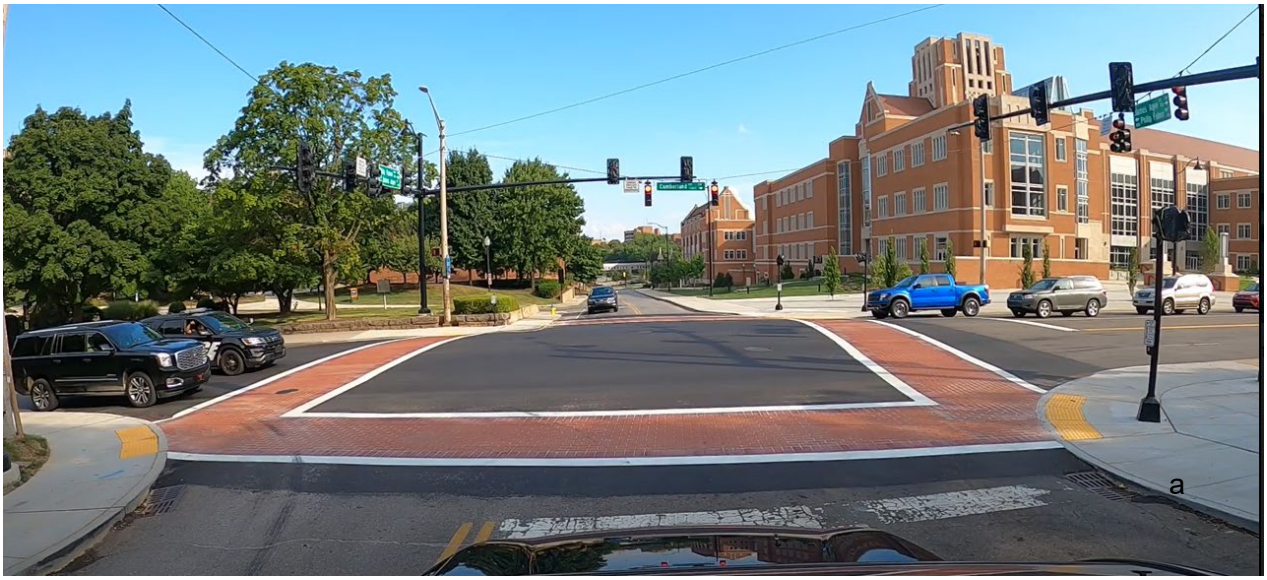
By utilizing the aforementioned metrics, models' performance is provided in the Table 6. The results revealed that the 1DCNN-LSTM model performs the best compared to other AI models. It can be inferred that by addressing temporal dependency of observations and extortion of additional features using the CNN layers, model performance can substantially improve compared to other models. By focusing on the extreme events, it can be observed that 70% of crashes are predicted correctly with the precision of 95%. Referring to the baseline (no events), 99% of events are predicted correctly with precision of 92%.

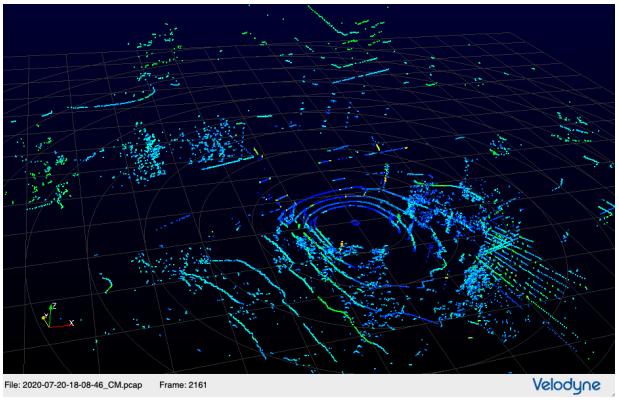
Table 6 – Performance of the developed models

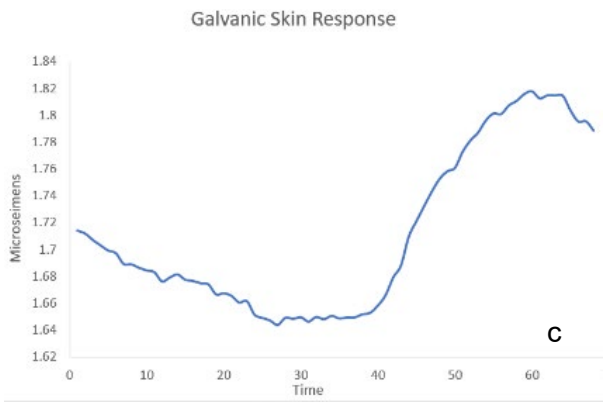
		Train Data				Test Data			
	Metric	**DNN**	**1D-CNN**	**LSTM**	**1DCNN -LSTM**	**DNN**	**1D-CNN**	**LSTM**	**1DCNN -LSTM**
Overall	*Accuracy (%)*	93.07	94.96	93.05	94.16	88.51	91.49	91.04	**92.5**
	Loss	0.2128	0.1477	0.2015	0.1998	0.31	0.25	0.25	**0.24**
Baseline	*Precision*	0.92	0.94	0.92	0.94	0.90	**0.93**	0.90	0.92
	Recall	0.99	0.99	0.99	0.99	0.94	0.96	**0.99**	**0.99**
	F_1*-Score*	0.96	0.97	0.96	0.97	0.93	**0.95**	**0.95**	**0.95**
Critical Event	*Precision*	0.97	1.00	0.97	0.97	0.77	0.90	**0.97**	0.95
	Recall	0.67	0.75	0.65	0.76	0.69	0.67	0.61	**0.70**
	F_1*-Score*	0.79	0.85	0.77	0.85	0.72	0.77	0.75	**0.80**

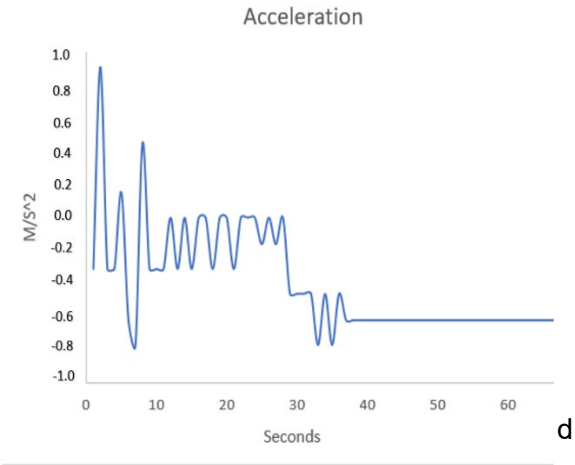
4. Driving experimentation in simulated and naturalistic settings and next steps

The analysis presented previously sets up a foundation for further experimentation in simulated and naturalistic settings. The next phase of the research will provide diverse sets of biometric data that can be analyzed further. In this regard, a review of the relevant literature was conducted to understand the state-of-the-art in driver monitoring systems. The review focuses on peer-reviewed journal papers, as described in the Appendix. While the driving simulator data experimentation was not possible, given the circumstances created by the pandemic, the team is in the process of collecting driving data in a naturalistic driving setting. Specifically, vehicle, biometric, driver, and roadway data are obtained using multiple sensors under different driving scenarios Experimental participants are asked to complete an approximately 1.5 km driving course located around the University of Tennessee, Knoxville campus without participating in “distracted” behavior (e.g., operating a cell phone, eating, talking). This area was chosen due to the presence of several crosswalks, light and sign-controlled intersections, as well as predictable levels of automobile, pedestrian foot, and bicycle traffic. This unique location gives our team the ability to increase or decrease the potential cognitive workload load of participants during our experiments based on the degree of activity. Biometric sensors including, galvanic skin response (GSR), electrocardiogram (EKG), and electromyographic (EMG) data are used to monitor driver physiological response to changes in cognitive load while driving. GSR sensors measure changes in skin conductance related to perspiration due to an emotional response. EKG measures the electrical signals throughout different parts of the heart as well as heartbeat tempo. EMG measures electrical activity in muscles and are useful in determining if a muscle is contracted. Video data and LiDAR are collected from two externally-mounted cameras and a Velodyne Puck respectively to capture a 360° field of view while an additional camera records the behavior of the driver. Simultaneously, vehicle dynamical data are collected with an advanced driver assistance system (ADAS) that directly integrates with the vehicle computer. These multiple streams of data will be used to develop a real-time monitoring system to determine “normal” driving behavior from distracted driving behavior (see Figure 13).









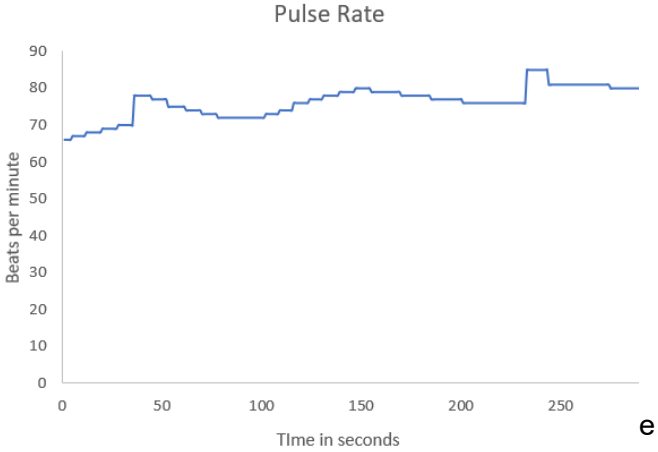


Figure 13: a) Image obtained at stoplight at a busy intersection b) Corresponding LiDAR point cloud. c) Galvanic Skin Response and vehicle acceleration data obtained while approaching a stoplight at a busy intersection. Note the increase in skin conductance as the driver processes information at a busy intersection. d) Acceleration data obtained approaching intersection. e) Pulse rate recorded for duration of the driving course.

5. Summary

This report documents the activities undertaken by the research team during the first year of the project. Combining the team's earlier work with new efforts, we have developed a framework for obtaining, processing, and analyzing high-frequency multi-dimensional large-scale data using sensors that monitor the driver, vehicle, and roadways. The framework harnesses the data by exploring volatility. Detailed naturalistic driving study data from the NDS SHRP-2 program was analyzed for obtaining insights on impairment and distracted driving. The risks associated with engagement in non-driving tasks in terms of safety critical events are quantified and discussed. A real-time artificial intelligence method is applied to harness the data and quantify instantaneous crash risk by monitoring driver biometrics (in terms of distraction), vehicular movements, and volatility in driving. The analysis presented can detect anomalies in driving, which can lead to crashes and near-crashes. Finally, the use of experimentation in simulated and naturalistic settings is demonstrated. The entails collection and processing of driver biometric, vehicle, and roadway surroundings data. This effort further includes a review the literature on driver monitoring, as well as setting up the experimentation procedures, which will contribute to future research in driver biometric monitoring and impairment detection.

6. Limitations and future studies

There are several limitations in this study which needs to be addressed and can be venue for future researches:

1. While this study attempted to account for roadway and environmental factors by incorporating these variables in the modeling (such as locality, traffic density, relation to junction, and weather conditions), the research team does not have access to the Roadway Information Database (RID), which provides more detailed information on roadway factors. Future research is needed to explore the association of roadway factors and impairment/distraction.
2. Several studies in the literature have explored the association of impairment and distraction on vehicle lane positioning and deviation from lane. These studies have found that impairment and distraction can significantly reduce drivers' ability to perform lateral vehicle control [1-3]. It is worth noting that performing such an analysis requires data on relative lateral position of vehicle to lanes, which is not available in the SHRP2 NDS data. Future study should address this limitation by collecting this information and explore the role of impairment on driver lane keeping performance.
3. This research has explored the role of impairment and distraction on instability of driving, in terms of variations in speed and acceleration. However, distractions may also affect the speed choice of drivers as they compensate for intentional distractions. Future research can focus on exploring how much reduction in speed is observed in distraction situations and to what extent such reduction in speed reduces the heightened crash risk due to distraction.

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Appendix: Literature Review

Overview

This Appendix describes a historical overview of the events leading up to the current state of driver monitoring systems. An in-depth review was offered regarding several significant peer-reviewed articles from the last five years. Moreover, approximately 200 articles were surveyed to gain insight into the development of this field. Driver monitoring is continually growing and accelerating at an astonishing pace in both industry and academia (see Figure A 1).

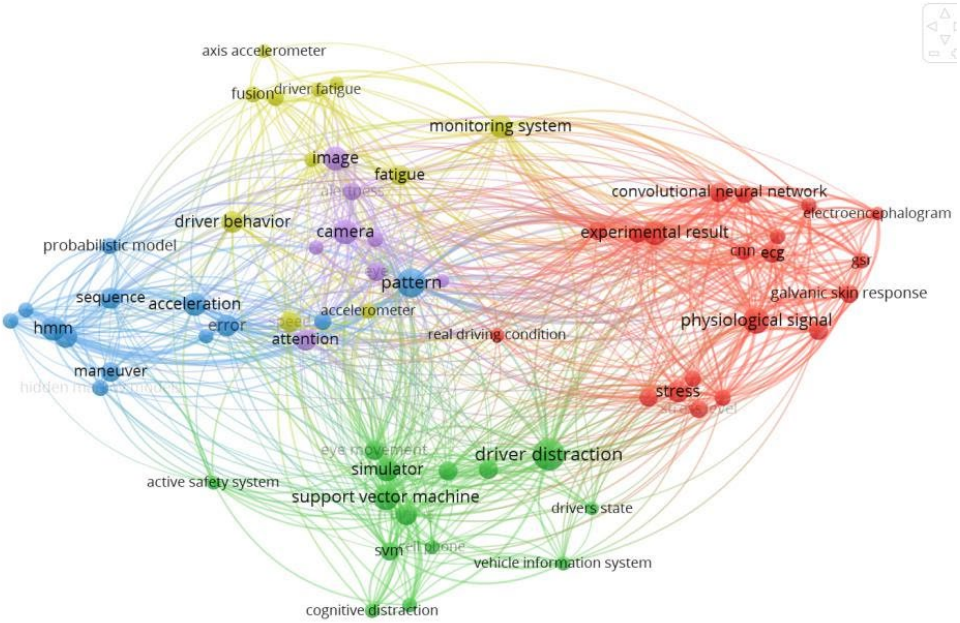

Figure A 1: Additional insight into the complex web of research encountered for this review alone can be gained by a bibliographic analysis map.

Note: This map displays the relationships of vocabulary used in approximately 200 journal abstracts. Map created in VOSViewer. Sphere size displays the frequency of key terms in all abstracts and titles. Distance from nodes display similarities in overall text analysis.

Since the car became ubiquitous in society, distracted driving has been a problem. Distracted driving became a problem almost immediately. Serious debates occurred on whether to install radios in cars in the 1920s and 1930s. Though research progress has been extremely slow pace at times, researchers have investigated driver behavior for approximately 80 years. Vehicle operator fatigue appears to have been studied approximately 20 years earlier than distraction. Investigations on the effects of fatigue on World War 2 pilots and Army truck drivers began appearing in the 1940's (Pugh et al.1942, Epstein 1944). These investigations on distraction focused on topics ranging from the effects of musical tempo (e.g., "slow" vs Tijuana Brass band) on driving speed (McDougal 1967) in 1967, to driver behavior at railroad crossings and stop lights in 1976 (Alberg 1976). Due to a lack of computing power and slow information spreading, many earlier e orts seemed to be more qualitatively oriented rather than based on statistical modeling or any AI methodology. As portable technologies (e.g., cell phones, and car phones) became more prevalent and affordable in vehicles, accidents as a result of distraction became more prevalent. These new portable communication devices motivated studies in the early 1990s on distraction due to cell phone use while driving (McKnight and McKnight 1993).

The 1990's

Early work in defining stages of driver fatigue began in the 1990s. This work helped understand nuances of fatigue so appropriate measures could be considered in proposals of a theoretical monitoring system (Brown 1997). Concurrently, image analysis, and physiologic sensor-based techniques were being developed from a computer science point of view (Ueno et al. 1994, Artaud el al. 1995). The late 1990s brought about two particularly interesting papers in driver monitoring. Huang et al., 1998 investigated identifying face poses with SVM (Huang et al. 1998). Contemporaneously, drowsy driver detection systems were developed using NN to monitor %age eye openness tracking (PERCLOS) and lane position holding for heavy commercial vehicles (Grace et al. 1998).

The 2000's

The beginning of the 2000s was an exciting time for computers and computer science. From 2000-2009, driver monitoring research accelerated and began to progress much quicker than the previous decades. Following the invention of Graphical Processing Units (GPU), techniques such as hyper-threading and virtualization enhanced the ability to process data more efficiently and faster (Marr et al. 2002).

The new millennium brought about some of the first studies using an array of biosensors to detect driver stress levels with linear discriminate analysis (Healy et al. 2000), dynamic Bayesian networks (Liao et al. 2005), and emotional classification with Fisher Projection (Picard et al. 2001). Other researchers attempted to complete the same task autonomously using NN with great success (Haag et al. 2004). From a navigational point of view, Mitrovic (2005) began looking into prediction driving patterns through analysis of vehicle dynamics using HMM with a 98.3 % accuracy of predicting seven possible driving maneuvers (Mitrovic 2005). (Lee et al. 2006) used HMM as well to predict lane keeping behavior with imagery rather than vehicle dynamic data. However, the model encountered several problems and was overall unsuccessful. A particularly interesting study by Liang et al., 2007 investigated driver cognitive distraction with SVM and logistic regression eye-gaze data collected in a simulator (Liang 2007). With increasing graphics capabilities and affordability, simulator-based data collection became more common.

Highly accurate drowsy driver detection became more of a realization in the 2000s as well. Several years after Yoav Freund and Robert Schapire constructed the AdaBoost algorithm, it was employed to detect fatigued drivers by analysis of facial movements collected from subjects that played a driving video game. This study successfully predicted crashes at approximately 96 % accuracy (Vural et al. 2007). Automobile crash and reckless driving detection by vehicle dynamic analysis with fuzzy logic were also investigated in this decade (Imkamom et al. 2008, Boonmee and Tangamchit 2009)

Lastly, the late 2000s brought about the development of driver monitoring systems and attempted to design the first mitigation systems (Malik and Rakotonirainy 2008) conceptually. Critical work in this area was completed by Dr. Michael Regan and team at the University of South Wales throughout the 2000s and on into the 2010s. His group researched a variety of distraction type including: effects of texting (Horberry et al. 2006), driver age (Horberry et al. 2006), cell phones (Hallett et al. 2011), and enhanced road markings (Horberry et al. 2006). Most importantly, Regan explored and attempted to quantitatively measure various stages of distraction (i.e., visual, physical, cognitive, and all possible combinations of the three) and established the definition that is commonly accepted by the majority of researchers in this field (Regan et al. 2011). As time progressed into the 2010s, research in driver monitoring continued to accelerate at an incredible pace with a goal for real-time driver monitoring.

An in-depth look: 2015-2020

Craye and Karray (2015)

Craye and Karray (2015) used a combination of HMM and AdaBoost to detect and classify distracted behavior with RGB data. Approximately eight hours of driving data were collected under simulated conditions from eight diverse participants in age, sex, gender, and nationality using Microsoft's Kinect, an accessory component of the Xbox gaming console. The Kinect was designed to provide a hands-free gaming experience and collects/tracks multiple persons at once as well as collect audio data. The unit also was created with a user-friendly software development kit (SDK) that computer vision specialists have utilized greatly. Four modules were constructed to capture and extract: 1) gaze orientation and pupil tracking 2) arm position 3) face orientation 4) mouth and eyebrow position. Steering wheel orientation, acceleration, and heartbeat data were also collected. Participants were asked to emulate different distraction events (e.g., phone calls, drinking, texting, diverting eyes from the exterior, and normal driving). After data collection, distraction events were manually recorded for half of the experimental drivers to be used as training data. The second half was used as testing data. Lastly, the authors used AdaBoost and the Viterbi algorithm from a previously constructed HMM SDK on collected data. The results of these two classifiers were averaged and compared. Both AdaBoost and HMM detected some distraction events at approximately 90 %. However, the average accuracy of the two classifiers was somewhat lower (approximately 85 %). HMM performs better than AdaBoost for some drivers but worse for others. The authors explained that these results are due to a low sample size compared to the number of features they attempted to classify. Though humans mechanically operate in similar ways, subtle body movements between only eight subjects could cause unintended results. The authors do not explain why such a small sample size was chosen but it is conceivable that a larger sample group could have improved results. Though the results of this study were not the best in the driver monitoring arena, the authors demonstrated some creative methodologies in the definition of types of distraction and certain aspects of the experimental design. It was refreshing to see a study attempt to have diverse subjects as well. However, the low sample size and simulation design of this study could have contributed to the relatively low accuracy reported. A brief description of the simulator is given without details on the actual set up. Also, it is unclear why the authors chose to remove the background from the driver completely. The Kinect is capable of capturing relatively high-resolution data. It is possible that background 3D data from the driver seat and cockpit could be used to decrease any error. Moreover, the organization of the article could have greatly improved (e.g., Methods described in Results.) (Craye and Karray 2015).

Lee et al., 2016

Lee et al., 2016 presented work on drowsy driver detection through a wearable smartwatch and SVM. The team used accelerometer and gyroscopic data collected from 20 participants (5 female and 15 male). From the smartwatch based sensors, radial velocity and linear acceleration data were recorded while participants navigate a simulated track in the Eurotrack Simulator 2. Participants were asked to verify their level of drowsiness based on the Karolinska Sleepiness Scale (KSS), ranging from 1 ("Extremely Alert") to 10 ("very sleepy, can't stay awake"). Though this scale might appear to be subjective, participants were monitored by a physician throughout the experiment in hopes to improve objectivity. The experiment included 60 minutes of training on the simulator and 60 minutes for data collection. Participants were asked to keep hands on the steering wheel for the entire experiment. Data were excluded for any time duration that the participants deviated from this instruction. For data preprocessing, 3D data points were converted to a resultant magnitude. Next, their moving averages were calculated over one minute

increments. Through their statistical analysis, 14 features were chosen from linear acceleration and 14 from radial velocity. For drowsiness detection, kernelized SVM were constructed for both right and left hands. Manual monitoring of the data points shows that 8.64 % contained a drowsy signal. The SVM was then trained on the identified 8640 drowsy points.

Impressively, the two SVM algorithms provided an accuracy of approximately 98 %. A positive aspect of this study was the recruitment of a physician to help determine KSS. Their experimental design was well thought out and executed superbly. Though this team captured outstanding results, several aspects of the paper lacked organization (e.g., results listed in methodology, and methodology in results). It also lacked a thorough explanation of why two separate SVM for each hand would have been beneficial. This paper was fairly short (less than 8 pages) and could have augmented most sections for more detailed explanations. Although some sections of this article could have been improved, the motivation for the study was highly relevant. Electroencephalogram usage has been proposed and studied to detect driver distraction, drowsiness, and many other conditions. However, it seems highly unlikely that an EEG would be practical for use in cars due to the awkwardness of design, discomfort to the wearer, extreme sensitivity, and provide latent data streams. Nonetheless, the high accuracy reported in their study makes up for some of the shortcomings (Lee et al. 2016).

Masood et al., 2018

Masood et al., 2018 developed an optimized version of two CNN architectures (VGG16 and VGG19, for a thorough description, see (Simoyan and Zisserman 2014) to detect distraction from imagery alone. Their study used the popular State Farm Distracted Driver (SFDD) data set (https://www.kaggle.com/c/state-farm-distracted-driver-detection). The SFDD is collection of approximately 22,000 images of subjects emulating either normal driving or a variety of distracted behaviors including right and left hand texting, right and left hand phone call, adjusting the radio, reaching behind the seat with a right hand, applying makeup, and looking at a passenger. After resizing imagery to be compatible with VGG16 and VGG19, the authors applied an innovative technique to increase training image quantity by applying alterations to each image. For example, an image could be sheared or translated o -center. If executed correctly, the image would appear different but still retain the original distraction classification. This process enabled the authors to input new imagery for each epoch ran. Additionally, the authors normalized imagery by calculating and then subtracting the mean from each image. After image processing and data augmentation, their team utilized the Keras and TensorFlow DL libraries in Python. In their attempt to increase processing speed, weights were pretrained on a relatively small portion of an additional data set, ImageNet (Deng et al. 2009, Masood et al. 2018). Both VGG16 and VGG19 were tested using pretrained and randomly assigned weights. The authors reported convergence in both models was achieved after very few epochs (less than 10). Accuracy for each model variation was very high and ranged between 98.54 and 100 %. The pretrained weighted variations performed much faster as well. VVG19 was reported to be less accurate than VVG16. The authors suspected that this result of the model learning superfluous features that lead to overfitting of the training data. Nonetheless, the combination of work presented in this study and the article composition was excellent. CNN can be very slow to train (especially with thousands of images and many epochs. Until recently (Kapoor et al. 2020), this fact often leads to many challenges regarding real-time detection with CNN. The technique that used pretrained weights increased training by approximately 50 times faster than randomly assigned weights. The inventive methodology demonstrated in this study has been incorporated other real-time detection systems with VGG16 in particular. Significant strides have been made in real-time driver monitoring as well as several other scientific fields since this article was published. Besides the very high accuracy reported,

the justification for reviewing this article was that it was written and organized well, even though it was a relatively shorter article (approximately 8 pages).

Gjortski et al., 2020

Gjortski et al., 2020 investigated distracted driver detection by monitoring a combination of video and biometric data. Their study evaluated the performance of seven (each) machine and deep learning algorithms on video and biometric data. Video data were recorded (gaze, pupil diameter, nasal electrodermal activity (nEDA), and facial features) to detect emotional response while wearable sensors collected palm electrodermal activity, heart rate, and breathing rate. Data were collected from a previous study by (Pavlidis et al. 2016).

These 88 channels of data were collected in a driving simulator from 68 participants. Subjects were asked to complete "normal" driving sessions, as well as sessions were distractions were emulated. The study employed a previously developed software tool (AUReader) that was trained to recognize 22 facial expressions by monitoring subtle facial features (e.g., lip corner, inner-outer brow.) (Hassan et al. 2016). After data channels were normalized, facial feature values were statistically (Wilcoxon test) analyzed so that features could be removed that were not informative. Additional steps were taken to extract meaningful GSR signal from the pEDA and nEDA. Interestingly, the statistical test results showed that the most meaningful data were recognized emotions (e.g., joy or sadness) and GSR data from the nEDA

For the ML analysis, decision trees, random forest, naive Bayes, KNN, SVM, bagging, AdaBoost, and extreme gradient boosting (XGBoost) were tested with the Scikit-Learn Machine Learning Python Library. For the DL analysis, seven different architectural designed networks were tested implementing layers that were based on fully-connected NN, CNN, and LTST Memory. All data variables were used except for pupil tracking. Pupil tracking was removed due to an unexplained 50 % loss in data collection. Algorithms were trained on approximately 85 % of the test subjects while the remaining 15 % were used as test data. The ML algorithms were tested in two types conditions 1) window classifier for real-time monitoring and 2) session for analysis of a past driving event. The results of the tested ML analysis show that XBG and GB performed best overall in both conditions. However, accuracy was reported much higher in the session classifiers. For the deep learners, STRNet and eLSTM performed best for both tests but were significantly higher for the session classifiers. A second evaluation of the top two performing ML and DL algorithms was performed on variations of the complete data set at different time intervals. The authors found that XGB performed best out of all algorithms (DL and ML) and reported an accuracy of 99 % for the session classifier, and 79 % for the windowed classifier (see Fig A2). This result was unexpected to the authors and they speculate that a DL did not excel due to the relatively low sample numbers needed for an end-to-end DL solution. Moreover, the highest accuracy reported was based on the facial expression library. The authors seemed surprised that accuracy was the exact same for combining the top two meaningful features compared with combined features.

This article represents one of the more well written and organized articles encountered. Their study extensively investigated sensor fusion and a multitude of ML and DL algorithms. Multimodal data acquisition is a particularly hot topic in the field nowadays. Utilizing statistical analysis to gain insight into which sensors provide the most informative data was clever and may influence researchers to take a more simple approach, especially if there are budgetary concerns. Though the authors did not collect their data, a detailed explanation was provided. Moreover, this study is one of the few that utilize a larger number of samples.

		All		Selected		AUs		EMO		HR		BR		nEDA		pEDA	
Win.	Classifier	F1	F1-s	F1	F1-s	F1	F1-s	F1	F1-s	F1	F1-s	F1	F1-s	F1	F1-s	F1	F1-s
20	GB	73	87	73	87	76	92	73	87	61	76	55	54	63	66	42	27
	XGB	72	88	72	88	76	90	72	82	61	76	55	65	63	63	42	27
	eLSTM	67	75	64	65	53	70	62	69	42	28	58	67	52	46	42	28
	STRNet	67	80	68	83	51	65	65	79	48	41	60	74	52	48	42	28
40	GB	77	85	77	85	79	92	75	88	64	78	57	55	65	65	41	30
	XGB	75	88	75	88	79	88	74	92	63	74	57	60	65	65	41	26
	eLSTM	70	74	68	71	54	67	66	72	55	52	59	54	63	60	42	28
	STRNet	72	82	73	87	53	61	66	77	48	41	60	74	63	64	42	28
60	GB	77	88	77	88	78	86	74	86	65	79	59	58	65	63	45	33
	XGB	76	88	76	88	**78**	**94**	74	83	66	83	59	54	65	65	45	38
	eLSTM	69	72	64	67	55	63	63	66	50	51	66	78	62	64	45	38
	STRNet	74	86	75	87	54	65	66	72	58	57	67	77	61	63	42	28
80	GB	75	92	75	92	78	92	71	82	69	83	61	64	63	65	49	33
	XGB	77	94	77	94	78	90	62	69	68	83	62	69	65	65	49	33
	eLSTM	66	71	64	67	55	61	64	70	55	52	62	69	58	59	42	33
	STRNet	72	82	73	85	56	56	66	71	58	57	69	74	60	61	42	28

Figure A 2: Evaluation of top performing algorithms from Gjortski et al., 2020.

Note: All represent every data stream. Selected represents "Informative" variables. AU represents facial action units, EMO represents emotional response. HR represents heart rate, BR represents breath rate. nEDA and pEDA represent GSR data for the nose and palm respectively.

Though the article was superb in many ways, some minor details could have been improved. Some seemingly meaningful statements went without citation and explanation. Also, an enormous amount of information was packed into 12.5 pages of text. It would: have been beneficial for the authors to offer more detailed information at times, and divide the article into two papers. Lastly, absolutely no description of the biosensors was given. Biosensor quality and data resolution can vary widely and therefore hold the potential to alter results (Gjortski et al. 2020).

Shahyverdy et al., 2020

More recently, Shahverdy et al., 2020 proposed an innovative method to detect and classify different driving styles including aggressive, drowsy, normal, distracted, and drunk. Acceleration, gravity, speed, throttle, and revolutions per minute (RPM) data were collected by an onboard diagnostic tool while three subjects attempted to emulate the aforementioned driving behaviors. Data were then processed from normal spectral-like input into 2D, RGB color images with the recurrence plot technique. Recurrence plots are a method typically used to visually display non-linear data that may appear to be chaotic (see Fig A 3). After the driver data conversion, a three-layer convolutional NN was constructed (CNN). CNN's are a specific architecture of NN that has proven successful for image analysis over many studies (too many to cite). Their CNN consisted of three convolutional layers and used ReLu as an activation function. Dropout and maxpooling were used after layers two and three. Dropout randomly drops the filter from one convolutional node in e orts to avoid overfitting the network. Maxpooling essentially reduces the dimensionality of the data by a user specified amount. Finally, SoftMax is applied at the last step before output. Several versions of the filter quantities in convolutional layers, and other parameters were experimented with and associated accuracy compared. It was found that two convolutional layers with 16 filters in the first layer increased overall accuracy in detection to 99.9 % with a loss of 0.48 %.

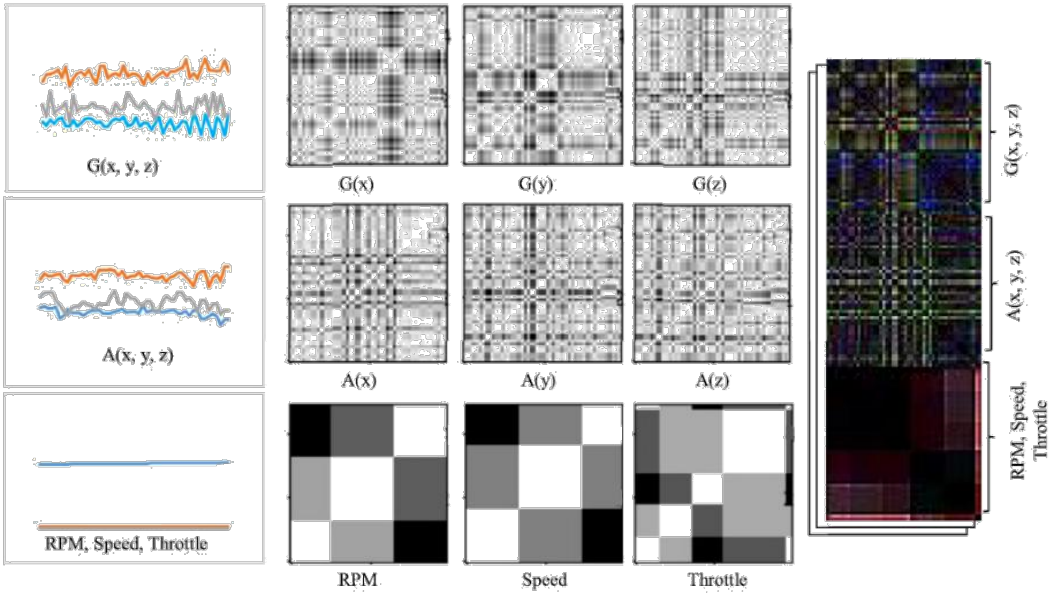

Figure A 3: Recurrence plots from Shahverdy et al., 2020.

Note: The first column displays raw data from the Onboard Diagnostic tool. The middle three columns represent 50 x 50 pixel greyscale converted images. The third column displays the same images post assignment of an RGB scale related to DN number of greyscale pixels.

This study displayed many creative and innovative methods, especially utilizing the recurrence plots to employ CNN. Also, many studies in distracted driver detection utilize simulations for their data collection. It was refreshing to see a study that collected naturalistic driving data with an actual car. Though simulators are usually more affordable and allow for more dangerous situations to be tested, some simulation setups fail to reproduce a realistic scene. While driving mechanics may be appropriately modeled, still and jerky animations from pedestrians and other graphical artifacts could potentially alter the response from the participant. Ideally, future studies would investigate the response between simulated and naturalistic driving experiments. While this study

was exemplary on many accounts, it could have produced more thorough results by utilizing a sample group larger than three people. Also, the use of some sensors appears to be redundant (e.g., RPM and acceleration). Descriptions of modeled behavior seem a bit uninformed. Finally, parts of this paper seemed a bit unorganized. For example, some methodologies were explained in the results section. Despite these few shortcomings, the technical aspects of the paper and creative methods were superb (Shahverdy et al. 2020).

Li et al., 2020

Li et al., 2020 proposed a distracted driver detection system based on recognition of the ear and hand position of the driver. These researchers built a system consisting of two established DL algorithms, "You Only Look Once" (YOLO), and a multilayer perceptron (MLP). Video data were collected of twenty participants (8 female, 12 male) by a camera mounted from the passenger perspective in a vehicle cockpit based simulator (RTI Driving Simulator, Ann Arbor, MI). Subjects were asked to drive a fifteen-minute course with several navigational directions. Drivers were also asked to complete several manual tasks to emulate a distraction. These tasks included talking on a cell phone, texting, drinking water, operating a touchscreen, and placing a marker into the cup holder. The detection system was designed to work in two modules. YOLO detected ear and hand position and the MLP classified the type of distraction that occurred. The algorithm was manually pretrained on half of the collected data as well as the Viva hand tracking data set. After image frames were resized and assigned a grid system, YOLO with help from a KNN determined bounding boxes for recognizable features in the image. A probability of class prediction was then calculated based on their manually labeled ground truth. The MLP was designed with six layers and a ReLu activation function, and batch normalization after each dense or connected layer. Results from this study reported that YOLO took approximately three hours to run while the MLP only took minutes. Though creative approaches were practiced with this study (i.e., pretraining) the achieved results reported relatively low accuracy (overall 82 % at 28 frames per second). The authors suggest that accuracy could be improved at the expense of processing speed, rendering this method to be ineffective for real-time monitoring.

This work presented in this paper demonstrated many positive qualities. First, their team used a proper, high quality simulator for data collection that included three 46" monitors to provide the driver with ap-proximately 200 degrees of visual perception. More than often, research groups use overly simple simulation set-ups that consist of only an office chair, a single PC sized computer monitor, and a gaming console control or steering wheel. Likely, a higher quality simulator with multiple larger screens and a realistic cockpit would provide a more immersive environment for the experiment subjects, as well as realistic imagery for trained algorithms. However, realism in simulators, especially virtual reality (VR) can cause motion sickness. This condition affected several participants and inhibited the completion of the course. This is the only article reviewed that the authors mentioned approval of an Institutional Review Board (IRB). IRB is important in that they specify and protect personal identifying information from human subjects.

Despite the positive aspects of this study, the document was fairly unorganized and challenging to follow. These proposed algorithms could have possibly performed better with a larger training size. Though Li et al., 2020 demonstrated limited success, it was chosen to review because it represents a pivot in research direction. It is doubtful that the methods described in this study will be able to hold up against higher accuracy reported by many other contemporary investigations (Li et al. 2020).

Industry Efforts

External vehicle monitoring systems

Several patents have been led by technology and automotive companies in the United States related to autonomous stopping and autonomous vehicle control of both commercial and private vehicles by external monitoring. These companies include OMNItracs LLC (Emergency stopping for autonomous commercial vehicles), Baidu USA LLC (Speed control for a full stop of an autonomous driving vehicle), Ford Global Technologies (Autonomous vehicle control for an impaired driver), nuTonomy Inc (Identifying a stopping place for an autonomous vehicle), Delphi Technologies Inc (Automated vehicle safe stop zone use notification system), and Volvo Car Corporation (Device and method for safety stoppage of an autonomous road vehicle). Currently, many popular automotive companies have implemented assisted breaking for newer models that sense an imminent collision. The vehicles typically retail at a medium to a high price point. These same companies have also implemented adaptive cruise control down to a complete stop.

Internal vehicle monitoring systems

Several automotive companies (Toyota, Honda, Volkswagen, BMW) utilize internal driver monitoring systems. For example, new Honda models analyze lane position relative to side markings. If the on-board computer recognizes certain patterns, the driver will be alerted with a coffee cup signal that suggests the driver take a break. All available Tesla models (3, S, X) have a function that will detect if a driver is inattentive and attempt to alert the driver. If the driver fails to take control of the vehicle, they are determined to be neglectful by the vehicle. The vehicle will then autonomously turn on hazard lights and stop the vehicle. However, the vehicle will not navigate to the shoulder. While impressive, this function could be considered somewhat dangerous if this function is engaged in heavy or high velocity traffic. Over the last 20 years, a diverse roster of companies has led patents for driver monitoring systems. Currently, State Farm Mutual Automobile Insurance holds the most patents (2.2 %), while Magna Electronics (1.9 %, GM Global Technologies Operations LLC (1.9 %), and Zonar Systems (1.6 %), Honda (1.6 %), and Toyota (1.6 %) follow closely. These patents are a mix of instruments that can be integrated with vehicle systems or operate externally as a module, sensor, or camera.

Future work and Precision Driver Monitoring

What is next for driver monitoring? Currently, the field seems to be expanding at a terrific pace across many scientific domains. One subject that will certainly be explored is precision driver monitoring. Techniques discussed in this document could be applied to observe certain behaviors that occur directly before acute driver impairment due to a medical event such as a seizure. Further insight into driver behavior can be gained by collecting vehicle dynamic data (e.g., steering motion, acceleration, and deceleration) combined with road conditions (e.g., heavy traffic, rain, unexpected events). These data would be used to differentiate biometric signals typical of seizures from baseline signals characteristic of a driver under various but "normal" stress states. An ideal solution for this problem is the development of a seizure detection system that could recognize a seizure was imminent, take evasive action (i.e., safely pull over), and contact emergency medical services. The design of such a tool would require the development of two main components: 1) highly accurate detection and prediction of driver impairment including the ability to distinguish environmental stress from physiological stresses (e.g., a near collision vs. a heart attack). 2) The ability for a semi-autonomous vehicle to detect an optimal location to pull over, negotiate traffic to reach the destination, and to decelerate to a complete stop safely. Besides saving the lives of drivers, passengers, and bystanders, we expect this technology to increase the quality of life of people who suffer from this condition. It is highly conceivable that these techniques could be

applied to a variety of medical conditions in a precision driver monitoring module that could be easily integrated into existing automotive systems.

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