EXAMINING THE RELATIONSHIP BETWEEN DRIVER DISTRACTION, CRASH, AND NEAR-CRASH RISK USING NATURALISTIC DRIVING DATA

By

Anshu Bamney

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Civil Engineering—Doctor of Philosophy

2022

ABSTRACT

EXAMINING THE RELATIONSHIP BETWEEN DRIVER DISTRACTION, CRASH, AND NEAR-CRASH RISK USING NATURALISTIC DRIVING DATA

By

Anshu Bamney

Distracted driving is among the leading causes of motor vehicle crashes worldwide, though the magnitude of this problem is difficult to quantify given the limitations of police-reported crash data. A more promising approach is to evaluate the impacts of distraction in real-world driving events. To that end, this study leverages data from the second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS) to gain important insights into the risks posed by driver distraction. The objectives of this study are to assess the risk of crash and near-crash events under different contextual environments based upon whether the driver was engaged in any secondary (i.e., non-driving related) tasks. The research also compares speed profiles of distracted drivers in low-speed and high-speed environments, providing important insights into how driver behavior changes based upon the type and intensity of distraction.

The first analysis uses the standard SHRP 2 data to compare the differences between near-crash risks on limited access freeways and two-lane highways. Mixed-effects logistic regression models were estimated to discern how the risks of near-crash events varied by distraction type while controlling for the effects of driver, roadway, and traffic characteristics. In general, the risks were more pronounced for those distractions that were a combination of cognitive, visual, and manual distractions (for e.g., cell phone texting). While the same factors tended to increase near-crash risk on both types of facilities, the impacts of several factors tended to be more pronounced on two-lane highways where interaction with other vehicles occurred more frequently.

The second analysis uses a subset of the NDS data that were focused on naturalistic engagement in secondary tasks (NEST). The NEST data were used to assess how the type and duration of distraction impacted the likelihood of crash and near-crash events. Separate comparisons were made between crashes and near-crashes with “normal” baseline driving events. The results show the duration of distraction to be a strong predictor of both crash and near-crash risk and were found to have similar relationships with crashes and near-crashes. The risks were highest for those secondary tasks that introduce a combination of visual and manual distractions that provides evidence that distractions requiring higher levels of engagement have more pronounced impacts on safety.

The third and final analysis uses NEST data to analyze how driver speed selection varies based upon the types of secondary tasks that a driver is engaged in. Comparisons are made as to differences between high-speed and low-speed environments. Two-way random effects linear regression models were estimated for both speed regimes while controlling for driver, roadway, and traffic characteristics. In general, engagement in all tasks was found to decrease speeds in high-speed environments, while the effects were mixed in low-speed settings. These changes in speeds are much pronounced for secondary tasks that include a combination of visual, manual, and cognitive distractions, such as cell phone use. Among all secondary tasks, handheld cellphone talking was associated with highest speed changes in both environments followed by reaching/manipulating an object and holding an object.

Ultimately, the results of this study provides further motivation for more aggressive legislation and enforcement against distracted driving. This can be achieved by enforcing strict laws and fines, graduated licensing process, public campaigns, modified infrastructure (rumble strips and tactile lane marking), and other such measures.

ACKNOWLEDGMENTS

I wish to express my most sincere appreciation and gratitude to my Ph.D. advisor, Dr. Peter Savolainen for his invaluable guidance at every step of my Ph.D. He inspired me not only by his scientific temperament and by research acumen but also by his kindness and thoughtfulness that makes him the best advisor. Working with him has been a great learning and rewarding experience.

I am thankful to my Ph.D. committee members Dr. Timothy Gates, Dr. Ali Zockaie, Dr. Mehrnaz Ghamami, and Dr. Tongbin Teresa Qu for providing their immense support during my Ph.D. They have been highly supportive and provided constructive feedback during my research.

I am grateful to Laura Post and Bailey Weber for answering my queries and helping me in every step of my Ph.D. program. Their support has been invaluable and they took care of countless items that have made my life easier as a graduate research assistant.

Most importantly, I would like to thank my family who made a lot of sacrifices to build my career and supported me in every possible way. I would also like to express my gratitude to my friends for staying with me and walking with me on any path of life I choose.

Lastly, I would like to thank Almighty God for blessing me with such an amazing advisor, teachers, family, and friends.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

1.1 Overview and research motivation

Road crashes are a leading cause of death around the world. As per the World Health Organization (WHO), road injuries kill 1.35 million people and injure 20-50 million people, each year globally. Seventy three percent of all traffic deaths occur among males under 25 years of age. For most countries, road traffic crashes costs three percent of their gross domestic product (GDP) (WHO, 2020). Distracted driving (DD) is one of the leading causes of motor vehicle crashes. Most commonly used definition of Driver Distraction is- “Driver Distraction is a diversion of attention away from activities critical for safe driving towards a competing activity” (Regan et al., 2008). In the United States, in 2020, 13 percent of the total crashes were distraction-affected that comprised 2,880 fatal, 215,310 injury and 462,106 property damage crashes (NHTSA, 2022b). Figure 1.1 shows the percentage of distraction-affected crashes in the United States from 2014-20.

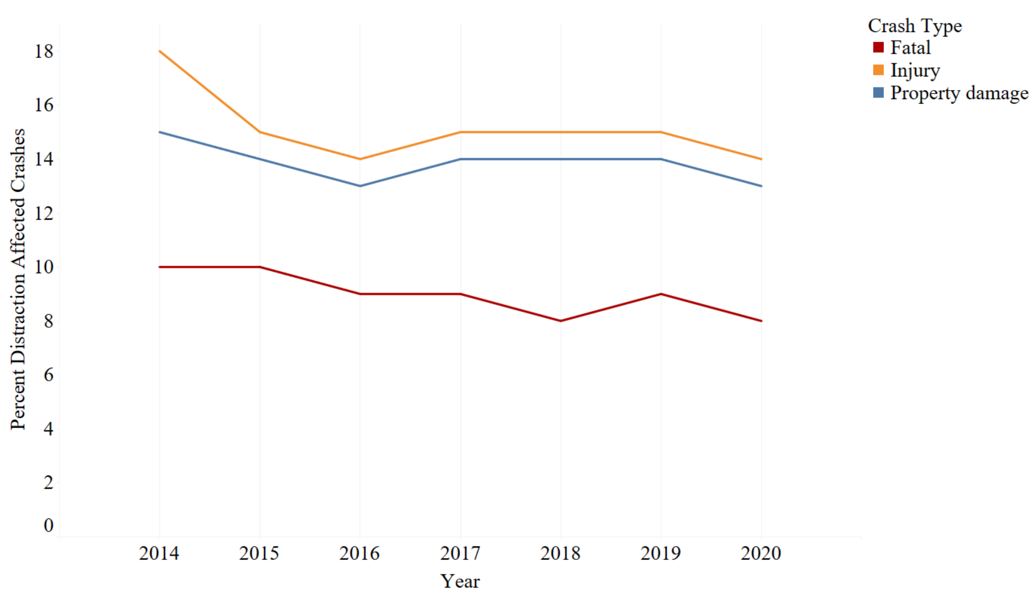

Figure 1.1 Percentage of Distraction Affected Crashes in the United States (NHTSA, 2018b, 2022b)

A slight drop in distraction-affected crashes was observed in the year 2020 as compared to prior years, because of pandemic; however, the trends remained consistent before 2020 i.e. non-pandemic years. In 2019, distraction-affected crashes accounted for 15 percent of total crashes (2,895 fatal, 287,000 injury, and 696,000 property damage crashes) (NHTSA, 2021). Furthermore, in this year, 566 non-occupants (pedestrians, bicyclists, and others) were killed due to distracted driving. Teenagers (15-19 years) were the most vulnerable group, 9% of the fatal crashes in this group were distraction-affected, which is highest in any age group (NHTSA, 2021). It should be noted that these statistics significantly underrepresent the actual scenario as follow-on interviews and on-site crash investigations showed the rate of distraction to be more than 2.5 times greater than similar rates based on police crash reports (NHTSA, 2018a). Furthermore, a 100-car naturalistic driving study showed that driver distraction was present in more than 22 percent of the crash/near-crash events (Klauer et al., 2006). These findings indicate that driver distraction is ubiquitous and the integration of smart technologies within mobile phones has exacerbated the situation. Besides this, there can be multiple causes of driver distraction- eating and drinking, adjusting climate control and audio, reaching for a device in the vehicle, outside person or event, talking with passengers etc.

Among all the types of distractions, cell phone usage has been studied a lot due to its ubiquitous and easily identifiable nature. Driving while using cell phone affects- reaction time, headway, spacing, lane departure, and gap acceptance (Dumitru et al., 2018; Haque et al., 2016; Haque & Washington, 2014; Oviedo-Trespalacios et al., 2017a; Saifuzzaman et al., 2015). Among all the driving performance metrics, operating speed has been studied vastly and it was found that drivers tend to reduce their speed subconsciously/consciously while they are distracted, hoping that it may reduce the likelihood of any safety critical event (crash or near-crash). Because of these compensatory behaviors and the association of cell phone distractions with safety critical events many transportation organizations and institutes have launched certain campaigns and passed legislations to prohibit cell phone usage while driving. The following maps in Figure 1.2 show the states where cell phones are banned in the U.S. as of January 2022.

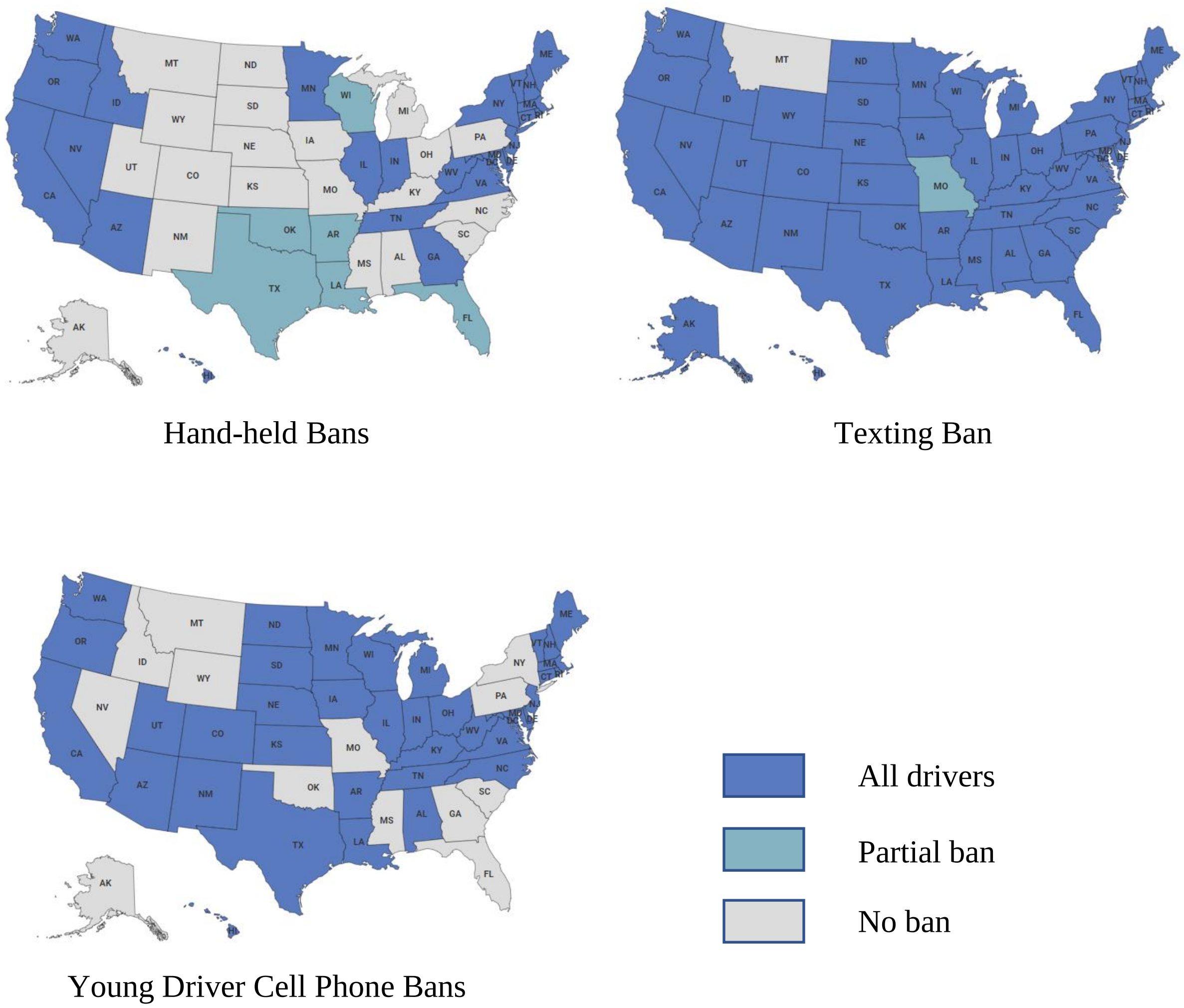

Figure 1.2 State Wise Cell Phone Bans in the U.S. (GHSA, 2021)

A recent national survey reported that 86 percent of the drivers believed that cell phone use while driving is a threat to personal safety and 77 percent of the drivers believed texting and emailing is a serious threat to road safety (AAA, 2016). The same report shows that 85 percent of the drivers feel that distracted drivers are much of a bigger problem than it was three years ago.

However the same study reported that more than two-thirds of the respondents had talked on phone while driving in the last 30 days (AAA, 2016).

Along with cell phone distractions other types of distractions were also found to deteriorate driving performance. Some studies showed in-vehicle activities like smoking, reaching for an object, distracted by outside events, reaching for an object, using radio/instrument panel, eating/drinking etc., affects the driver performance by increasing the- duration of eye glance away from the road, instances of drivers taking hands away from steering wheel and lane encroachments. All of these factors affect vehicle dynamics and increase the likelihood of a crash or near-crash (Bakiri et al., 2013; Simons-Morton et al., 2014; Stutts et al., 2005).

Although it is well established that the crash risk increases due to various types of distractions, there is a need to compare these risks based on roadway contexts. Such type of comparison has not been conducted in prior literature and it can lead to a better understanding of how risks vary due to distractions in different contexts. Beyond overall crash risk, there is also substantive interest in better understanding how distractions may impact related driver behavior measures, such as speed selection and lane positioning and, in turn, impact the resultant crash risk. Speed selection has been an area of investigation in prior studies, with results showing that drivers tend to reduce their speed to compensate for the mental workload due to distraction (Li et al., 2020; Oviedo-Trespalacios et al., 2017a; K. Young et al., 2003). However, the question remains do distracted drivers compensate for speed in all the types of environment or their speed selection varies in high-speed and low-speed environments? This is a potential area of exploration as no prior research has explicitly compared the speed selection of distracted drivers in these two environments.

Many of the prior studies that concluded distraction degrades driver performance used the data obtained from driving simulator, and the main focus of these studies was cell phone distraction (Dumitru et al., 2018; Haque et al., 2016; Haque & Washington, 2014; Oviedo-Trespalacios et al., 2017a; Saifuzzaman et al., 2015). Consequently, there is a clear need to better understand the impacts of a wide range of distractions on real-world driving behavior.

Naturalistic driving studies provide distinct advantages when investigating such questions. In such studies, real-world driving data is obtained through high-quality and high-resolution cameras, sensors, and data acquisition systems (DAS) that are instrumented inside the participant's car. These data reflect real-world driving and provide high-fidelity information as to driver behavior, including engagement in various secondary tasks (Klauer et al., 2006). These data can also be integrated with very detailed contextual information about the driving environment, providing opportunities for robust investigations into how various types of distraction impact fundamental driving behavior.

The main benefit of this research is that it uses naturalistic driving data that has been leveraged from the second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS). To achieve the overarching goal of understanding driver behavior and risks associated with distracted driving the following objectives were established:

1.2 Objective 1: Assess the near-crash risk associated with various secondary tasks in freeway and two-lane highways

As a part of this objective, the difference between near-crash risks for various types of distractions is compared for different roadway contexts i.e. freeway vs two-lane highways. As driving environment of freeways is different from two-lane highways, this analysis can assist in understanding how the risks vary between these two environments.

1.3 Objective 2: Assess the occurrence of near-crashes and crashes due to various duration of distractions

In this objective, the relationship between duration of various distractions and the occurrence of near-crashes vs. crashes is explored with Naturalistic Engagement in Secondary Task (NEST) dataset. This analysis can help in understanding if any difference exists between the occurrence near-crashes and crashes w.r.t distraction duration.

1.4 Objective 3: Study drivers' speed selection in high-speed vs low-speed environment

As a part of this objective drivers' speed selection is explored in low-speed vs. high-speed environment due to various types of distractions. It is expected that drivers' performance may vary w.r.t. secondary tasks in low-speed vs high speed environment. This analysis can help in understanding the risk compensation behavior due to distraction in low vs. high-speed environment.

1.5 Dissertation structure

This research study is a holistic investigation of the effects of driver distraction on crash risk and surrogate safety measures using naturalistic driving data. Various aspects of driver distraction and its impact on driver performance are presented in the following chapters:

Chapter 1 Introduction: The introduction provides the recent statistics and figures for distraction affected crashes. This is followed by the general findings in the literature regarding distraction and its relationship with driver performance and crash/near-crash risk. It also includes motivation for the study and finally the objectives of the study.

Chapter 2 Literature Review: This chapter provides a brief on the history of distracted driving studies and research methods used to study driver distraction. It provides a comprehensive literature review on various types of distractions, their impacts on driver performance and crash/near-crash risk associated with each category.

Chapter 3 Data Description: This chapter provides the details about the naturalistic driving data used in this report. Two naturalistic datasets were used in this study: Standard SHRP 2 data and NEST data, and are covered in two subsections of this chapter.

Chapter 4 Assessing Near-Crash risk in Freeways vs Two-lane highways: This chapter explains the data preparation, summary, methodology, and results and discussion of first objective, where the aim is to compare the near-crash risk due to various distractions in freeways vs two-lane highways.

Chapter 5 Duration of Distraction and Occurrence of Crash vs Near-Crash: This chapter explains the data preparation, summary, methodology, and results and discussion of second objective, where the aim is to compare the near-crash vs crash risk due to various duration of distractions.

Chapter 6 Drivers' Speed Selection in Low-speed vs High-speed Environment: This chapter explains the data preparation, summary, methodology, and results and discussion of last objective, where the aim is to compare the vehicles' speed in low-speed and high-speed environment, due to engagement in various distractions.

Chapter 7 Conclusions: This chapter includes the conclusions of each of the objectives, recommendations based on the research conducted and directions for future research so that the problem of driver distraction can be studied in detail.

2. LITERATURE REVIEW

This chapter includes the literature review that highlights the impact of driver distraction on driving performance and crash risk under various roadway and traffic conditions. It underlines the findings of prior driver distraction studies and identifies the gaps in them. This chapter can be divided into six sections- history of driver distraction, distraction categories, driver distraction research methods, safety impacts of driver distraction, countermeasures to prevent distraction, summary and problem statement.

2.1 History of driver distraction

Driver distraction has been there since mid-1950s when the audio systems and mobile record player named Highway Hifi were installed in the vehicles (Stutts et al., 2015). The early studies of driver distraction started back in 1960s by Senders and colleagues where they mentioned listening to radios, music, and news, lighting cigarettes, talking with passengers, reading advertisement boards etc. as distractions (Senders et al., 1967). This study tasked to figure how much time a driver needs to spend observing the road in order to drive effectively (Kentucky Farm Bureau, 2017; Senders et al., 1967). Later, in 1969 a study was conducted to find the effect of telephoning on driving and it was reported that it impairs the perception and decision making ability of drivers with a reduction in speed (Brown et al., 1969).

Later in 1983, cellphones were introduced in the United States which changed the scale of distracted driving. Despite its high usage the first cellphone ban came in 1992, Florida (Kentucky Farm Bureau, 2017), which was then followed by other states. Through time along with cellphone, music player, radio, iPods etc. became inevitable part of human life which escalated distracted driving. A lot of research on distracted driving has been conducted since 1960s and there is a lot that is yet to be discovered.

2.2 Driver distraction categories

Driving is primarily a visual-spatial-manual task and any activity or task that interferes with it may be called as distraction. Driver distraction can be divided into four main categories visual, auditory, biomechanical (physical or manual), and cognitive (Regan et al., 2007):

- Visual distraction: These distractions occur when drivers take their eyes off the road and give visual attention to non-driving task for an extended period of time.
- Auditory distraction: These distractions occur when drivers give their auditory attention to non-driving tasks.
- Biomechanical/manual distraction: These distractions occur when drivers take their hands off the steering wheel, for extended period of time to manipulate a device.
- Cognitive: These distractions occur when drivers take their mind off the driving and perform some mental work or get immersed in thoughts.

Besides these, there can be multiple categories of driver distraction that can be formed by combining any two, or more than two categories. Any form of driver distraction is precarious but there are evidences that suggest driving performance decreases to a greater degree when driver was distracted visually-cognitively as compared to auditory-cognitively (Hurwitz & Wheatley, 2002).

2.3 Driver distraction research methods

It has been challenging to study and quantify driver distraction as there is a lot of dynamics involved. There are six main types of research methods to study driver distraction and are described below (ERSO, 2018; Ranney, 2008)-

1. Observational studies: These studies provide information about the tasks in which drivers are engaged while driving. In these studies, an observer records the demographic and distraction engagement details of driver and passenger, while they pass through the observer. These types of studies are quicker and cheaper but the main drawback of these is time available to record the driver details is limited and the data is subjected to observer bias.
2. Survey based studies: Survey based studies are also quick, cheap, cover a large geographical area and can provide the details that is difficult to observe on roadside. But these studies are highly dependent on the memory of the respondents and honest replies. Respondents tend to give answers that are socially acceptable rather than actual ones, which can make the study biased. Furthermore, internet surveys do not include the people with no internet connection.
3. Crash-based studies: These studies provide the details of crash and distraction type at the time of crash, through crash report form. It is tough to determine whether the driver was engaged in distraction at the time of crash as it is subjected to driver's acceptance of secondary tasks, while reporting to police. Hence this data highly underestimates the number of crashes due to distraction as the drivers are less likely to accept that they were engaged in secondary tasks, seconds before the crash.

4. Driving simulator studies: These are the experimental studies conducted in transportation laboratory. In these studies, a virtual environment or animation on a computer screen is created and the driver drives through it. The main advantage of these studies is that driving environment can be controlled and the exact driving context can be created which helps the experimenter in getting answers to the research questions. A large number of roadways, weather and illumination conditions can be created and studied without waiting for them to actually occur. The disadvantages of these studies are the drivers know that the driving conditions are not real, and they know that they are being observed, this can make them change their behavior.
5. Test track studies: The test track studies are one step ahead of driving simulator. The advantages of these studies are performed on a closed track but with real car. In these studies, the conditions are more controlled as compared to natural driving environment. The experimenter can design the traffic conditions as per the research question and collect the data. The main disadvantage is the drivers are aware of experiments and they can modify their actual driving behavior. Other drawbacks are that these studies cannot be performed to study the long-term impacts of a policy. A modification of these studies is field study on a special test route where real-life driving conditions exist. There are lesser opportunities to control the other variables, but the main disadvantage is that the observations are limited to that special test route.
6. Naturalistic studies: In these studies participants drive the vehicles with cameras and sensors which allows the researchers to obtain details like speed, acceleration, lane change, weather, secondary tasks, eye glance etc. This is the most robust method as the driver and related secondary tasks can be seen through camera and pertinent information can be

obtained. Furthermore, the details of every one-tenth of a second can be obtained through this method. This method generates a huge amount of data which has to be processed to make interpretations. One issue that can arise is drivers are aware that they are being observed which may affect their behavior but after 2-3 weeks they return to their original behavior.

2.4 Safety impacts and prevalence of driver distraction

This section details out the safety impacts of various types of distractions and their prevalence under various environmental conditions and demographic background. This section also details the impacts of various types of distractions on driver performance and crash risk, however the relationship between these two is not well-known.

The driver performance is mostly studied through driving simulator, test track and naturalistic driving. The driver performance indicators generally used are speed, acceleration/deceleration, lateral position of vehicle (lane keeping, steering wheel) headway, gap acceptance, reaction time, braking behavior, eye glance or visual behavior (looking on road, looking in mirror, missed objects etc.), driving errors etc. (Regan et al., 2008; ERSO, 2018). These performance indicators are recorded in all conditions distracted vs non-distracted, baseline vs crash/near crash and finally become the basis of comparison. The general finding suggests that secondary tasks of any type- texting, eating, drinking etc. degrades the driving performance, however different tasks affect different driver performance metrics (ERSO, 2018).

Identifying the crash risk due to distracted driving is a tough task because a. crashes are rare and random event b. distracted driving is not the only cause of crashes, it may happen partly or totally by other factors. The first challenge can be overcome by using surrogate safety measures such as near-crashes. Dingus et al. used 100 Car-study data and found a strong correlation between the frequency of near crashes and crashes, under different environmental conditions (Dingus et al., 2016). It was concluded by Guo that crash surrogates can be used when there are not enough crashes available, though its validity depends on the purpose of research and caution must be used while interpreting results (Guo, 2019). The second challenge can be overcome by using naturalistic driving data as it comes with video clips (forward, backward, hand and facial view) and provides the details of driver movement (with eye glances and secondary task details), roadway and vehicle dynamics for every one-tenth of a second.

These crash studies are mostly based on police reported crash data. The biggest challenge in this method is the underrepresentation of distracted driving crashes. The other methods that can be used for this study are driving simulator and naturalistic driving. The driving simulator allow the researchers to artificially create an environment and study it, but the issue remains that driver knows that it is not actual driving, and the sample size cannot be extended beyond certain limit. Naturalistic driving can be the best method to analyze the relationship between crash risk and distraction as it can give details about the driver behavior and the events just before the crash. This type of data helps researchers to compare the crash and near crash data with baseline driving episodes, which are considered normal driving periods.

Lastly, prevalence of distracted driving is an important parameter to study. Firstly, to determine the increment/decrement in crash risk that are associated with different types of distraction. Secondly, it can help in developing the countermeasures that can address most precarious distractions. It can also help in understanding efficacy of the countermeasures. Lastly, prevalence of distraction can help in knowing the roadway environment and conditions that are most conducive to distraction. The prevalence of distracted driving can be studied through surveys, observational studies, and naturalistic driving. Among these, the most reliable method is naturalistic driving.

2.4.1 Cell phone use

Cell phone use while driving is the most studied and ubiquitous type of distraction. Cell phone usage includes tasks such as dialing, browsing, texting, locating/reaching/answering, talking (handsfree, handheld), holding etc. Cell phone usage can require visual, auditory, and manual attention of drivers, or a combination of these three. Cell phone use accounts for 13 percent of the distraction affected fatal crashes in 2018, and the drivers of age 20-29 years were the most affected group by this type of distraction (NHTSA, 2020). The following subsections explain the prevalence of cell phone related secondary tasks its impact of driver performance and crash risk associated with it.

2.4.1.1 Cell phone prevalence

Among all forms of distraction, cell phone related distractions are most prevalent, at any given daylight moment in the US 660,000 drivers are either using cell phone or engaged in electronic devices while driving, which is equivalent to 5 percent of all American drivers in a typical daylight moment (NHTSA, 2013). As per NHTSA's survey, almost half (48.6 percent) of the drivers answer incoming calls and one-fourth (23.9 percent) were willing to place calls. These figures exacerbated for young drivers, while driving nearly 60 percent of these drivers answered the incoming call and 33 percent were willing to place a call (NHTSA, 2013). A study based on young drivers utilized naturalistic driving data found that electronic device use such as texting and talking (hand-held or hands-free) on the cell phone was the most frequent type of distracted behavior observed among this group (Foss & Goodwin, 2014). A survey-based study conducted on emerging adults had a total of 2,874 participants found texting is the most frequently reported distraction and it occurs on 40.2 percent of driving days (Trivedi et al., 2017).

Another survey-based study found approximately 60 percent of respondents engaged in texting within the last 30 days of completing the survey. The most frequent form of distractions were reading text messages (48 percent), navigating through GPS (43 percent), and typing a message (33 percent) (Gliklich et al., 2016). A similar study by AAA foundation had a sample size of 2,545 respondents where, 42 percent, 32 percent, and 70 percent reported reading, typing, and talking on phone while driving in the past 30 days (AAA, 2016). Table 2.1 shows the breakdown of reported cell phone related behaviors with age group. This makes it clear that cell phone distraction is prevalent in teen and young people.

Table 2.1 Cell Phone Distractions Reported at Least Once in Past 30 days by Age Group (N = 2,545) in Percent (AAA, 2016)

Driver age (years)	Read text message or email	Typed/sent text message or email	Talked on a cell phone of any kind
16-18	47.3	32.5	62.6
19-24	59.2	44.6	77.2
25-39	64.8	54.8	77.5
40-59	41.7	30.1	73.7
60-74	20.5	9.9	60.0
75+	5.8	5.6	42.2
All drivers	42.3	31.5	69.9

Interestingly this same study showed that 86 percent of respondents believe cell phone use is a threat to personal safety and 87.7 percent of respondents support strong laws against, reading, typing, or sending a text message or email while driving (AAA, 2016). These findings and engagement in secondary tasks highlight the self-perception risk among individuals where people believe that their driving performance is not much affected by secondary tasks. A roadside interview study conducted in Catalonia, Spain interviewed 426 people, reported cell phone use is the most frequently reported form of distraction, where 43.7 percent reported texting while driving and 32.2 percent people reported handheld cell phone use (Prat et al., 2017). This study also found that texting while driving was considered the most dangerous activity, followed by handheld talking. This again confirms that drivers are aware of the risks against distracted driving but still they engage in a wide variety of distractions (Prat et al., 2017).

Distracted driving is not limited to cars a survey conducted in Vietnam focused on motorcyclists among university students (741 respondents) found that majority of respondents are most likely to use a cell phone while riding with 57 percent used for talking and 62 percent used for texting (De Gruyter et al., 2017).

2.4.1.2 Cell phone and driver performance

Distracted driving adversely affects driver performance. A lot of distracted driving studies used speed as a metric to study the driver performance, and it was a general finding that drivers tend to lower their speed when they are distracted. This increases the speed differential on the road and increases the chances of crashes. A research aimed to study the self-regulation of driver speed among distracted drivers utilized the data from a high-fidelity driving simulator where all the participants (N = 32) were young drivers (18-26 years) (Oviedo-Trespalacios et al., 2017a). The system of seemingly unrelated equations (SURE) model was developed, to account for correlations between cell phone use and it was found that drivers tend to reduce speed while talking on cell phone in both handheld (HH) and handsfree (HF) condition. Furthermore, in both conditions the standard deviation in speed was higher (3.47 kph for HH and 4.16 kph for HF) than baseline (2.5 kph) i.e., no distraction condition.

Another study by the same researchers found that speed is not only affected by distraction, roadway environment and traffic complexity also play a role in it (Oviedo-Trespalacios et al., 2017b). This study also utilized the data from a high-fidelity driving simulator where all the participants (N = 32) were young drivers (18-26 years). A Generalized Linear Mixed Model (GLMM) with repeated measures was developed to infer about the speed adaptation behavior of distracted drivers in various roadway and traffic conditions- urban straight roads, suburban straight/curved roads (free flow, lead vehicle, radius <350m and >350m). It was found that distracted drivers tend to select a lower speed while driving along the curved roads and when a lead vehicle was present. In addition, drivers who consider that cell phone use is dangerous while driving reduced speed significantly while they were distracted.

A closed test track study, utilized the data from 20 drivers to evaluate driver performance while text messaging through handheld cell phones and in-vehicle texting system (Owens et al., 2011). It was observed that handheld text messaging that includes sending and receiving messages induces more mental demand, degrades steering control, and requires longer duration of eye glances away from the road. On the other hand, sending and receiving message through in-vehicle texting system showed lesser degradation in driver performance. A driving simulator study was conducted to determine the reaction time of distracted drivers particularly by cell phone conversations (Haque & Washington, 2014). This study utilized the data from 32 participants and a parametric accelerated failure time duration model was developed to estimate the reaction time of distracted and non-distracted drivers. It was found that the drivers engaged in cell phone conversation had 40 percent higher reaction time than non-distracted drivers. A similar driving simulator study in India examined the effects of simple and complex cell phone tasks (conversation and texting) on driver performance (Choudhary & Velaga, 2017b). The study concluded that simple/complex conversation and simple/complex texting had significantly higher reaction times as compared to no distraction condition. Figure 2.1 shows the details of reaction time observed by this study.

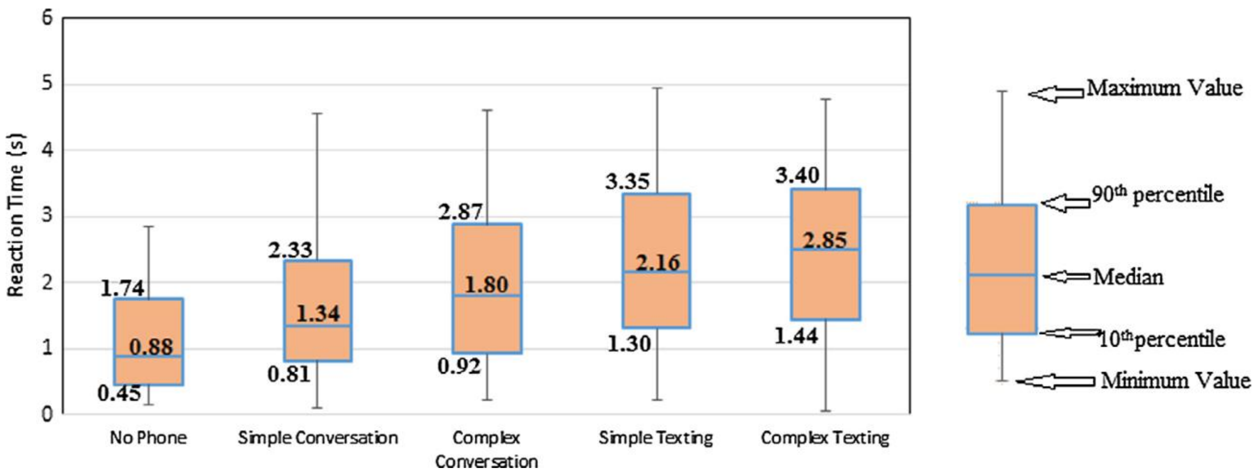

Figure 2.1 Boxplots of Reaction Times of all Cell Phone Use Conditions (Choudhary & Velaga, 2017b)

Another driving simulator research aimed to study the gap acceptance behavior of cell phone distracted drivers at roundabouts (Haque et al., 2016). There were 32 participants in this study and the cell phone handheld, hands free and no distraction (baseline) conditions were studied. It was found that the cell phone distracted drivers (both HH and HF) started responding to gap acceptance when they were close to roundabout and they approached it at slower pace. In addition, the deceleration rate of distracted drivers was higher than non-distracted drivers.

To study distracted drivers visual behavior and physiological techniques have been utilized a lot. But few studies focus on vehicle-based performance measures. A driving simulator study was conducted in India to examine the effects of simple and complex cell phone tasks (conversation and texting) on vehicle performance (Choudhary & Velaga, 2017a). There were 100 participants in this study and repeated measures ANOVA test was used. It was found that simple and complex texting significantly increased the standard deviation of lane positioning, number of lane excursions and standard deviation of steering wheel angle. Furthermore, 10-degree steering wheel reversal rate was significantly higher for all the distraction conditions- simple/complex conversation and simple/complex texting.

Lastly, a study utilized the data from driving simulator and aimed to investigate relationship between distracted driving (talking and texting) and traffic congestion (LOS A, C and E), where all the participants (N = 75) were 16-25 years old (Stavrinos et al., 2013). Repeated measures ANOVA and Generalized Estimate Equation were both used in this study and it was found that cell phone texting increased lane deviations and crashes. In general distractions reduced the driver performance in all the traffic flow conditions, which was indicated by speed fluctuation and fewer lane changes.

2.4.1.3 Cell phone and crash risk

This section focuses on the crash risk due to cell phone related distractions. To study crash risk databases such as hospital records, police reported crashes, General Estimation System (GES), Fatality Analysis Reporting System (FARS), Crash Report Sampling System (CRSS) etc. are majorly used. It was found through a crash based study that nearly 13 percent of the distraction affected fatal crashes involved cell phone use (NHTSA, 2020). However, the number of crashes due to cell phone use and other communication devices is highly underrepresented (Kircher et al., 2011). Naturalistic driving research has shown the risk of crash and near-crash events is most pronounced for more activities such as dialing, texting, or reaching for a cell phone. This was supported by a study that utilized FARS data and found that the number of fatalities would increase more than 75 percent in an average state for every one million additional text messages sent per month (Wilson & Stimpson, 2010). The next paragraphs summarize the crash risk associated with various cell phone uses in the U. S. and other countries.

In the U. S. a 100-car naturalistic driving study was conducted in 2006 to explore the driver behavior and driver performance including engagement in secondary tasks, traffic violations, risk taking behavior, aggressive driving etc. (Dingus et al., 2006). The data was collected for 12 to 13 months for each vehicle and it was found that the crash risk due to cell phone dialing talking HH was 2.79 and 1.29 times higher than baseline events. Similarly, a naturalistic study utilized the data from SHRP 2 aimed to study the crash risk associated with different types of distraction and socio-economic characteristics found cell phone holding and texting increases the crash risk by 2.19 and 2.77 times as compared to baseline events (Ye et al., 2017). Another naturalistic study utilized data from SHRP 2 developed logistic regression models to identify the crash risk associated with different cell phone uses (Owens et al. 2018). This study confirmed that crash risk increases by 2.8 and 1.3 times for cell phone dialing and talking HH as compared to normal driving events/baselines. However, cell phone HF usage does not increase the crash risk. Another naturalistic study utilized SHRP 2 data found that the participants made 1.6 texts and 1.2 calls per hour of driving, but for teenage drivers the texting rate was 2.9 texts per hours of driving, which is worrying (Atwood et al., 2018).

Two case-crossover studies conducted in Australia and Canada utilized the data from hospitals, conducted interviews and found that the crash risk due to cell phone increases four times when the call was placed within 5 minutes before the crash (McEvoy et al., 2007; Redelmeier & Tibshirani, 1997). A case-control study used the data from Insurance Corporation of British Columbia Traffic Accident System, Canada, to determine whether cell phone use increase the crash risk (Asbridge et al., 2013). This study used a three to one matching approach where 936 crashes with no cell phone use were selected and 312 crashes with confirmed cell phone use were selected for analysis. Logistic regression model with robust cluster variance estimators and a modified ‘Robertson-Drummer’ scale were used to estimate the crash culpability due to cell phone. It was found that cell phone use increases the odds of culpable crash by 1.7 times as compared to crashes with no cell phone use.

The crash risk not only varies by the type of cell phone distractions but also by the demography. A naturalistic study was conducted to estimate the crash risk associated with secondary tasks for different age groups 16-20, 21-29, 30-64 and 65-98 years (Guo et al., 2017). This study found the crash risk due to complex cell phone tasks like texting and visual-manual tasks was 25 times higher than baseline for people of age 65-98 years. However, the crash risk for texting and visual-manual tasks were in the range of 2 to 6 times for all other age groups. It was also found the crash risk for the overall cell phone use was the highest for senior drivers (OR = 5.72), followed by young adults (OR = 4.25), teenagers (OR = 3.53) and middle-aged drivers (OR = 2.11).

Lastly, driver distraction is studied for commercial motor vehicles (CMVs) as well. A naturalistic study utilized data from 203 CMV and 55 truck drivers showed through logistic regression that the crash risk due to cell phone texting and dialing increases by 23.2 and 5.9 times as compared to normal driving (Bocanegra et al., 2009). This study also showed that cell phone HH talking is quite benign as it increases the crash risk by only 1.04 times as compared to baseline. Similar were the findings of another naturalistic study on CMVs that concluded the crash risk due to cell phone dialing and cell phone HH talking/listening are 3.5 and 0.8, respectively (Hickman et al., 2010).

2.4.2 Consumption (Eating/Drinking/Smoking)

Consumption related secondary tasks includes eating and drinking related activities. The typical activities include drinking from open container, drinking with lid and straw/no straw, eating with/without utensils, lighting/smoking/extinguishing a cigar or cigarette etc. The following subsections explains the prevalence of consumption related secondary tasks, its impact of driver performance and crash risk associated with it.

2.4.2.1 Consumption prevalence

A roadside observational study was conducted in England at six urban centers, with the aim to determine the prevalence of various secondary tasks (Sullman, 2012). The observers randomly selected the drivers and noted down the age group (young, middle, and old), secondary task engagement and other pertinent details of 7000 drivers. Nearly 7 percent of the distracted drivers were engaged in eating/drinking, and 15 percent of these were engaged in smoking related tasks. A naturalistic study found that eating/drinking related secondary tasks are prevalent when the average lane width is more, clear weather conditions exist, and LOS A and F exists (Kirsch, 2018). The study also found that females, drivers with average annual mileage above 30,000 miles and drivers with no advanced degree tend to have a higher rate of consumption related distraction. The same study found that smoking was prevalent when the average number of lanes were less, LOS A was present, and the driver had two or more crashes in last 12 months.

2.4.2.2 Consumption and driver performance

A naturalistic driving study that utilized the data from 70 volunteer drivers was conducted to determine the prevalence and driver performance of distracted drivers (Stutts et al., 2005). As a measure of driver performance, no hands-on steering wheels, eyes directed inside the vehicle rather than outside, and lane wanderings were used, and it was found that these three metrics worsened when the driver was engaged in eating, drinking, and smoking. Another naturalistic study that utilized SHRP 2 data found eating and drinking are the distractions whose duration was maximum

(8.67s) as compared to other distractions (cell phone checking, talking/singing, focusing on object etc.) under familiar road conditions (Wu & Xu, 2018).

2.4.2.3 Consumption and crash risk

A 100-car naturalistic driving study estimated the crash risk associated with various types of secondary tasks (Klauer et al., 2006). The study found eating and drinking related distractions increases the likelihood of crash/near-crash by 1.57 to 1.03 times as compared to baseline events. However, it was not significant, but this study categorized these secondary tasks into moderate category i.e., it requires at most two glances away from the roadway. These findings are reflected in a roadside interview based study which was conducted to identify the perceived risk associated with a variety of secondary tasks (Prat et al., 2017). The study reported that consumption related secondary tasks were considered with the lowest perceived crash risk, with eating or drinking have a score of 5.3 and smoking 5.7 out of 10 (where 10 being the maximum crash risk on a 0 to 10 scale).

2.4.3 <u>External Distractions</u>

Secondary tasks that fall under the category of external distractions are looking at an object external to the vehicle (e.g. looking at construction, roadside advertisements, pedestrian, animals, previous-crash and other external objects). These distractions attract drivers' attention and reduces focus on current roadway and traffic situation. The following subsections explains the prevalence of external distractions its impact of driver performance and crash risk associated with it.

2.4.3.1 External distractions prevalence

A study was conducted to identify the major sources of driver distraction and their potential in causing crashes (Stutts et al., 2001). This study used the Crashworthiness Data System (CDS) data along with crash narratives and studied the crashes from 1995-99 and almost half of the drivers were distracted at the time of crash. 29.4 percent of the distracted drivers were engaged in any form of external distractions at the time of crash; this was the most prevalent form of distraction. For the distracted drivers above 65 years of age, 42.8 percent were found engaged in external distractions which also underlines the ubiquity of this distraction. A roadside observation study found external distraction is the third most frequently occurring distraction, where 20 percent of the distracted drivers were engaged in this distraction type (Huisingh et al., 2015). Similar were the findings of a naturalistic study that was conducted to determine the prevalence of various types of distractions in teens and found external distractions were present in 12 percent of the sampled video clips and it was the third most prevalent distraction in this age group (Gershon et al., 2017).

2.4.3.2 External distractions and driver performance

A naturalistic study was conducted to determine the prevalence and driver performance of distracted drivers and found that external distractions decrease the driver performance by increasing the instances of no hands on wheel, eyes off the road and lane wanderings however not significant (Stutts et al., 2005). A driving simulator study was conducted to understand the effects of external distractions on driving behavior of experienced and inexperienced drivers (Divekar et al., 2012). This study found experienced driver have lane deviations in 4 percent of driving scenarios, but inexperienced drivers have lane deviations in 26 percent of the driving scenarios when engaged in external distraction. Lastly, few studies focused on roadside advertisements/billboards exclusively. One such study utilized driving simulator data used static and video advertisements and found video advertisements significantly reduced the driving speed in nearly all of the driving scenarios (Chattington et al., 2009).

2.4.3.3 External distractions and crash risk

A 100-car naturalistic driving study estimated the crash/near crash risk associated with external distractions and found the crash/near crash risk increased by 3.70 times as compared to baseline events (Klauer et al., 2006). Another naturalistic study found external distractions increase the crash risk by six times as compared to that of baseline (Ye et al., 2017). An interview-based study aimed to estimate the crash risk associated with various distractions gathered the data from an hospital in France found external distractions increases the likelihood of crashes by 3.15 times as compared to normal driving scenario (Bakiri et al., 2013). A survey-based study examined the factors that influence the perception of risk for distracted driving among college-aged adults (Rupp et al., 2016). This study used a scale of 1 to 10 to examine risk where 1 is least dangerous and 10 being most dangerous. Out of 16 distractions, looking at roadside crashes, traffic and work zones ranked 5th (score 6.41 out of 10), looking at addresses/sign ranked 10th (score 5.29 out of 10) and looking at billboards/advertisements ranked 14th (score 4.06 out of 10) most dangerous tasks.

2.4.4 Internal and Instrument Panel Related Distractions

Secondary tasks that fall under the category of internal distractions are reaching for an object, moving object in the vehicle, internal eye glances etc.; and the tasks under instrument panel are adjusting/monitoring climate control, radio, inserting/retrieving CD etc. These distractions require visual and manual attention of drivers, or a combination of these two and reduces focus on current roadway and traffic conditions. The following subsections explains the prevalence of internal and instrument panel secondary tasks its impact on driver performance and crash risk associated with it.

2.4.4.1 Internal/instrument panel distraction and prevalence

A study was conducted to identify the major sources of driver distraction and their potential in causing crashes used Crashworthiness Data System (CDS) data along with crash narratives from 1995-99 found among distracted drivers, 14.2 percent were engaged in instrument panel related tasks and 7.2 percent were engaged in any form of internal distractions at the time of crash (Stutts et al., 2001). A survey-based study conducted in Australia found adjusting stereo, air conditioner, in-vehicle equipment and reaching for objects were reported by 40.1, 28.3, 44.3 and 23.1 percent of the drivers in the last trip (McEvoy et al., 2006). A naturalistic study found that all the drivers were engaged in internal distractions at any point during study period of 3h and 91.4 percent of the drivers were engaged in manipulating audio/music controls, which shows the ubiquity of this secondary task (Stutts et al., 2005). Furthermore, 3.8 and 1.5 percent of the vehicle moving time was spent on internal distractions and manipulating music/audio. The study also found that participants were engaged in music/audio related distractions 7.4 times per hour of driving and for internal distractions this was 10.8 times per hour of driving. Another naturalistic study was conducted to understand the adolescents' distracted driving behavior and its prevalence (Foss & Goodwin, 2014). This study used 20 s video clips and found adjusting controls was the second most frequent distraction and was present in 6.2 percent of the total clips, reaching for an object was not that frequent and was present in only 2.5 percent of video clips.

2.4.4.2 Internal/instrument panel distraction and driver performance

A naturalistic study was conducted with 70 volunteer drivers to study the prevalence and driving performance of distracted drivers (Stutts et al., 2005). The study found engaging in instrument panel and internal distractions significantly increases the percentage of no hands-on wheel duration as compared to baseline. For manipulating music/audio controls, manipulating vehicle controls, reach/look for/lean etc., and other internal distractions; drivers had no hands-on wheel for 2.3, 9.79, 3.80 and 6.97 percent of the time. This study also found that these distractions significantly increased the percentage of internal eye glances as compared to no distraction conditions. A driving simulator study was conducted to study the driver performance when they were engaged in a variety of cell phone related tasks and in-vehicle entertainment tasks like hands free talking, and operating car radio and cassette player (Horberry et al., 2006). The study found that driving performance deteriorated in both types of tasks. Interacting with vehicle's entertainment system has greater negative impacts and it reduced the mean speed by 4 mph as compared to the baseline condition.

2.4.4.3 Internal/instrument panel distraction and crash risk

A naturalistic study estimated the crash risk associated with various distractions and found reaching for an object and adjusting/monitoring devices integral to vehicles increases the likelihood of crash risk by 10.22 and 4.47 times as compared to no distraction condition (Ye et al., 2017). Another naturalistic study focused on older drivers was conducted to establish the relationship between crash/near crash risk and driver distraction (Huisingh et al., 2019). This study found the internal eyes glances were one of the most precarious distractions and it increases the likelihood of major crash and near crash by 1.47 and 2.55 times, respectively. In addition, a survey-based study asked the participants to rate perceived crash risk due to various secondary tasks into five categories: extremely risky to no risk at all (K. L. Young & Lenné, 2010). This study found manipulating portable music system, manipulating in-vehicle entertainment system, and manipulating vehicle controls were considered moderate to little risky secondary tasks by most of the participants.

2.4.5 Passenger Interaction/Singing/Dancing

Secondary tasks that fall under this category of distractions are conversing with a passenger, singing/talking with unknown audience, and dancing. These distractions require mostly auditory attention of drivers and sometimes visual or a combination of these two. Generally, these secondary tasks are considered benign. The following subsections explains the prevalence of passenger interaction, singing and dancing related secondary tasks its impact on driver performance and crash risk associated with it.

2.4.5.1 Passenger interaction prevalence

Interacting with passenger is one of the most common secondary tasks. An observational study was conducted in Alabama U.S. to understand the prevalence of various types of distractions using a roadside observational study (Huisingh et al., 2015). During the study 3,265 drivers were observed at 11 selected intersections and pertinent information like driver characteristics, distraction behavior and vehicle speed and flow were gathered. The study found passenger interaction was the most frequently reported secondary task (when passenger was present) and was present in 53.2 percent of distracted driving observations. The same study found singing was one of the least reported form of distraction and constituted only 0.4 percent of the distracted driving observations. Findings were similar for a survey-based Australian study that found talking to passenger was present in 39.8 percent of the trips, which was the third most prevalent factor after lack of concentration and looking outside (McEvoy et al., 2006). An observational study was conducted in the U.S. with an aim to estimate the prevalence of secondary tasks with various roadway, contextual and driver characteristics (Kidd et al., 2016). This study collected the data at 12 observational sites and a total of 16,556 vehicles were observed. It was found that talking or singing with passenger was prevalent among female and old age drivers, as compared to male and young drivers. It was prevalent in morning, afternoon, and evening as compared to night, and was also predominant at intersections and roundabouts as compared to straight roadways.

2.4.5.2 Passenger interaction and driver performance

A naturalistic study was conducted to find the relationship between various metrics of driver performance and secondary tasks (Stutts et al., 2005). This study found passenger interaction does not affect driver performance and it did not increase the percentage of no hands-on wheel, percentage of in-vehicle eye glances and lane deviations. Another study was conducted to determine the influence of passenger interaction on driver behavior, utilized the data from young drivers in simulated driving environments (Toxopeus et al., 2011). For this study three scenarios were created, first where passenger was interacting or asking questions to drivers, second passenger was silent, and third no passenger present. In the first scenario the driving performance decreased drastically with 0.5 missed turns per driver, whereas in second and third scenario this was 0.1 missed turn per driver. Driver's speed selection was largely affected by first scenario where on average driver's drove 4kph above speed limit, whereas in second and third scenario it was 1.9kph above speed limit. However, in the first scenario standard deviation of lane position (SDLP) was lesser (avg. = 143 cm) as compared to second (avg. = 165 cm) and third scenario (avg. = 165 cm). Another driving simulator study was conducted to understand the driving performance of drivers when they were engaged in passenger interaction (Ross et al., 2016). This study also found driving with passengers, increased the percentage of total distance driven above speed limit and increased red light running. The study also found presence of passenger reduces amber light running, and lower hazard reaction time.

2.4.5.3 Passenger Interaction and crash risk

A 100-car naturalistic study was conducted to estimate the crash/near-crash risk due to various secondary tasks. This study found, the crash/near-crash risk due to passenger interaction was significantly lower than baseline events and have an O.R of 0.5, which indicates the benignity of this task (Klauer et al., 2006). Another naturalistic study focused on older drivers determined the crash/near-crash risk associated with secondary tasks (Huisingh et al., 2019). This study also confirmed that passenger interaction, and singing does not increase crash/near-crash risk (OR<1). Apart from naturalistic driving a study was conducted to understand driver's perception of the risks associated with various secondary tasks, where the risks were divided into five categories extremely risky to not risky at all. This study found talking to passengers is the one of the least risky rated secondary task (K. L. Young & Lenné, 2010). Another study was conducted to understand the driver's risk perception of various secondary tasks where they have to rate dangers associated with tasks from 1 (least risky) to 10 (most risky) (Rupp et al., 2016). This study found passenger interaction was considered the least risky among all the secondary tasks. Furthermore, it has the highest engagement score which indicates its prevalence and benignity.

2.4.6 Hygiene/Grooming

Hygiene and grooming related secondary tasks include applying make-up, biting nails/cuticles, combing/brushing/fixing hair, removing/adjusting jewelry, adjusting contact lenses or glasses and other personal hygiene. These secondary tasks require a combination of visual and manual attention of drivers. The following subsections explains the prevalence of hygiene/grooming related secondary tasks its impact on driver performance and crash risk associated with it.

2.4.6.1 Hygiene/grooming prevalence

An observational study was conducted in Alabama U.S. to understand the prevalence of various types of distractions took the sample from 3,265 drivers at 11 intersections (Huisingh et al., 2015). This study found grooming was present in only 5.8 percent of the distracted driving observations. Similar were the findings of an Australian survey-based study which reported grooming was present in only 3.5 percent of the most recent trip (McEvoy et al., 2006). The prevalence of grooming was drastically different in a naturalistic study that focused on adolescent drivers (Foss & Goodwin, 2014). This study utilized 7,858 clips of 20 seconds each, and out of which 1,186 clips had driver distraction. This study found grooming was present in 24 percent of the distracted driving clips, the reason finding could be adolescent drivers.

2.4.6.2 Hygiene/grooming driver performance

A naturalistic study was conducted with 70 participants with an aim to study the prevalence of secondary tasks and study the impacts of these tasks on driver performance (Stutts et al., 2005). This study found when driver was distracted by grooming and hygiene related secondary tasks, they had no hands-on wheel 12.8 percent of the time and their eyes were directed inside 34.62 percent of the time with increased lane deviations. However, it was also found that these distractions were prevalent when the vehicle is at stop and the average duration of a hygiene/grooming was 11.8 seconds (Stutts et al., 2003).

2.4.6.3 Hygiene/grooming crash risk

A 100-car naturalistic study estimated the crash/near-crash risk associated with various types of distractions and found personal hygiene related distractions do not increase the crash/near-crash risk (Klauer et al., 2006). But another naturalistic study that aimed to find the crash risk associated with various secondary tasks found personal hygiene related secondary tasks increases the likelihood of crash by 2.13 times as compared to baseline (Ye et al., 2017). Similarly, a naturalistic study on commercial vehicles was conducted and utilized data from 203 CMV and 55 truck drivers (Bocanegra et al., 2009). This study showed through logistic regression that the crash risk due to personal grooming, putting/removing eyeglasses, remove /adjust jewellery increases by 4.48, 3.63 and 1.25 times as compared to baseline driving episodes.

2.5 Distracted driving countermeasures

It has been observed in many studies that despite being concerned about distracted driving people frequently get engaged in it (AAA, 2016). To overcome this issue many studies have put forth various mitigation measures to reduce driver distraction like educating the drivers, stricter laws and enforcement, infrastructure related measures, public campaigns, and technological innovation.

Majority of the literature indicated education/training as the main strategy to alleviate driver distraction, especially for younger drivers. One such training program is the graduated driver licensing (GDL), where the young drivers are not directly given license and they drive with some restrictions like no night-time driving, limited number of passengers etc. Several researchers studied the impact of GDL on crashes and found it useful in reducing crashes and injuries (Hedlund et al., 2003; Hedlund & Compton, 2005). A study on targeted prevention programs for teenagers, suggest these programs should include their peers and relevant social circles as these were most influencing factors in this age group (Trivedi et al., 2017). Another study suggested to include further understanding of risk knowledge such as the causes and duration of distraction that leads to driving error and crash, this may contribute to changes in risk attitudes (Sween et al., 2017).

Nearly all the states in the US have moved towards stricter laws and enforcement against distracted driving, as currently 48 states ban on texting while driving and 24 have ban on handheld cell phone use (IIHS, 2022). However, the researches that examined the effectiveness of these laws in reducing handsfree phone and texting while driving found mixed results (IIHS, 2022). There are some research, that concluded banning hand-held cell phone use has a long term effect, but it is uncertain whether it is due to law or people are switching to handsfree cell phone use.

Around 30 percent of the distracted driving crashes occur from sources outside the vehicle (Regan et al., 2008). These sources can be advertising billboards, pedestrians, architecture, bicyclist, construction zone etc. Research on advertisement billboards and driver distraction suggested the position of Street Level Advertisement and Raised Level Advertisement board must be carefully chosen so that any unsafe situation can be avoided (Crundall et al., 2006). Some research even suggested to ban such advertisements in places where maximum driver attention is required for e.g., dangerous bends, black spots etc. (Bendak & Al-Saleh, 2010). Furthermore, it was also found that positive written content on bill boards and negative auditory content were most associated with distracted driving (Chan & Singhal, 2013, 2015). Hence proper guidelines must be developed for the placement of such advertisement boards.

Public campaigns and outreach programs are often used to educate/inform people about distracted driving and cause a change in their behavior. A survey conducted by the Governors Highway Safety Association (GHSA) found majority of the US states have public campaigns against distracted driving. Some states and organizations like NHTSA even use social networking platform like Facebook, Twitter, and YouTube to educate motorists (Vegega et al. 2013). As per *Countermeasures That Work, 2015* there is no study that has documented the effectiveness of outreach programs on driver knowledge, attitudes and behavior w.r.t. driver distraction (Goodwin, 2015). Many organizations communicate with general public through outreach campaigns for e.g., USDOT launched a nationwide campaign titled “Put It Down” to discourage people from distracted driving. Similar campaigns include National Safety Council's "On the Road, Off the Phone", AT&T's "It Can Wait" and similar others (Goodwin, 2015). However, most of these campaigns target against cell phone distraction.

Research found, countermeasures that address driver inattention in real time, can be useful for general inattention and distraction, e.g., rumble strips have the capability to alert the driver going off-lane (Ranney, 2008). Similarly, a distraction tolerant design like tactile lane markings, can be used as a countermeasure (Young et al., 2013). In addition, certain modifications in crosswalk like- high-visibility lighting, striping, and signing can increase the chance of pedestrians to get noticed by drivers and reduce pedestrian deaths (Brumfield & Pulugurtha, 2011). Moreover, installing overhead street lighting, proper placement of traffic control device or in-pavement warning lights can also be used in dark areas. Countermeasures like clear and visible road sign and markings, separate left turn lanes, and protected left turn signal phases can be used to avoid distraction or inattention (Goodwin, 2015). Finally, to fully understand and mitigate the driver distraction a system wide approach must be adopted which is a combination of- device, roadway and vehicle design, laws and working culture (K. L. Young & Salmon, 2012).

The use of technology, e.g., cell phones and in-vehicle entertainment system have been the heart of driver distraction the past two decades. It is befitting that there is a technological approach to counter the negative. A driver assistance system embedded within cell phone for example that mimics warning program for over speeding in vehicular GPS may provide the mechanism to prevent distracted driving condition by warning the driver should they be detected to be distracted using their cell phones (Dumitru et al., 2018). Furthermore, collision evading technological advancements for e.g., collision mitigation system, crash-imminent braking system (also referred to as automatic emergency braking system), and lane departure warning (lane keeping system) etc.

are useful in reducing crashes related to driver inattention (Goodwin, 2015). Additionally, the application of sensor technology can enable a system to detect the state of driver within a vehicle, indicating drivers' inattentiveness to driving relating to various forms of distraction such as using a cell phone, picking up objects, smoking and others.

2.6 Problem statement

Driver distraction is one of the prominent causes of motor vehicle crashes in the U.S. over the past few years. Many state governments have taken strict actions to reduce distracted driving such as public outreach and educational campaigns and aggressive legislation against distracted driving. Besides this, a lot of technological advancement has been made by automobile manufacturers such as collision mitigation system, crash-imminent braking system, and lane departure warning etc., so that drivers can be prevented from any mishap. Despite all these efforts, there is no significant reduction in the number of distraction-affected fatal crashes. Figure 2.2 shows the distraction-affected fatal crashes over the past 8 years, and it is evident that these crashes are stable over time. Hence, there is a stark need to study the occurrence of safety critical events (i.e., crashes and near-crashes) especially which are preceded by distraction.

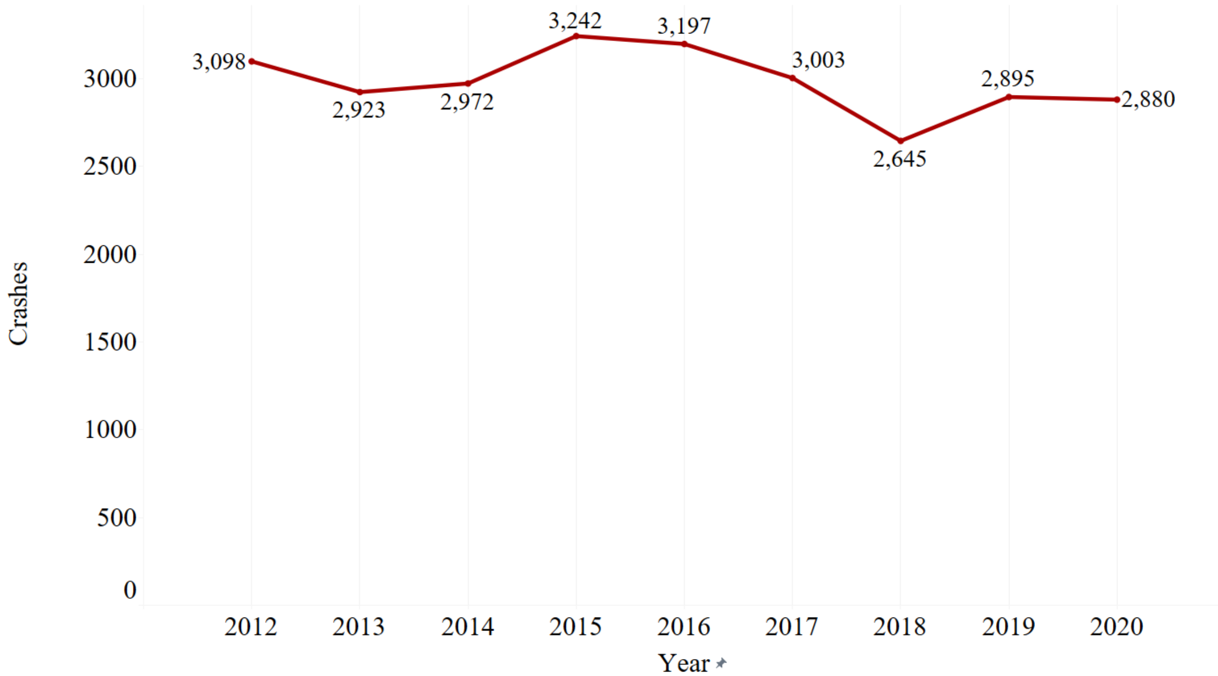

Figure 2.2 Distraction Affected Fatal Crashes 2012-19 (NHTSA, 2018b, 2022b)

Based on literature review it can be concluded that distracted driving is a growing concern, and it increases the likelihood of the occurrence of safety critical events. There is plenty of research on distracted driving and the crash/near-crash risks associated with it. However, there are only few studies that assess this risk based on driving environment. This need to be explored as some driving environments are fundamentally different from each other, in terms of vehicle-to-vehicle interaction, speed limits, right-of-way availability etc. These differences in driving environments calls for separate analysis. As such, one aim of this study is to analyze the crash/near-crash risk associated with distracted driving in different driving contexts.

In addition, the duration of distraction is also a key factor that has not been much explored by many researchers due to data limitations. Some prior studies found that duration of distraction tends to be positively associated with safety critical events (near-crashes and crashes combined). However, no research has studied the impact of duration of distraction on the likelihood of the occurrence of near-crashes and crashes separately. As such, this study also aims to compare the crash and near-crash risk separately due to various duration of distractions.

Lastly, prior literature has explored the impact of various types of distractions on driver performance, particularly speed selection. Majority of the studies concluded that distraction tends to reduce the speed of drivers, but no study has explored this effect in different driving environments. As such, this study aims to investigate the impact of various distractions on driver speed selection under different driving contexts.

3. DATA DESCRIPTION

Naturalistic driving data are used for the purposes of his research. It represents a robust source to study and analyze the impact of driver distraction on roadway safety. The second Strategic Highway Research Program 2 (SHRP 2) provides various subsets of naturalistic data that can be utilized to answer different questions related to driver distraction. The following section describes the two datasets.

3.1 Standard Strategic Highway Research Program 2 Naturalistic Driving dataset

The SHRP 2, Naturalistic Driving Study (NDS) is the largest video based naturalistic driving database in the whole world to date. Above 3,400 drivers participated in this study and the data were collected from October 2010 to December 2013 at six sites around the United States, that includes Seattle, Washington; Tampa, Florida; Buffalo, New York; Durham, North Carolina; State College, Pennsylvania; and Bloomington, Indiana (Hankey et al., 2016). Figure 3.1 shows the data collection sites of SHRP 2.

To recruit the participant drivers craigslist, multimedia advertisements, emails, phone calls, flyers etc. were used in each of the six regions. It was also ensured that the male and female participants should be equal, and range from teenage to old age/elderly drivers. Each participant's license status was checked before the start of data collection. Along with this, participant's vehicle ownership, model, year and condition were also considered for recruitment. (Campbell, 2012). Lastly, all the vehicles recruited were passenger cars, this was purposefully done to ensure the consistency among the data collected and it also eased the process of device installation within vehicle.

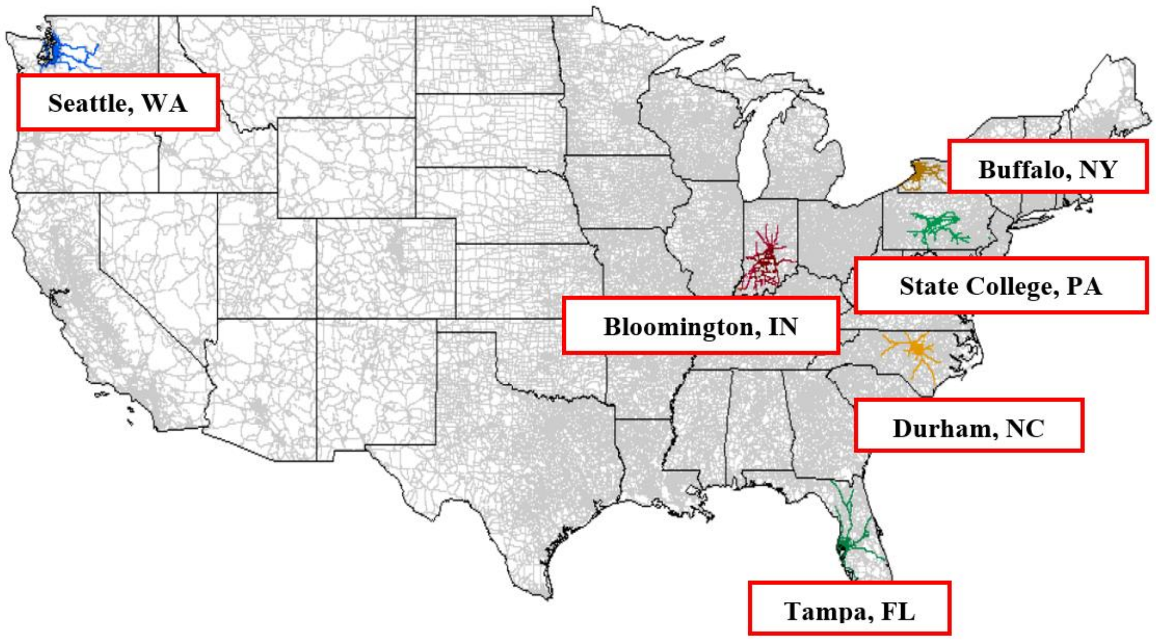

Figure 3.1 Data Collection Sites of SHRP 2 (CTRE, 2021)

Data acquisition system (DAS) were installed inside the participant's vehicle, that has cameras, sensors, and radars which collected four video camera views (forward roadway, backward roadway, driver's face, and driver's hand), vehicle's dynamic information (speed, acceleration, brake application etc.), and addition data like distance from an object, yaw rate etc. (Campbell, 2012). This DAS installation and testing (whether all equipments are connected well and gives real time information) takes approximately three hours. During this time the participants fill the information regarding their demographics, socio-economic condition, behavior, medical condition, personality traits, visual perception, risk perception, sleep patterns etc. Special care has been taken to remove all personally identifying information from this database (Campbell, 2012). Figure 3.2 shows the details of DAS, and Figure 3.3 shows the four camera views.

After the DAS installation, filling up the questionnaire, and consent form the vehicles were ready for use. The data collected using DAS was stored in the portable hard drive that is installed inside participant's vehicle, which was removed biannually from the vehicle so that all the data could be retrieved securely and it could be reissued for further data collection (Campbell, 2012).

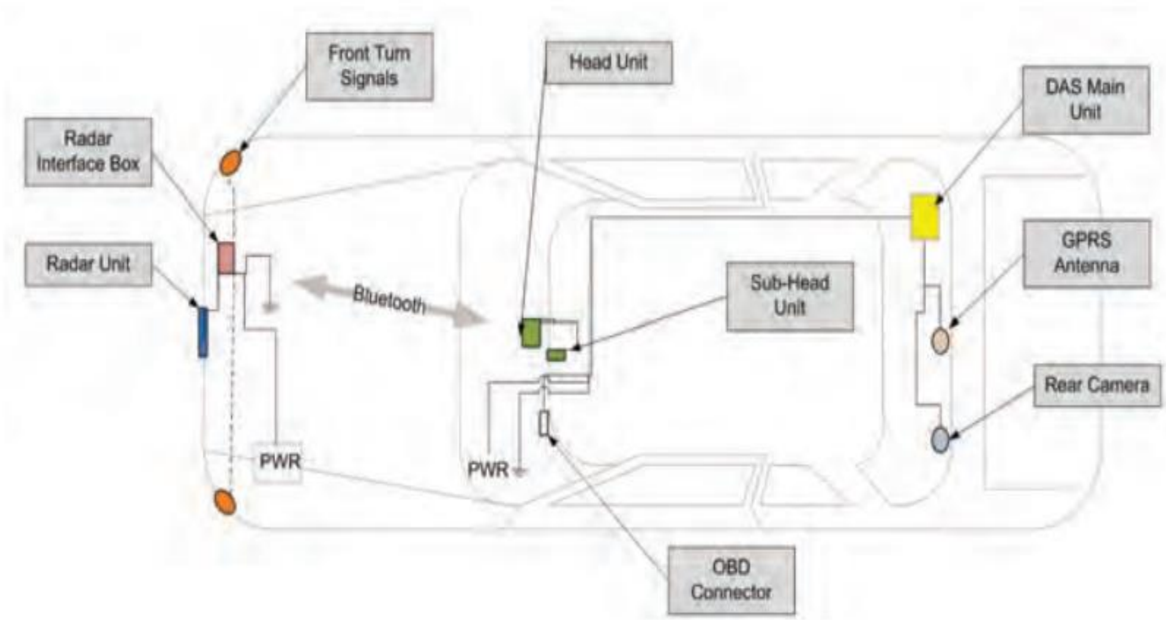

Figure 3.2 Schematic of SHRP 2 Data Acquisition System (Campbell, 2012)

All the data were collected and reduced by Virginia Tech Transportation Institute (VTTI). Approximately 6.4 million trips were reduced by VTTI's data reductionists and after removing trips that have unconsented drivers and technical issues nearly 5.5 million trips (85 percent) were left which were included in SHRP 2 database (Hankey et al., 2016).

Figure 3.3 Four Video Views (Virginia Tech., 2021)

All this SHRP 2 NDS data was more than two petabytes, which can be accessed at the InSight website (https://insight.SHRP2nds.us/). This can be used by the transportation research community to answer a wide variety of research questions. This website also has the detailed data dictionary to assist researchers in interpreting the variables. The whole data on InSight website can be divided into seven parts, which can be seen in Figure 3.4 and the website query page is shown in Figure 3.5.

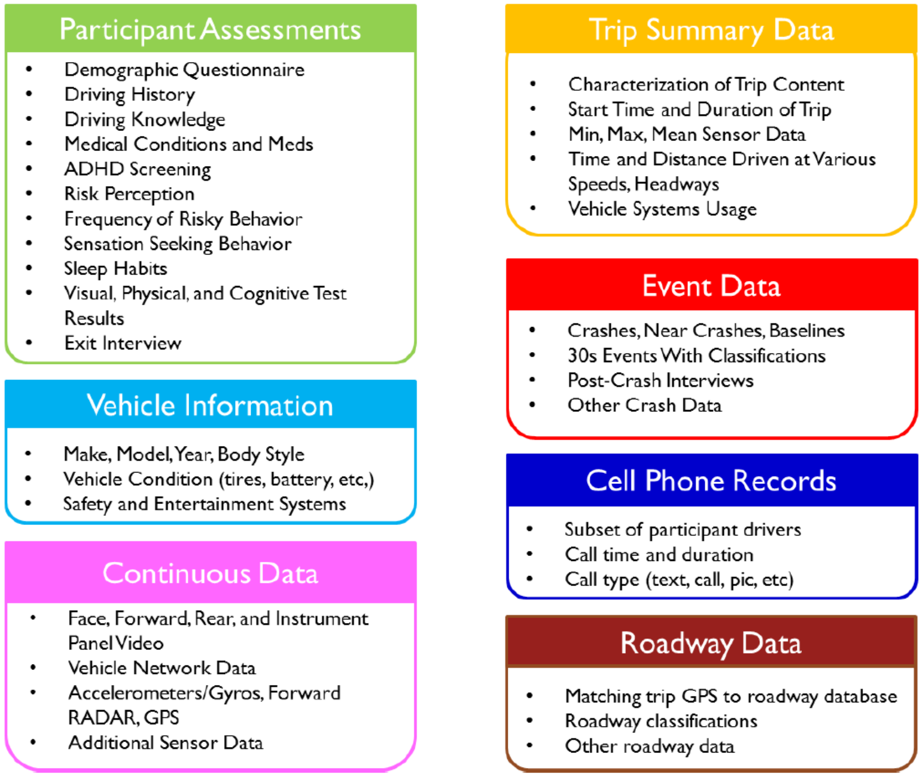

Figure 3.4 Data Categories in SHRP 2 Project (Hankey et al., 2016)

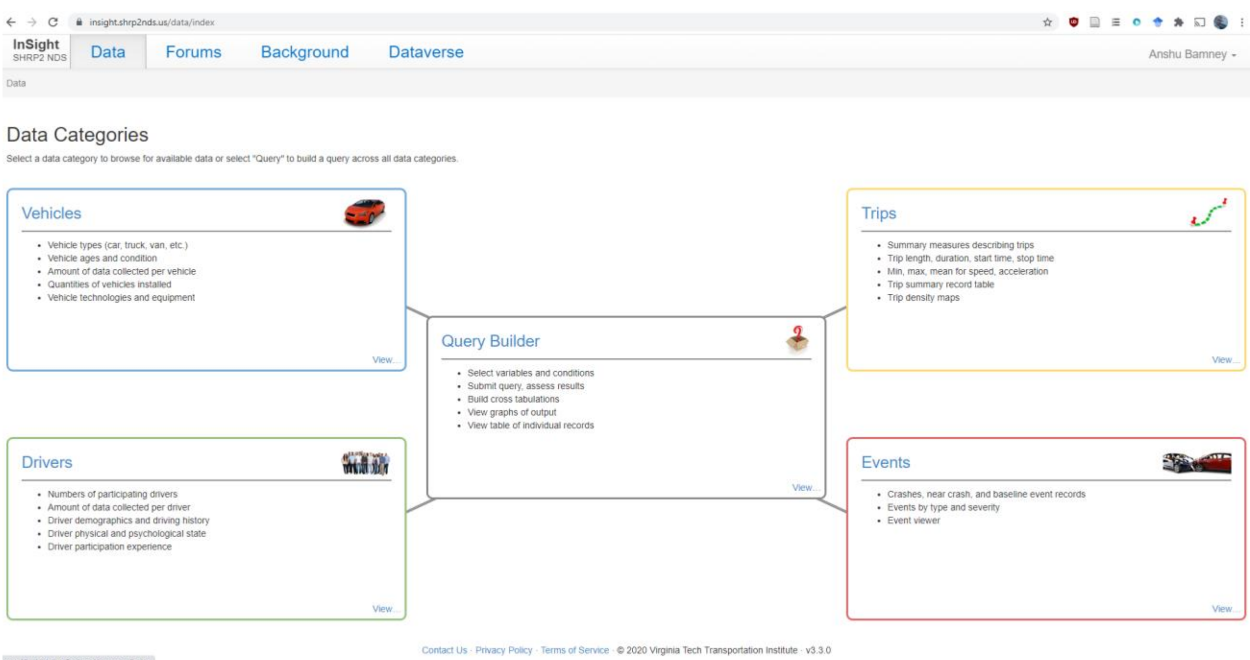

Figure 3.5 Data Query Page from InSight Website (InSight SHRP 2 NDS, 2021)

The SHRP 2 data includes data for all balanced-baselines, additional baselines, near-crashes and crashes, and are available at InSight website. This includes a total of 40,630 unique events, and 8,536 crash and near-crash events. For each event front camera view, event detail table and time series data (available at every 10 Hz) are available, and the following information can be extracted from each (not limited to):

- Front camera view: number of lanes, shoulder type, median type, context type etc.
- Event detail table: secondary task type, traffic flow, traffic density, weather etc.
- Time series data: speed, acceleration, deceleration, yaw rate etc.

In the case of crash and near-crash events the epoch length is 30 s, where first 20 s are before the precipitating event and the last 10 s are after the precipitating events. Where precipitating event is described as- “The state of environment or action that began the event sequence under analysis” (InSight SHRP 2 NDS, 2021). On the other hand baselines are randomly selected epochs of 20 s.

The focus of this study is on driver distraction and this a rich dataset with more than 60 types of secondary tasks (e.g., cell phone texting, eating with spoon, moving object in vehicle etc.) It should be noted that the data is sampled in a way that the driver distraction information are provided for a duration of 6 s for all events. For baselines this includes the last 6 s of the epoch, and for crash or near-crash it includes 5 s immediately preceding the precipitating event, until the end of event.

This is a case-cohort design dataset that can be used to assess the crash risk due to various types of secondary tasks and the prevalence of same under various driving contexts. It should be noted that this data contains mainly the driver characteristics and time series details that includes vehicle dynamics. Integration of detailed roadway information can make this dataset more comprehensive. As such, the Center for Transportation Research and Education (CTRE) of Iowa State University in partnership with the SHRP 2 program developed a large-scale database that contains roadway information and geometric characteristics called roadway information database (RID). This database combined the roadway data from the state highway departments of all the six sites with data collected by CTRE on field. This field data collection was done by a data collection van (Fugro Roadware-equipped vans) that has cameras, sensors and other instruments installed in it. It travels at the posted speed limits on all the routes selected by SHRP 2 and gathers information like lane type, width, grade, curve radius, speed limit, median type etc. This dataset can be integrated with the SHRP 2 data with the help of latitude and longitude, which is also gathered by this van (Campbell, 2012).

The data collection van of ISU CTRE collects the data at every second and it undergoes a quality assurance and quality check process. To determine the roadways from where the data should be collected, the ISU research faculty were provided the location details of participant trips, and based on these locations the data collection van is directed to collect data on these routes. Ultimately, more than 12,500 miles of roadway information was collected to assist the SHRP 2 program. The picture of data collection van can be seen in Figure 3.6.

Figure 3.6 Data Collection Van for Roadway Information Database (RID) (Campbell, 2012)

Ultimately, SHRP 2 NDS program provides details of driver characteristics (socio-demographic, risk taking behavior, medical history etc.), vehicle dynamics (speed, acceleration, yaw rate etc.) and RID information (geometric characteristics, speed limit, median type etc.). This extensive data provides an avenue to explore the driver and roadway characteristics that affect the driving performance and increases the crash/near-crash risk.

3.2 Naturalistic Engagement in Secondary Tasks (NEST) dataset

Naturalistic Engagement in Secondary Tasks (NEST) dataset is a subset of SHRP 2 data and was created with an aim to study driver distraction in greater detail. This dataset was produced as result of collaboration between Virginia Tech. Transportation Institute (VTTI), and Toyota Collaborative Safety Research Center (Owens et al., 2015). With help of this dataset, it is possible to investigate numerous aspects of secondary tasks, including the factors that may lead to distraction and distraction-related crash and near-crash events. This also includes high-level data about secondary tasks engagement and distraction-related events during real-world driving, as well as de-identified, extremely detailed time-series data (Owens et al., 2015). The NEST dataset provides detailed information for 1180 events. This includes 236 crash and near-crash events (combined referred to as safety critical events or SCEs) and 944 baseline events. The crash events were divided into: most severe crash, police reportable crash, minor crash, and low-risk tire strikes; and near-crash was a standalone category. It should be noted that all the safety critical events are distraction-related but baselines may or may not have any type of distractions (Owens et al., 2015). For distraction, breaks of less than five seconds between engagement in the same secondary tasks are coded as a continuous task.

The NEST dataset includes information of 204 drivers, and events were sampled such that approximately four baseline events were provided for each safety critical event from the same driver (Owens et al., 2016). In contrast to the standard SHRP 2 NDS data coding protocol, additional information is obtained for the NEST data as illustrated in Figure 3.7.

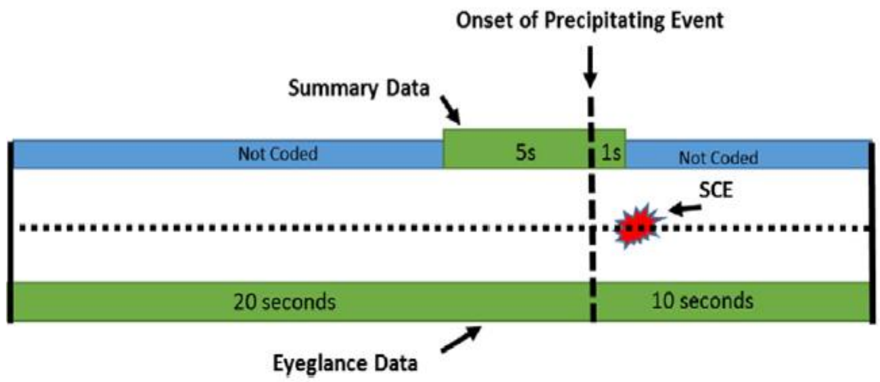

Fig 3.7a Standard SHRP 2 Data Coding

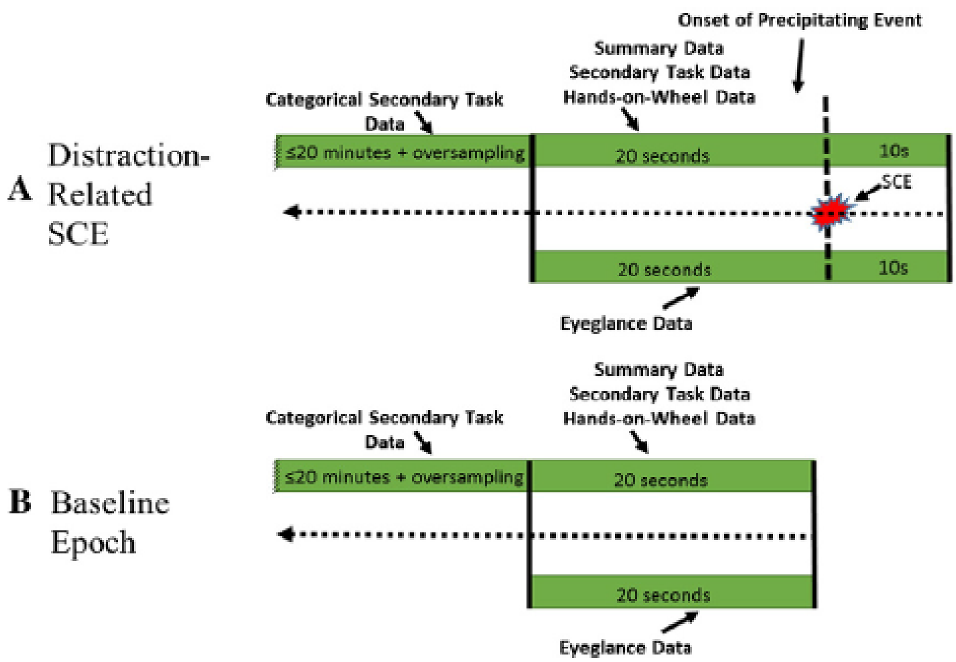

Fig 3.7b NEST Data Coding

Figure 3.7 Comparison of SHRP 2 Data and NEST Data (Owens et al., 2015)

In NEST data, first, the categorical trip-level coding was done to indicate the general level of involvement in secondary tasks for a driver into three categories: simple, moderate, or complex. In addition to the general summary data that is recorded as a part of the standard coding procedures, further information is collected as it relates to when the drivers' hands are on the wheel (e.g., both hands on wheel, one-hand-on one-off, no hands, etc.). The NEST data also provides greater detail as to the degree of secondary task involvement; it has an extended epoch length of 30 s for safety critical events and 20 s for baseline (resolution 0.1 s). This detailed data also provides frame-by-frame resolution for both the eyeglance and hands-on-wheel information, further supplementing available information about the nature of distraction. NEST dataset has the detailed information (speed, acceleration, yaw rate etc.) of drivers over the course of 30 s and 20 s for safety critical events and baseline events, respectively. The 30 s detailed coding of SCE comprised of 20 s prior to precipitating event and 10 s after it. The following variables were present and keep on changing for every 0.1 s for the last 30 s and 20 s data of SCE and baselines, respectively (Owens et al., 2015)-

1. Detailed secondary task (e.g., eating/drinking, talking handheld, holding object etc.)
2. Hands on wheel information (e.g., both hands on wheel, one hand on one off, no hands etc.)
3. Eye glance data (e.g., forward, right/left windshield, cell phone etc.)
4. Dynamic variables (e.g., speed, acceleration, steering wheel position etc.)

In addition, roadway information (e.g., presence of intersection, traffic density, traffic control device), locality information (moderate residential, interstate/by-pass/divided highway, divided highway etc.) and weather condition (e.g., snow, rain, no adverse weather etc.) were also given for each event at every 10 s epoch for both SCE and baselines. Driver level details (e.g., age, gender, annual miles driven etc.) were same for an event (Owens et al., 2015).

The main advantage of NEST data over the standard SHRP 2 data is the greater degree of detail of secondary task, it has an extended epoch length 30 s for SCE and 20 s for baseline. While on the other hand in standard SHRP 2 data the secondary task information is present for 6 s only.

In addition, standard SHRP 2 data does not give a frame-by-frame resolution of the eye glance data and hands-on wheel information that also serves as an important indicator of degree of engagement in secondary task. Lastly, NEST dataset has potential to analyze the dynamic variables (speed, acc., yaw rate etc.) of distracted drivers over the course of 30 s and 20 s for SCE and baseline events. Thus, it can be used to develop the speed profile of distracted drivers and analyze the crash and near-crash risk associated with various distractions.

4. ASSESSING NEAR-CRASH RISK IN FREEWAYS VS TWO-LANE HIGHWAYS

There are many studies in the past that have analyzed the crash/near-crash risk associated with different types of distraction but none of them specifically focused on different roadway facilities. The aim of this chapter is to utilize the standard SHRP 2 dataset was to estimate the differences in near-crash risk due to various distractions between different roadway facilities (i.e. freeways vs. two-lane highways). The following section explains the data preparation, data summary, statistical methodology, results and discussion and conclusion of this study objective.

4.1 Data preparation

For the purposes of this study the sample of near-crash events was compared to a series of similar baseline events. These baseline events serve as controls, which are used as a part of a case-cohort design in order to discern how the risk of involvement in a near-crash event varies in consideration of engagement in various types of distracting behaviors while controlling for other pertinent roadway, driver, and traffic characteristics. Consistent with prior work in this domain, data are sampled from the last six seconds of each baseline event (Owens et al. 2018). For near-crash events, the last five seconds immediately preceding the precipitating action (i.e., the event that caused the near-crash to occur), as well as the remaining timestamped data of that event (Owens et al. 2018) were considered.

Each near-crash or baseline event corresponds to one observation in the dataset. As geometric and traffic characteristics change over the analysis period, these data are extracted to correspond to the time of the precipitating event for near-crashes and for the last second of observation for the baseline events. Vehicle speeds are averaged over the five-second period preceding the precipitating event for near-crashes and averaged over the entire six-second period for the baseline events. Table 4.1 shows the data reduction for a hypothetical event.

Table 4.1 Data Reduction for Standard SHRP 2

Time series data								Data prepared			
Event ID	VTTI TIMES	vtti.speed gps mph	Event Severity 1	Event Start	Secondary Task1	Secondary Task1 Start time	Secondary Task1 Endtime	Event ID	vtti.speed gps mph (avg.)	Event Severity1	Cell phone, Holding
1352	1200	34.80	Near-Crash	21000	Cell phone, Holding	16200	20200	1352	31.02	Near-Crash	1
1352	2200	36.60	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	3200	37.66	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	4200	37.80	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	5200	38.04	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	6200	36.87	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	7200	35.54	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	8200	34.57	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	9200	33.55	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	10200	33.46	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	11200	32.54	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	12200	31.68	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	13200	28.01	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	14200	26.02	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	15200	25.49	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	16200	26.62	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	17200	29.23	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	18200	32.60	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	19200	33.07	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	20200	33.59	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	21200	34.69	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	22200	34.34	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	23200	24.51	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	24200	12.38	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	25200	0.15	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	26200	0.13	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	27200	2.16	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	28200	2.16	Near-Crash	21000	Cell phone, Holding	16200	20200				
1352	29200	2.65	Near-Crash	21000	Cell phone, Holding	16200	20200				

Additionally, events where pertinent data were not available were removed from the analysis dataset. It is possible for a single event to include more than one distraction. A binary variable was created for each secondary task, where one indicates the presence of a secondary task and zero shows its absence.

This study focused on two facility types: (1) limited-access freeways; and (2) two-lane highways. The InSight data includes a “locality type” field, which was used to select potential freeway events from the category “interstate/bypass/divided highway with no traffic signals” and two-lane highway events from the category “bypass/divided highway with traffic signal”.

As the locality field from InSight is not necessarily reflective of where the event occurred, an extensive quality control process was conducted for all events using the RID attributes and Google Earth. Different criteria, including maximum speed limit, number of lanes, and presence of intersections along segments were used to categorize the associated roadways into freeways and two-lane segment categories.

The initial dataset included a total of 3,640 events that occurred on freeway facilities and 4,642 events that occurred on two-lane highways. After a quality assurance review and elimination of observations with missing or incomplete data, the final freeway dataset was reduced to 3,100 events involving 1,280 unique drivers. The two-lane highway dataset was reduced to 3,204 events involving 1,507 unique drivers. The near-crash events comprised of 13.7 and 8.8 percent of the total driving events for freeways and two-lane highways, respectively.

A primary concern for this analysis was the aggregation of various types of distractions into coherent categories. Initially, there were a total of 53 different types of secondary tasks included in the dataset. These were ultimately aggregated into the ten categories shown in Table 4.2. This aggregation was based upon similarities in the types of actions required to perform the tasks and the degree to which each task introduced visual or manual distraction to the driver.

Table 4.2 Distraction Type by Category

Secondary Task Categories	Details of Secondary Tasks in each Category
Talking/singing/dancing	Dancing, Talking/singing, Audience unknown.
Cell phone: visual and manual	Cell phone-Browsing, Cell phone-Dialling hand-held, Cell phone-Locating/reaching/answering, Cell phone-Texting, Tablet device-Operating, Tablet device-Other Writing.
Cell phone: visual or manual	Cell phone-Dialling hands-free using voice-activated software, Cell phone-Holding, Cell phone-other, Cell phone-Talking/listening, hand-held, Reading
Eating/drinking	Drinking from open container, Drinking with lid and straw, Drinking with lid, no straw, Drinking with straw, no lid, Eating with utensils, Eating without utensils.
External distraction	Distracted by construction, Looking at an object external to the vehicle, Looking at pedestrian, Other external distraction.
Hygiene-related	Applying make-up, Biting nails/cuticles, Combing/brushing/fixing hair, Other personal hygiene Removing/adjusting clothing, Removing/adjusting jewellery, Removing/inserting/ adjusting contact lenses or glasses.
Instrument panel	Adjusting/monitoring climate control, Adjusting/monitoring other devices integral to vehicle, Adjusting/monitoring radio, Inserting/retrieving CD (or similar).
Internal activity	Moving object in vehicle, Object in vehicle-other, Other known secondary task, Other non-specific internal eye glance, Reaching for food-related or drink-related item, Reaching for object-other, Reaching for personal body-related item,

Table 4.2 (cont'd)

	Unknown type (secondary task present).
Passenger interaction	Child in adjacent seat – interaction, Child in rear seat – interaction, Passenger in adjacent seat – interaction, Passenger in rear seat – interaction, Pet in vehicle.
Smoking	Extinguishing cigar/cigarette, Lighting cigar/cigarette, Smoking cigar/cigarette.

It should be noted that cell phone use (including tablets) use was divided into two categories: (1) visual and manual distraction; and (2) visual or manual distraction. These categories distinguish between the types of cell phone use that introduce one versus both types of distraction. Visual and manual tasks included tasks such as browsing and texting while visual or manual tasks included dialing, holding, or talking on the phone. This classification also considered the level of cognitive action these different cell phone uses would require. Reading and writing were also grouped into one of the cell phone use categories as they account for less than 0.2 percent of the dataset.

4.2 Data summary

Table 4.3 and Table 4.4 provides summary statistics for each of these secondary task categories for freeways and two-lane highway facilities, respectively. These tables show how frequently a secondary task occurs in each of these facilities. A binary variable was created for each secondary task, where one indicates the presence of a secondary task and zero shows its absence. For events on freeways, passenger interaction is the most frequently occurring secondary task and was present in 13.6 percent of the total events and 28 percent of the distracted driving events. This is followed by talking/singing/dancing (i.e., singing with audience unknown and dancing) and external distraction (i.e., focusing on objects outside of the vehicle unrelated to the primary driving task) comprising 8.7 and 7.5 percent, respectively.

Table 4.3 Data Summary Statistics for Freeways

Secondary tasks	Total	Mean	Min.	Max.	SD
Cell phone: visual and manual	109	0.035	0	1	0.184
Cell phone: visual or manual	192	0.062	0	1	0.241
Eating/drinking	96	0.031	0	1	0.173
External distraction	232	0.075	0	1	0.263
Hygiene-related	129	0.042	0	1	0.200
Instrument panel	87	0.028	0	1	0.165
Internal activity	182	0.059	0	1	0.235
Passenger interaction	422	0.136	0	1	0.343
Smoking	33	0.011	0	1	0.103
Talking/singing/dancing	271	0.087	0	1	0.282
No secondary task	1602	0.517	0	1	0.500

Table 4.4 Data Summary Statistics for Two-lane Highways

Secondary tasks	Total	Mean	Min.	Max.	SD
Cell phone: visual and manual	85	0.027	0	1	0.043
Cell phone: visual or manual	138	0.043	0	1	0.203
Eating/drinking	57	0.018	0	1	0.132
External distraction	345	0.108	0	1	0.310
Hygiene-related	80	0.025	0	1	0.156
Instrument panel	79	0.025	0	1	0.155
Internal activity	184	0.057	0	1	0.233
Passenger interaction	313	0.098	0	1	0.297
Smoking	21	0.007	0	1	0.081
Talking/singing/dancing	175	0.055	0	1	0.227
No secondary task	1960	0.483	0	1	0.500

For events on two-lane highways, external distractions were the most frequent type of distraction, comprising of 10.8 percent of the total events and 23 percent of all distracted events. This was followed by passenger-related distraction (e.g., engaging with adult/child passengers or pets) and internal distractions (e.g., reaching or moving objects in the vehicle).

Along with the secondary tasks the study also examined driver characteristics such as age, gender, average annual miles traveled, and driver impairment during the event. Driver age was aggregated into four groups, 16-24, 25-39, 40-59, and 60 years and above. The average annual miles traveled were grouped based on the U.S average miles traveled by light-duty vehicles in 2017 (FHWA, 2019). The data also includes details of driver impairment, which was determined using an ambient atmospheric analyzer that is capable of detecting the presence of alcohol in the passenger compartment under certain conditions.

Table 4.5 shows the summary statistics of driver, traffic and roadway characteristics for freeways. The driver characteristics for freeway events show that age is approximately normally distributed and the events had equal share of male-female drivers. Majority of the drivers (52 percent) have an average annual mileage of 10,000 to 20,000 miles. Lastly, only 2.5 percent of the drivers were impaired, in all the freeway events.

In freeways majority of the events have leveled gradient (85.2 percent). For freeways nearly 60 percent of the events have no relationship with any type of intersection/interchange. Nearly half of the events have free-flow (i.e., LOS A1 and LOS A2) and remaining were non-free flow (i.e. LOS B through LOS F).

Table 4.6 shows the summary statistics of driver, traffic and roadway characteristics for two-lane highways. The driver characteristics show a higher representation of younger drivers (16-24 years) and the events had equal share of male-female drivers. Nearly 50 percent of the drivers had average annual mileage between 10,000-20,000 miles. Lastly, 2 percent of the drivers were impaired in all events. In two-lane highways also majority of the events have leveled gradient (84.6 percent). Majority (75 percent) of the events have no relationship with any type of intersection/interchange. The LOS A (LOS A1 + LOS A2) i.e., free flow makes up 80 percent of the total events, and the remaining 20 percent was the non-free flow from LOS B to F.

Table 4.5 Driver Traffic and Roadway Characteristics on Freeway

Characteristics	Total	Min.	Max.	Mean	SD
Driver Details					
Age 16-24 (1 if yes, 0 otherwise)	702	0	1	0.226	0.419
Age 25-39 (1 if yes, 0 otherwise)	798	0	1	0.257	0.437
Age 40-59 (1 if yes, 0 otherwise)	826	0	1	0.266	0.442
Age 60+ (1 if yes, 0 otherwise)	774	0	1	0.250	0.433
Average annual miles <10,000 (1 if yes, 0 otherwise)	714	0	1	0.231	0.421
Average annual miles 10,000 - 20,000 (1 if yes, 0 otherwise)	1627	0	1	0.525	0.499
Average annual miles > 20,000 (1 if yes, 0 otherwise)	759	0	1	0.245	0.430
Gender: Female (1 if yes, 0 otherwise)	1600	0	1	0.516	0.500
Gender: Male (1 if yes, 0 otherwise)	1500	0	1	0.484	0.500
Impairment: No (1 if yes, 0 otherwise)	3022	0	1	0.975	0.157
Impairment: Yes (1 if yes, 0 otherwise)	78	0	1	0.025	0.157
Traffic and Roadway Characteristics					
Grade Level (1 if yes, 0 otherwise)	2641	0	1	0.852	0.355
Grade down (Downward and dip) (1 if yes, 0 otherwise)	141	0	1	0.045	0.208
Grade up (Upward and crest) (1 if yes, 0 otherwise)	318	0	1	0.103	0.303
Free-flow (Level-of-service A) (1 if yes, 0 otherwise)	1572	0	1	0.507	0.500
Non-free-flow (Level-of-service B-F) (1 if yes, 0 otherwise)	1528	0	1	0.493	0.500
Intersection/interchange-related (1 if yes, 0 otherwise)	1188	0	1	0.381	0.486
Not intersection/interchange-related (1 if yes, 0 otherwise)	1912	0	1	0.617	0.486

Table 4.6 Driver Traffic and Roadway Characteristics on Two-lane Highways

Characteristics	Total	Min.	Max.	Mean	SD
Driver details					
Age 16-24 (1 if yes, 0 otherwise)	1216	0	1	0.380	0.485
Age 25-39 (1 if yes, 0 otherwise)	508	0	1	0.159	0.365
Age 40-59 (1 if yes, 0 otherwise)	617	0	1	0.193	0.394
Age 60+ (1 if yes, 0 otherwise)	863	0	1	0.269	0.444
Average annual miles <10,000 (1 if yes, 0 otherwise)	957	0	1	0.299	0.458
Average annual miles 10,000 - 20,000 (1 if yes, 0 otherwise)	1580	0	1	0.493	0.500
Average annual miles > 20,000 (1 if yes, 0 otherwise)	667	0	1	0.208	0.406
Gender: Female (1 if yes, 0 otherwise)	1554	0	1	0.485	0.500
Gender: Male (1 if yes, 0 otherwise)	1650	0	1	0.515	0.500
Impairment: No (1 if yes, 0 otherwise)	3133	0	1	0.978	0.147
Impairment: Yes (1 if yes, 0 otherwise)	71	0	1	0.022	0.147
Traffic and Roadway Characteristics					
Grade Level (1 if yes, 0 otherwise)	2712	0	1	0.846	0.361
Grade down (Downward and dip) (1 if yes, 0 otherwise)	150	0	1	0.047	0.211
Grade up (Upward and crest) (1 if yes, 0 otherwise)	342	0	1	0.107	0.309
Free-flow (Level-of-service A) (1 if yes, 0 otherwise)	2571	0	1	0.802	0.398
Non-free-flow (Level-of-service B-F) (1 if yes, 0 otherwise)	633	0	1	0.198	0.398
Intersection/interchange-related (1 if yes, 0 otherwise)	761	0	1	0.238	0.426
Not intersection/interchange-related (1 if yes, 0 otherwise)	2443	0	1	0.76	1.290

4.3 Statistical methodology

As noted previously, the data used in this study include a series of near-crash and baseline driving events. The baseline driving events represent control driving segments of the same duration as the crash/near-crash events to ensure consistency in exposure. This study design allows for the estimation of a logistic regression model to determine those variables that are over (under) represented in crash/near-crash as compared to "normal" baseline driving events. Consequently, the dependent variable in this study is binary in nature and coded to be equal to one for cases where a driver was involved in a safety-critical (i.e., crash or near-crash) event and zero in the case of baseline driving events. Such data are well suited for analysis using logistic regression models. Within the context of this study, the underlying model is structured according to equation 1:

$$Y_i = logit(P_i) = ln\left(\frac{P_i}{1 - P_i}\right) = \beta X, \tag{1}$$

where the dependent variable, Y_i, is the logistic transformation of the probability of driver i being involved in a near-crash event, denoted as P_i. The vector X represents a series of explanatory variables affecting the near-crash risk for each driver (e.g., age, engagement in distractions, geometric characteristics, traffic conditions), and β is a vector of regression parameters associated with each of these explanatory variables that is estimable using maximum likelihood techniques.

One concern that arises given the nature of the study design is that repeated observations occur of the same drivers over time. Consequently, correlation is introduced due to important, unobserved factors that are unique to each driver. Failure to account for this correlation may result in biased or inefficient parameter estimates. As such, a random effects framework is introduced wherein a driver-specific intercept term, δ_i, is added, resulting in equation 2:

$$Y_i = logit(P_i) = ln\left(\frac{P_i}{1 - P_i}\right) = \beta X + \delta_i, \tag{2}$$

This term allows the constant to vary across drivers, but retain the same value for all events involving the same driver, allowing the model to capture the unobserved heterogeneity that is due to these omitted variables. The SHRP 2 NDS data have a unique identifier, Participant ID, which is used to index the individual drivers.

When examining the model results, positive coefficients are reflective of factors that are overrepresented among those drivers involved in near-crash events while negative coefficients reflect factors that are associated with lower risk of a near-crash. To aid in interpretation of the model results, odds-ratios are provided, which represent the change in the odds of a near-crash event associated with a one-unit increase in the associated predictor variable.

4.4 Results and discussion

Separate random effects logistic regression models were estimated for events occurring on two-lane highways and freeways. The estimates from the models for each facility type are shown side-by-side in Table 4.7. For each model, the coefficient estimate is provided for each variable included in the model, along with the associated standard error, p-value, and odds-ratio. The reference level for each type of distraction was “no secondary task” in which the driver was not engaged in any kind of distraction. This was similar to model driving reference level in which drivers are sober, alert and attentive i.e. they do not show any sign of visual impairment, fatigue and distraction (Guo, 2019). A graphical comparison of the odds ratios for each type of distraction is provided in Figure 4.1 for both facility types, along with 95-percent confidence intervals.

It is interesting to note that, in general, similar relationships are found with respect to factors of interest on both freeways and two-lane highways, with limited exceptions. Turning to the primary factor of interest, the risks of near-crash events were higher for nearly all forms of distraction, with the exceptions being when the driver was eating or drinking (on either facility type) or when the driver was interacting with a passenger in a freeway environment.

Cell phone use was found to increase the odds of a near-crash event in both environments. On two-lane highways, risks were significantly heightened (OR=5.09) when the phone was creating both a visual and manual distraction versus one of the other (OR=2.07). On freeways, the increase in risk was similar for the two types of distractions (OR=1.62 for both and OR=1.80 for either). A SHRP 2 NDS study found that the cell phone visual-manual task (OR=1.83) increases the crash risk (Owens et al. 2018). This risk was similar to the near-crash risk on freeways, but quite higher than the near-crash risk of two-lane highways, that the present study has observed. The risks were markedly higher on two-lane highways, which is likely a reflection of the more complex driving environment that includes more frequent interaction with other vehicles, traffic signals, stop signs, on-street parking, and other sources of traffic disruption. Further support for this is reflected by the increased risks in the vicinity of intersections and interchanges, which were comparable for both two-lane highways (OR=1.33) and freeways (OR=1.31). This was consistent with the findings of Ho et al. who reported that increase in environmental complexity reduces the driving performance and increases crash risk (Ho et al., 2001).

Distractions related to other activities internal to the vehicle also showed higher risks. These types of activities included reaching for, or moving, other objects inside the vehicle. These types of distractions are concerning as they require drivers to direct their attention completely away from the roadway and to manually remove at least one, if not both, hands from the steering wheel. These types of distractions also generally require a longer duration. The existing literature also suggest that in-vehicle tasks degrades the driver performance by significantly reducing the mean speed and increasing the deviation from the posted speed limit, which in turn leads to increased crash risk (Horberry et al., 2006).

Engaging in hygiene-related activities, such as applying makeup, combing hair, and adjusting or removing clothing, jewelry, and contact lenses, were also among the highest risk activities, particularly in the freeway environment (OR=4.94). As with the preceding distractions, these activities affect the cognitive, visual, and manual driving tasks. A similar SHRP 2 study found personal hygiene increases the crash risk by 2.13 times as compared to no secondary task condition (Ye et al., 2017). Though the magnitude of risk increment was not so high as the present study found for freeways.

Table 4.7 Model Estimate for Crash Near-crash Risk for Two-lane Highways vs Freeways

	Two-Lane Highways				Freeways			
Variable	Coeff.	S.E	p-value	Odds Ratio	Coeff.	S.E	p-value	Odds Ratio
Intercept	-1.453	0.238	<0.001***	0.234	-0.862	0.231	<0.001***	0.422
No secondary task (baseline)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Talking/singing/dancing	0.608	0.244	0.013*	1.836	0.131	0.207	0.527	1.140
Cell phone: visual and manual	1.626	0.273	<0.001***	5.085	0.485	0.286	0.090	1.624
Cell phone: visual or manual	0.728	0.248	0.003**	2.071	0.586	0.220	0.008**	1.797
Eating/drinking	-0.449	0.549	0.414	0.638	-0.347	0.412	0.400	0.707
External distraction	0.436	0.191	0.022*	1.547	0.133	0.227	0.558	1.142
Hygiene-related	0.566	0.339	0.095	1.761	1.597	0.233	<0.001***	4.937
Instrument panel	0.329	0.361	0.362	1.389	0.309	0.338	0.360	1.363
Internal activity	1.773	0.184	<0.001***	5.889	1.018	0.212	<0.001***	2.768
Passenger interaction	0.550	0.191	0.004**	1.733	-0.202	0.203	0.320	0.817
Smoking	0.973	0.595	0.102	2.646	0.213	0.603	0.723	1.238
Average speed (mph)	-0.026	0.005	<0.001***	0.974	-0.033	0.004	<0.001***	0.967
Level grade (baseline)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Grade down (1 if yes, 0 if no)	0.514	0.265	0.053	1.671	0.732	0.300	0.015*	2.079
Grade up (1 if yes, 0 if no)	0.261	0.211	0.216	1.298	0.063	0.204	0.759	1.065
Non-intersection (baseline)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Intersection (1 if yes, 0 if no)	0.284	0.145	0.050*	1.328	0.267	0.124	0.031*	1.306
Non-free-flow (baseline)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Free-flow (1 if yes, 0 if no)	-0.909	0.136	<0.001***	0.403	-1.033	0.133	<0.001***	0.356
Age 60+ (baseline)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Age 16-24 (1 if yes, 0 if no)	0.203	0.171	0.235	1.225	0.763	0.205	<0.001***	2.146
Age 25-39 (1 if yes, 0 if no)	0.173	0.204	0.395	1.189	0.413	0.206	0.045*	1.511
Age 40-59 (1 if yes, 0 if no)	0.085	0.200	0.669	1.089	0.480	0.205	0.019*	1.616
Not impaired (baseline)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Impaired (1 if yes, 0 if no)	0.208	0.411	0.612	1.232	1.027	0.3139	<0.001***	2.794
AIC		17,355.174				16,137.033		
BIC		17,361.239				16,143.064		
Standard deviation	0.881	0.143	<0.001***	n/a	0.002	0.002	0.500	n/a

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

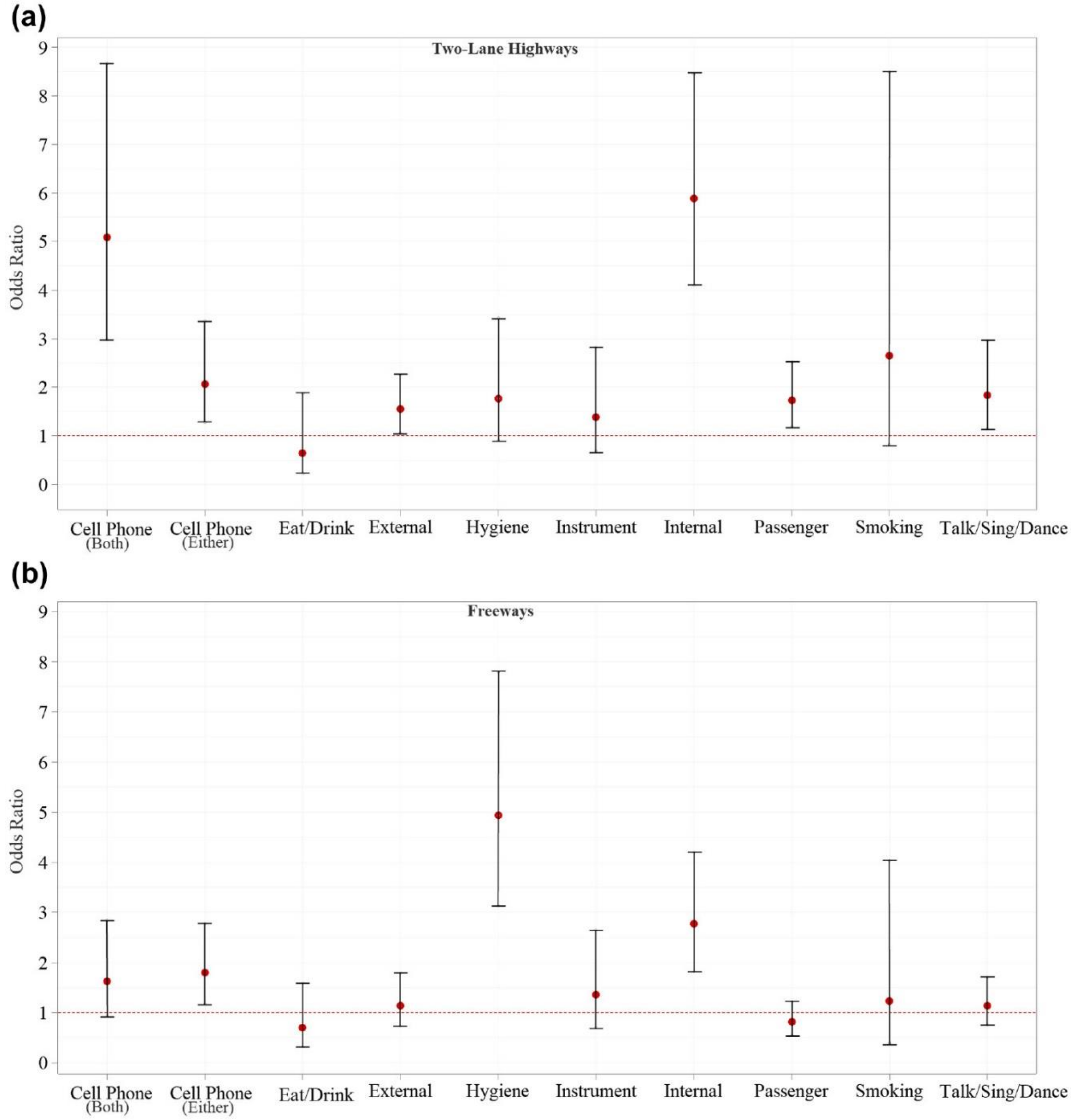

Figure 4.1 Odds Ratio and 95% Confidence Intervals by Type of Distraction

On two-lane highways, even seemingly benign tasks such as looking at objects external to the vehicle (OR=1.55), interacting with a passenger (OR=1.73), talking/singing/dancing (OR=1.84), and smoking (OR=2.65) were shown to increase crash risks. The risks under these scenarios are generally lower, which may be reflective of the fact that such activities still allow the driver to maintain their visual focus on the road ahead. Guo et al. compared the crash risk between different age groups and found that the OR for crash involvement varies from 5.88 to 12.70 for external distraction, which was quite high as compared to the present study. The same study found that crash risk increases by passenger interaction (OR varies from 0.95 to 1.48 for different age groups), which was very much consistent with the present study (Guo et al., 2017). When drivers were eating or drinking while driving, their risk of near-crash involvement reduced on both two-lane highways (OR=0.64) and freeways (OR=0.71), which was counterintuitive and warrants further research though it was not statistically significant. This may provide potential evidence of risk compensation, wherein drivers engage in these types of activities under more favorable traffic conditions. However, these results were different than one of the SHRP 2 studies which found that the crash risk increases with eating and drinking related distractions (Guo et al., 2017).

Beyond distractions, a number of other factors were also found to affect the likelihood of near-crash involvement. Interestingly, near-crash events tended to be less likely when average vehicle speeds were higher. This finding is consistent with various prior studies and is likely reflective of low density traffic conditions. Similarly, crash risks were also lower under free-flow (i.e., level-of-service A) traffic conditions. The risks of near-crash events were heightened on downgrades (OR=1.67 for two-lane highways; OR=2.08 for freeways) and marginally higher on upgrades and crest vertical curves.

Differences were also observed with respect to driver characteristics. Consistent with prior research, risks tended to be highest among young drivers (ages 16-24) and these risks generally plateaued among drivers ages 25-60. Interestingly, the risks were actually lowest among the oldest age group (ages 60+). This was quite surprising as another SHRP 2 study found that the crash risk was high in teenagers, young adults and old age drivers as compared to middle age drivers (Guo et al., 2017). Lastly, driver impairment significantly increased the likelihood of near-crash events on freeways, but only marginal differences were observed on two-lane roads.

5. DURATION OF DISTRACTION AND OCCURRENCE OF SAFETY CRITICAL EVENTS

NEST data allows for the investigation of numerous aspects of secondary task engagement, including factors that may contribute to distraction-related crash and near-crash events. The aim of this chapter is to understand the impact of duration of distraction on the likelihood of near-crashes vs crashes using NEST data.

5.1 Data preparation

To study the impact of duration of distraction on the occurrence of near-crashes and crashes (SCEs) NEST data was utilized as it has the detailed information of secondary tasks for 30 s of SCEs and 20 s of baselines, at the resolution of 0.1 s. This corresponds to 300 observations for SCEs and 200 for baselines. Since the last 100 observations (10 s) of the SCEs of the NEST data contains information after the precipitating event it is not useful for the purposes of this study. As such first 20 s of SCEs and whole 20 s of baselines were used in this study.

NEST data include a series of crash, near-crash, and baseline driving events. As all the crash and near-crash events are distraction-related and the baselines may or may not have any distraction, any sort of crash/near-crash risk analysis must be done with caution as it is not a random sample (since all crashes and near-crashes were precipitated by distraction). To make a fair comparison of crash and near-crash risk due to distraction, all the events with no distraction were removed from this analysis. In addition, low-risk tire strikes were also removed from the crash events as it includes tire strikes with little to no risk element (e.g., clipping a curb during a tight turn). After removing these events, the dataset was left with 603 baseline (distraction-related), 83 crash (distraction-related), and 72 near-crash (distraction-related) events. As the aim is to understand how the duration of distractions affects the likelihood of crash and near-crash, two separate datasets were prepared- distraction-related baselines with near-crash events (675 events) and distraction-related baselines with crash events (686 events). These two datasets were prepared in a way where one row represents one event. For each event, the duration for which a driver was distracted by a particular secondary task was also calculated which can range from 0 s to 20 s, where 0 s represent no distraction by a particular secondary task, and 20 s indicates the driver was distracted for the whole duration of the event. It is worth noting that within a single event driver may be distracted by more than one secondary task. Table 5.1 shows the data preparation procedure for the duration of distraction and SCE analyses.

Table 5.1 Data Preparation for Duration of Distraction and Occurrence of SCE analysis

No.	Event ID	Vtti timestamp	Speed network (mph)	Secondary task	Event ID	Avg. speed (mph)	Std. deviation (mph)	Duration for Talk to self (s)
1	25211	260800	45.63		25211	43.3	1.2	19
2	25211	260900	45.63					
3	25211	261000	45.63					
4	25211	261100	45.63					
5	25211	261200	45.63					
6	25211	261300	45.00					
7	25211	261400	45.00					
8	25211	261500	45.00					
9	25211	261600	45.00					
10	25211	261700	45.00					
11	25211	261800	45.00	Talk to self				
12	25211	261900	45.00	Talk to self				
13	25211	262000	45.00	Talk to self				
14	25211	262100	45.00	Talk to self				
15	25211	262200	45.00	Talk to self				
…	…	…	…	…				
…	…	…	…	…				
…	…	…	…	…				
190	25211	279800	43.13	Talk to self				
191	25211	279900	43.14	Talk to self				
192	25211	280000	43.00	Talk to self				
193	25211	280100	42.95	Talk to self				
194	25211	280200	42.80	Talk to self				
195	25211	280300	42.55	Talk to self				
196	25211	280400	42.21	Talk to self				
197	25211	280500	42.20	Talk to self				
198	25211	280600	42.18	Talk to self				
199	25211	280700	42.10	Talk to self				
200	25211	280800	42.05	Talk to self				

It is well established in the literature that secondary tasks are one of the main reasons for safety critical events. The role of duration of distraction on the occurrence of SCEs is not explored much. This study aims to explore this effect on both near-crashes and crashes separately. The following chapters show the data summary, statistical methodology, and results and discussion.

5.2 Data summary

This dataset initially had 16 types of detailed secondary tasks. Due to the similar nature of some secondary tasks, as well as limited sample sizes in some categories, several distraction types were combined into broader categories. There have been prior research in this domain that have combined various types of distractions (Gershon et al., 2019). For example, reaching for an object and manipulating an object were aggregated together, as they require similar degrees of attentiveness and often occur in sequence. For example, a driver reaches for an electronic device with an intention to manipulate it; such types of distractions are combined into one category. Reading and writing require similar attentiveness and given their infrequency in the sample (less than 0.5 percent of dataset), they were combined in this same group as this is the closest form of distraction. Adjusting devices and center stack control were also combined together as these were similar type of distractions where the driver interacts with controls either on steering wheel or manufacturer installed devices such as seat belts, doors, windows etc. Likewise, dancing, talking to self, and singing were also aggregated as these types of distractions fall under the same category of distractions for the purpose of this analysis. In each instance, the combination of these distraction categories did not show any substantive differences in terms of the direction or magnitude of effect. Ultimately, all 16 types of distractions were aggregated into 10 categories and are shown in Table 5.2 with definitions.

Table 5.2 Distraction Type by Category and Definition NEST Data

Secondary Task Categories	Definitions as per NEST
Adjusting Other Devices/Center Stack Controls and Others	Driver touches steering wheel, climate control etc. Driver interacts with manufacturer-installed device like seat belt, doors windows, sun visor etc.
Dancing/singing/talk to self	Driver moving hands, arms with beat of music Driver's lips are moving with audience unknown
Eating and Drinking	Driver is eating or drinking with/without utensil
Holding Object	Driver is holding an object not integral to vehicle
Looking External	Driver looking outside to a non-driving related object e.g., pedestrians, animals, other vehicles etc.
Looking Internal	Driver looking inside the vehicle e.g., passengers or searching for device
Personal Hygiene	Driver attending personal hygiene e.g., applying make up, biting nails etc.
Reaching/manipulating an object/reading/writing	Driver reaches for an object not integral to the vehicle e.g., food, drink etc. Driver manipulating an object not integral to vehicle e.g., cell phone etc. Driver is reading which is not part of driving; or writing with pen/pencil etc.
Talk to Passenger	Driver is interacting with passenger
Talking Handheld	Driver talking or has phone up to ear

Table 5.3 and Table 5.4 shows the descriptive statistics of secondary tasks for the two datasets i.e., distraction-related baseline with near-crashes and distraction-related baseline with crashes. These Tables show the number of events for which a secondary task was present and the percentage of SCEs that were preceded by a particular secondary task. As mentioned, an event can have multiple secondary tasks, in this case all the secondary tasks will contribute to the SCEs. Hence the summation of percentage of SCEs in each dataset is more than 100. The average duration of distraction was calculated across all events, which allows for interpretation of the typical impacts of each distraction on crash and near-crash risk. It was found that both the datasets-baselines with near-crashes and baseline with crashes have similar rate of occurrence of SCEs and average duration of distraction for all the types of distractions.

$$\% \; of \; SCEs \;=\; \frac{Number \; of \; SCE \; events \; for \; a \; particular \; secondary \; task}{Total \; number \; of \; events \; for \; the \; same \; secondary \; task} * 100 \quad (3)$$

$$Avg. duration \; of \; distraction = \frac{Sum \; of \; distracted \; seconds \; in \; all \; the \; events \; for \; a \; secondary \; task}{Number \; of \; events \; for \; which \; the \; secondary \; task \; was \; present} \quad (4)$$

The most precarious distraction in both the datasets (shown in Table 5.3 and Table 5.4) was reaching/manipulating an object. It was present in 17 percent of the baseline with near-crash events and 21 percent of the baseline with crash events. The second precarious secondary task was internal distraction which was present in 17 percent of the baseline with near-crash events and 19 percent of the baseline with crash events. This was followed by personal hygiene, adjusting devices/center stack control, and looking external distraction. Apart from frequency of distraction, it was also observed that the duration of distraction is also similar in both the datasets for various types of distractions. Talking handheld had the longest duration of distraction (18 s) followed by talking passenger (12 s), eating/drinking (10 s), dancing singing (10 s), holding an object (10 s) and others. The shortest duration of distraction was observed for the looking internal (2.5 s) related distraction. To summarize, there were a lot of commonalities between the two prepared datasets.

Table 5.3 Descriptive Statistics of Secondary Tasks by Type of Distraction for Baselines and Near-crashes

Secondary task	No. of events	No. of near-crashes	% of near-crashes	Total duration	Avg. duration	Min duration	Max duration
Adjusting devices/Center stack controls/Others	90	12	13.3	359.8	3.998	0	20
Dance/Sing/Talk to self	164	12	7.3	1700.3	10.368	0	20
Eating and Drinking	35	3	8.5	374.4	10.697	0	20
Holding object	132	15	11.3	1392.8	10.552	0	20
Looking external	155	19	12.2	412.1	2.659	0	12.4
Looking internal	64	11	17.1	168.8	2.638	0	20
Personal hygiene	49	8	16.3	356.7	7.280	0	20
Reaching/Manipulating an object/Reading/Writing	163	28	17.1	1546.7	9.489	0	20
Talk to passenger	171	11	6.4	2147.6	12.559	0	20
Talking Handheld	49	6	12.2	899.2	18.351	0	20

Table 5.4 Descriptive Statistics of Secondary Tasks by Type of Distractions for Baselines and Crashes

Secondary task	No. of events	No. of crashes	% of crashes	Total duration	Avg. duration	Min duration	Max duration
Adjusting devices/Center stack controls/Others	94	16	17.0	435.9	4.637	0	20
Dance/Sing/Talk to self	172	20	11.6	1822.8	10.598	0	20
Eating and Drinking	33	1	3.0	344.8	10.448	0	20
Holding object	139	22	15.8	1409.1	10.137	0	20
Looking external	164	28	17.0	437.7	2.669	0	12.3
Looking internal	66	13	19.6	165	2.500	0	20
Personal hygiene	50	9	18.0	340.9	6.818	0	20
Reaching/Manipulating an object/Reading/Writing	173	38	21.9	1577.3	9.117	0	20
Talk to passenger	176	16	9.0	2208.1	12.546	0	20
Talking Handheld	50	7	14.0	919.4	18.388	0	20

Table 5.5 and Table 5.6 shows the descriptive statistics of traffic characteristics for baselines with near-crashes and baseline with crashes, respectively.

Table 5.5 Descriptive Statistics of Traffic Characteristics for Baseline and Near-crashes

Traffic characteristics	No. of events	Min.	Max.	Mean	SD
Speed above median (1 if yes, 0 otherwise)	337	0	1	0.500	0.500
Speed below median (1 if yes, 0 otherwise)	338	0	1	0.500	0.500
LOS A (1 if yes, 0 otherwise)	404	0	1	0.599	0.491
LOS others (1 if yes, 0 otherwise)	271	0	1	0.401	0.491
Traffic flow: Divided median strip or barrier (1 if yes, 0 otherwise)	338	0	1	0.501	0.500
Traffic flow: others (1 if yes, 0 otherwise)	337	0	1	0.499	0.500
Number of lanes 2 or 3 (1 if yes, 0 otherwise)	489	0	1	0.724	0.447
Number of lanes others (1 if yes, 0 otherwise)	186	0	1	0.276	0.447
Surface condition dry (1 if yes, 0 otherwise)	595	0	1	0.881	0.323
Surface condition others (1 if yes, 0 otherwise)	80	0	1	0.119	0.323
Near crashes (1 if yes, 0 otherwise)	72	0	1	0.107	0.309
Baselines (1 if yes, 0 otherwise)	603	0	1	0.893	0.309
SD of speed (mph)	675	0	21.982	3.801	3.342

Table 5.6 Descriptive Statistics of Traffic Characteristics for Baseline and Crashes

Traffic characteristics	No. of events	Min.	Max.	Mean	SD
Speed above median (1 if yes, 0 otherwise)	343	0	1	0.500	0.500
Speed below median (1 if yes, 0 otherwise)	343	0	1	0.500	0.500
LOS A (1 if yes, 0 otherwise)	430	0	1	0.627	0.484
LOS others (1 if yes, 0 otherwise)	256	0	1	0.373	0.484
Traffic flow: Divided median strip or barrier (1 if yes, 0 otherwise)	330	0	1	0.481	0.500
Traffic flow: others (1 if yes, 0 otherwise)	356	0	1	0.519	0.500
Number of lanes 2 or 3 (1 if yes, 0 otherwise)	497	0	1	0.724	0.447
Number of lanes others (1 if yes, 0 otherwise)	189	0	1	0.276	0.447
Surface condition dry (1 if yes, 0 otherwise)	604	0	1	0.880	0.325
Surface condition others (1 if yes, 0 otherwise)	82	0	1	0.120	0.325
Near crashes (1 if yes, 0 otherwise)	83	0	1	0.121	0.326
Baselines (1 if yes, 0 otherwise)	603	0	1	0.879	0.326
SD of speed (mph)	686	0	17.562	3.701	3.272

It was found that both the datasets have similar traffic characteristics. Nearly 60 percent of the events have LOS A, and remaining were non free-flow. In both the datasets, 50 percent of the events have divided median strip or barrier, 70 percent have 2 or 3 lanes and 90 percent have dry surface conditions. The average standard deviation in speed was also same in both the datasets i.e. 3.7 mph. These similarities are indicating that traffic characteristics in both the near-crashes and crashes are comparable to each.

5.3 Statistical methodology

One of the objectives is to analyze how the duration of distractions affects the likelihood of crash and near-crash risk. This study design allows for the estimation of a logistic regression model to determine how the duration of various distractions in the given 20 s of data affect the likelihood of occurrence of a distraction affected safety critical event as compared to distraction affected baseline driving events. Consequently, the dependent variable for this regression analyses was binary in nature and coded to be equal to one for cases where a driver was involved in a safety critical event and zero in the case of distraction affected baseline driving events. Such data are well suited for analysis using logistic regression models. Within the context of this study, the underlying model is structured according to equation 5:

$$Y_i = logit(P_i) = ln\left(\frac{P_i}{1 - P_i}\right) = \beta X \quad (5)$$

where the dependent variable, Y_i, is the logistic transformation of the probability of an event being a safety critical event, denoted as P_i. The vector X represents a series of explanatory variables affecting the safety critical event (e.g., duration of various distractions, traffic, and geometric characteristics), and β is a vector of regression parameters associated with each of these explanatory variables that is estimable using maximum likelihood techniques. It should be noted the NEST data has one safety critical event per driver, which makes it unreasonable to use driver related characteristics in the model, as the likelihood of crash involvement would be same for each driver.

When examining the model results, positive coefficients reflect that the likelihood of safety critical events may increase, while negative coefficients reflect the factors that are associated with lower risk of a safety critical event. To assist in interpretation of the model results, odds-ratios (O. R.) are provided, which represent the change in the odds of a safety critical event associated with a one-unit increase in the related predictor variable.

5.4 Results and discussion

This study investigated the impact of duration of distraction on crash and near-crash risk. As noted previously, separate comparisons were conducted between the normal baseline driving events and the crash and near-crash events, respectively. Further, instances where baseline events included no distraction were removed as there were not any instances of similar distraction-free crash and near-crash events. As such, separate logistic regression models were estimated to compare: (1) crashes versus distraction-related baselines; and (2) near-crashes versus distraction-related baselines. In these analyses, variables were retained in these models based on their practical and statistical significance using a forward-selection approach. The model results are shown in Table 5.7 with coefficient estimates, standard errors, p-values, and odds ratios. The odds ratios for involvement in crash and near-crash due to average duration of distractions are shown along with 95 percent confidence intervals in Figure 5.1.

For these models, the total duration of distraction across the 20-s event was used as a predictor. In general, the duration of engagement in secondary tasks was positively associated with the occurrence of both near-crashes and crashes, with a few exceptions. Additionally, the risks due to distractions and other factors are almost the same for crashes and near-crashes.

The riskiest distractions in both datasets tend to be the ones that cause visual and manual distraction at the same time such as reaching for, or manipulating, an object. These distractions require drivers to take their eyes away from the road and hands away from the steering wheel simultaneously. These distractions tend to increase the likelihood of near-crash and crash risk by 1.8 to 2.0 times on average. These risks are similar to a naturalistic study that aggregated the secondary tasks into simple, moderate, and complex tasks; and found that complex task (includes reaching/manipulating an object) increases the likelihood of crash or near-crash by 2.1 times (Klauer et al., 2010). The risks posed by these distractions were found relatively higher in another naturalistic study which concludes reaching for an object increases the likelihood of crashes by 10 times (Guo et al., 2017).

Adjusting devices and the center stack control are other forms of visual-manual distraction. However, these distractions are generally less complex than reaching for and manipulating an object. If performed for an average duration these tend to increase the odds of near-crash and crash risk by 1.1 to 1.8 times. This is consistent with prior research that found simple and moderate tasks (include adjusting devices center stack control) increase crash and near-crash risk by 0.8 to 1.3 times (Klauer et al., 2010).

Visual distractions, where the driver was looking at something other than the immediate driving environment, were overrepresented in both crash and near-crash events. When this distraction was due to something external to the vehicle (e.g., deer, construction), the odds of a safety-critical event increased by 1.5 to 1.6 times on average. This was in-line with prior naturalistic studies that found crash/near-crash risk due to external distractions to increase by 3.70 (Klauer et al., 2006) to 6 times (Ye et al., 2017) as compared to cases where the driver was not engaged in a secondary task. For cases where the driver was looking at something inside the vehicle (e.g., passenger, object on seat), the increase in near-crash and crash risk was less pronounced and not statistically significant (p-value = 0.268 for crashes and 0.154 for near-crashes), though the average effect was in the same direction (odds ratio of 1.3 to 1.4 for an average length distraction).

When a driver was engaged in an average length conversation on a handheld cell phone, near-crash and crash risks increased by 1.3 to 1.7 times. This was similar to another naturalistic study where crash/near-crash risk due to cell phone handheld talking tends to increase by 1.16 times (Owens et al. 2018). Another study found that crash/near-crash risk increased by 1.7 percent for every second that a person was engaged in discussion on a handheld device while the risks were higher when the driver was dialing (5.6 percent increase per second) (Arvin & Khattak, 2020).

Table 5.7 Logistic Regression Model for the Occurrence of Crash and Near-crash Events

	Baseline and crash					Baseline and near crash				
	Coeff.	S.E.	p-value	O.R.	O.R. Avg. duration	Coeff.	S.E.	p-value	O.R.	O.R. Avg. duration
Intercept	-1.059	0.489	0.030*	0.347		-1.116	0.536	0.037*	0.328	
Duration of Adjusting devices/Center stack controls/Others (s)	0.130	0.037	<0.001***	1.138	1.824	0.027	0.060	0.652	1.027	1.114
Duration of Dance/Sing/Talk to self (s)	0.005	0.024	0.818	1.005	1.060	-0.053	0.034	0.120	0.948	0.577
Duration of Eating and Drinking (s)	-0.019	0.072	0.787	0.981	0.817	0.020	0.050	0.691	1.020	1.235
Duration of Holding object (s)	-0.014	0.027	0.609	0.986	0.870	-0.020	0.028	0.480	0.980	0.810
Duration of Looking external (s)	0.181	0.057	0.002**	1.199	1.622	0.156	0.066	0.017*	1.169	1.513
Duration of Looking internal (s)	0.097	0.087	0.268	1.102	1.274	0.122	0.085	0.154	1.129	1.378
Duration of Personal hygiene (s)	0.033	0.055	0.552	1.033	1.248	0.054	0.049	0.274	1.055	1.481
Duration of Reaching/Manipulating object/Reading/Writing (s)	0.078	0.021	<0.001***	1.081	2.040	0.064	0.023	0.004**	1.067	1.842
Duration of Talk to passenger (s)	0.004	0.022	0.853	1.004	1.053	-0.022	0.027	0.418	0.979	0.763
Duration of Talking Handheld (s)	0.028	0.026	0.284	1.028	1.673	0.015	0.028	0.585	1.016	1.328
Speed above median (1 if yes, 0 otherwise)	-0.754	0.304	0.013*	0.471		-0.412	0.341	0.227	0.662	
Std. Speed (mph)	0.061	0.037	0.098 .	1.063		0.137	0.040	0.001**	1.147	
LOS A free flow (1 if yes, 0 otherwise)	-0.748	0.273	0.006**	0.474		-1.954	0.326	<0.001***	0.142	
Divided median strip or barrier (1 if yes, 0 otherwise)	-0.857	0.298	0.004**	0.424		-0.687	0.313	0.028*	0.503	
Number of lanes 2 or 3 (1 if yes, 0 otherwise)	-0.632	0.263	0.016*	0.532		-0.503	0.291	0.084 .	0.604	
Surface condition dry (1 if yes 0 otherwise)	-0.319	0.365	0.382	0.727		-0.265	0.408	0.515	0.767	
AIC	465.726					390.753				
BIC	542.7513					467.503				
LL1	-215.863					-178.377				
LL0	-253.062					-229.155				
Chi-sq.	74.398***					101.557***				

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

A number of distractions were not found to exhibit significant relationships with near-crash and crash risk, including holding an object, eating/drinking, dancing/singing, personal hygiene, or talking to a passenger. These tasks generally do not require the same level of engagement as cell phone use and have been shown to have minimal impacts through prior research, as well (Klauer et al., 2006).

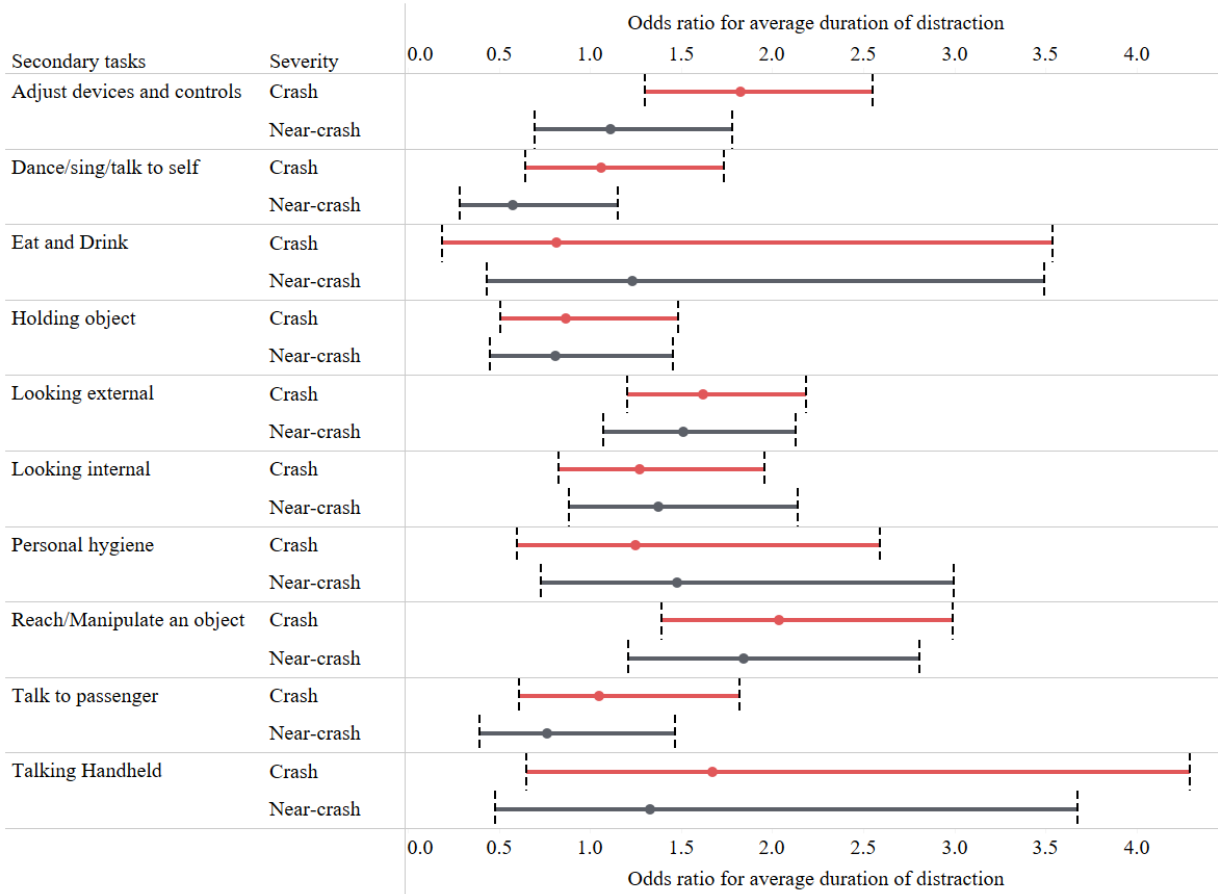

Figure 5.1 Odds Ratio of Engagement in Crash and Near-crash for Average Duration of Distraction

Interestingly, the risk of involvement in safety-critical events was lower in high-speed environments by 35 to 50 percent on average. While this result may at first appear counterintuitive, these environments are generally characterized by more favorable roadway characteristics (e.g., wider lanes and shoulders, lower levels of congestion) and provide greater accommodation for driver errors. Similarly, divided median or barrier was found to reduce the risk of near-crash and crash by 50 to 60 percent as compared to other roadway facilities like undivided roads. One-way traffic and dry roadway conditions also showed lower likelihood of both types of events.

In contrast, increases in the variability in travel speeds were associated with higher risks. For a one-mph increase in the standard deviation of speed, the risks of crash and near-crash events increased by 6 to 14 percent. This finding is in-line with the existing literature where a naturalistic study found a one-mph increase in speed was associated with a 12 percent increase in the chance of a safety-critical event (Hamzeie et al., 2017). Besides NDS, studies based on field data (loop detector) also suggest that variability in speed is associated with a heightened risk of a crash (Choudhary et al., 2018; Xu et al., 2012; Yang et al., 2018).

6. DRIVERS' SPEED SELECTION IN HIGH VS LOW SPEED ENVIRONMENT

Naturalistic engagement in secondary task data (NEST) data was used to understand the impact of distraction on the driver speed selection in high-speed vs low-speed environments. The following subsections explain data preparation, summary, methodology, and results and discussion.

6.1 Data preparation

NEST data was used to develop the speed profile of drivers in high-speed vs low-speed environment. The detailed summary data on driver distraction were available for 20 s intervals leading up to safety-critical events (i.e., crashes and near-crashes), as well as for randomly sampled 20 s intervals of normal baseline driving at a resolution of 0.1 s. These data were ultimately aggregated at a resolution of 1 s, which provides a reasonable level of precision and is consistent with the reporting of other covariates, such as GPS speed. To reduce the data, rolling averages of the 0.1 s resolution data are calculated for each second. This process is illustrated in Table 6.1 for a hypothetical event.

The focus of this chapter is on understanding the impacts of various secondary tasks on driver speed selection. Preliminary investigation suggested significant differences in terms of these underlying relationships when comparing high-speed and low-speed environments. As speed limit information is not available in the NEST dataset, all vehicle traversals were assigned to one of two categories based upon the average speed during the first three seconds of the event. If the speed during the first three seconds of the event was less than the median speed (38.75 mph) of the entire sample, the environment was classified as low-speed. Similarly, if the speed at the start of the event was above the median, then the event was characterized as high-speed. Several other aggregation strategies (e.g., splitting into three groups) were also considered. However, disaggregation into more than two groups created limited sample sizes within various distraction categories.

There were some cases of missing data within the speed observations. To address this issue, linear interpolation was used to fill the missing observations as long as the gap between the two observed values did not exceed 2 seconds, which is similar to prior naturalistic driving research (Sangster et al., 2013). Events where speed was missing for longer intervals, or where other pertinent data (e.g., secondary task engagement) were not available, were removed from the analysis dataset. The final dataset included 9,585 observations (i.e., vehicle-seconds) corresponding to 488 events from low-speed environments, as well as 9,815 observations among 500 events in high-speed settings.

A series of new variables were created for each event, which detailed the cumulative number of seconds during which the driver is engaged in a particular type of secondary task as shown in Table 6.1. This coding allowed for an assessment of the relationship between the duration of distraction with speed selection and crash/near-crash risk.

Other information like traffic conditions, proximity to intersections, estimated level-of-service, and roadway characteristics, were also provided for the detailed time series data and updated after every 10 s. Furthermore, drivers' demographic details (e.g., age, gender, number of traffic violations) were also provided and these values are consistent for all events involving the same driver.

Table 6.1 Data Preparation from for Drivers' Speed Selection and Secondary Task from NEST

No.	Event ID	Vtti timestamp	Speed network (mph)	Secondary task	Aggregated seconds	Avg. speed (mph)	Seconds for Talk to self	Cumulative seconds for Talk to self
1	25211	260800	45.63		1	45.3	0.5	0.5
2	25211	260900	45.63		2	…	…	…
3	25211	261000	45.63		3	…	…	…
4	25211	261100	45.63		4	…	…	…
5	25211	261200	45.63		5	…	…	…
6	25211	261300	45.00	Talk to self	6	…	…	…
7	25211	261400	45.00	Talk to self	7	…	…	…
8	25211	261500	45.00	Talk to self	8	…	…	…
9	25211	261600	45.00	Talk to self	9	…	…	…
10	25211	261700	45.00	Talk to self	10	…	…	…
11	25211	261800	45.00	Talk to self	11	…	…	…
…	…	…	…	Talk to self	12	…	…	…
…	…	…	…	Talk to self	13	…	…	…
…	…	…	…	Talk to self	14	…	…	…
…	…	…	…	Talk to self	15	…	…	…
…	…	…	…	Talk to self	16	…	…	…
191	25211	279900	44.80	Talk to self	17	…	…	…
192	25211	280000	45.00	Talk to self	18	…	…	…
193	25211	280100	45.00	Talk to self	19	…	…	…
194	25211	280200	45.00	Talk to self	20	44.3	1	19.5
195	25211	280300	45.00	Talk to self				
196	25211	280400	44.38	Talk to self				
197	25211	280500	43.75	Talk to self				
198	25211	280600	43.75	Talk to self				
199	25211	280700	43.75	Talk to self				
200	25211	280800	43.13	Talk to self				

6.2 *Data summary*

Table 6.2 and Table 6.3 shows the descriptive statistics for secondary tasks for above (high-speed) and below (low-speed) median speed environments. It should be noted that in this chapter as well 16 types of secondary task provided in NEST data were merged into ten as mentioned in the previous chapter. The average duration of distraction was calculated across all events for both high-speed and low-speed environment. This allows for interpretation of the typical impacts of each distraction on speed and crash/near-crash risk.

It is interesting to observe that in both the environments the duration of distraction was almost same, which indicates that it is unaffected by the environments. In both the environments, cell phone talking handheld has the maximum average duration of distraction (17 s - 19 s) followed by talking to a passenger (12 s) and eating/drinking (10 s - 12 s). For both environments, the minimum average duration of distraction was for internal and external distractions (2 s - 3 s).

Table 6.2 Descriptive Statistics for Secondary Tasks with Speed Above Median (High-Speed)

Secondary task	No. of events	Total duration	Avg. duration	Min duration	Max duration
Adjusting devices/Center stack controls/Others	48	218.2	4.55	0	20
Dance/sing/talk to self	93	941.7	10.13	0	20
Eating and Drinking	23	274.1	11.92	0	20
Holding Object	63	633.9	10.06	0	20
Looking External	96	235.4	2.45	0	12.3
Looking Internal	40	117.2	2.93	0	20
Personal Hygiene	28	192.8	6.89	0	20
Reaching/manipulating an object/reading/writing	91	836	9.19	0	20
Talk to Passenger	98	1210.7	12.35	0	20
Talking Handheld	25	487.7	19.51	0	20

Table 6.3 Descriptive Statistics for Secondary Tasks with Speed Below Median (Low-Speed)

Secondary task	No. of events	Total duration	Avg. duration	Min duration	Max duration
Adjusting devices/Center stack controls/Others	60	266.1	4.44	0	20
Dance/sing/talk to self	97	1038	10.70	0	20
Eating and Drinking	15	156.9	10.50	0	20
Holding Object	94	944.2	10.0	0	20
Looking External	99	327.2	3.31	0	19.3
Looking Internal	37	75.8	2.05	0	8.6
Personal Hygiene	31	217.8	7.03	0	20
Reaching/manipulating an object/reading/writing	113	1068.4	9.45	0	20
Talk to Passenger	96	1244.5	12.96	0	20
Talking Handheld	32	552.7	17.27	0	20

Besides average duration of distraction it can be seen that the frequency of distraction is almost same in both the types of distractions. Where, reaching/manipulating an object, talking to passenger, and looking external to vehicle were among the most frequent distractions in both the environments. On the other hand, eating/drinking, personal hygiene, and talking handheld on cell phone were the least frequent distractions.

Along with the secondary tasks, driver and traffic characteristics also play an important role in the driver speed selection. Table 6.4 and Table 6.5 shows the descriptive statistics of personal and traffic characteristics for above and below median dataset. The mean speed in low-speed and high-speed environment are 25.55 mph and 53.71 mph, respectively. All other variables are binary in nature where zero indicates the absence and one shows the presence of a variable. The drivers were divided into four age categories 16-19, 20-24, 25-49 and 50+ years, which is similar to other research (Obeidat et al., 2021; Guo et al., 2017). For both low-speed and high-speed environment it was found that most of the events have young drivers (below 24 years), and the age is normally distributed with a little skewness towards the right side. This is similar to the SHRP 2 data, as NEST is a subset of the latter. The majority of drivers did not have any traffic violations in the past three years prior to consent into the SHRP 2 program.

Further impaired drivers (angry, drowsy, sleepy, asleep, fatigued, emotional or impaired due to alcohol, drugs, previous injury) were present in almost 3 percent of the events in both the environments, whereas in majority events there was no driver impairment. In the low-speed environment a majority of the events (45 percent) occurred in business industrial areas, but for high-speed environments, a majority of events occurred on interstates (43 percent), which clearly shows the differences in driving contexts.

Table 6.4 Personal and Traffic Characteristics of NEST Dataset Above Median (High Speed)

Characteristics	No. of events	Min.	Max.	Mean	SD
Personal					
Age 16-19 (1 if yes, 0 otherwise)	99	0	1	0.198	0.398
Age 20-24 (1 if yes, 0 otherwise)	188	0	1	0.376	0.484
Age 25-49 (1 if yes, 0 otherwise)	103	0	1	0.206	0.404
Age 50+ (1 if yes, 0 otherwise)	110	0	1	0.220	0.414
Number of Violation = 0 (1 if yes, 0 otherwise)	256	0	1	0.512	0.500
Number of Violation = 1 (1 if yes, 0 otherwise)	117	0	1	0.234	0.423
Number of Violation = 2 or more (1 if yes, 0 otherwise)	127	0	1	0.254	0.435
Driver impairments: none (1 if yes, 0 otherwise)	480	0	1	0.960	0.196
Driver impairments: others (1 if yes, 0 otherwise)	20	0	1	0.040	0.196
Traffic					
Business industrial (1 if yes, 0 otherwise)	111	0	1	0.203	0.402
Bypass divided highway with traffic signals (1 if yes, 0 otherwise)	51	0	1	0.096	0.294
Interstate bypass divided highway with no traffic signals (1 if yes, 0 otherwise)	229	0	1	0.43	0.495
Moderate Residential (1 if yes, 0 otherwise)	55	0	1	0.103	0.304
Others, church, urban, school (1 if yes, 0 otherwise)	87	0	1	0.174	0.379
Divided median strip or barrier (1 if yes, 0 otherwise)	335	0	1	0.639	0.480
Other traffic flow (1 if yes, 0 otherwise)	187	0	1	0.374	0.484
LOS A (1 if yes, 0 otherwise)	296	0	1	0.516	0.500
LOS B (1 if yes, 0 otherwise)	216	0	1	0.377	0.485
LOS C, D, E, and F (1 if yes, 0 otherwise)	56	0	1	0.112	0.315
Traffic control any (1 if yes, 0 otherwise)	128	0	1	0.217	0.412
No traffic control (1 if yes, 0 otherwise)	462	0	1	0.783	0.412
Surface dry (1 if yes, 0 otherwise)	446	0	1	0.892	0.310
Surface others (1 if yes, 0 otherwise)	54	0	1	0.108	0.310
Number of travel lanes = 2 or 3 (1 if yes, 0 otherwise)	359	0	1	0.718	0.450
Number of travel lanes others (1 if yes, 0 otherwise)	197	0	1	0.394	0.489
Speed (mph)	500	0	84.11	53.71	13.38

The LOS was divided into three categories LOS A (free flow), B (free flow with restrictions), and C through F (congested traffic conditions). As per Highway Capacity Manual, free flow is defined as a traffic condition with low volume where drivers can drive at the desired speed and are not affected by other vehicles (Highway Capacity Manual, Sixth Edition: A Guide for Multimodal Mobility Analysis, 2016). As such, LOS A and B represent free flow, and LOS C through F was combined into one category to represent the congested flow. This compilation of LOS C through F was a pragmatic step as well due to less sample sizes in LOS C, D, E, and F.

Nearly, half of the events in both the speed-categories were in LOS A. As expected, nearly 20 percent of the events in low-speed were in congested flow as opposed to only 10 percent in high-speed environment.

Table 6.5 Personal and Traffic Characteristics of NEST Dataset Below Median (Low Speed)

Characteristics	No. of events	Min.	Max.	Mean	SD
Personal					
Age 16-19 (1 if yes, 0 otherwise)	128	0	1	0.262	0.440
Age 20-24 (1 if yes, 0 otherwise)	148	0	1	0.303	0.460
Age 25-49 (1 if yes, 0 otherwise)	94	0	1	0.193	0.394
Age 50+ (1 if yes, 0 otherwise)	118	0	1	0.242	0.428
Number of Violation = 0 (1 if yes, 0 otherwise)	286	0	1	0.586	0.493
Number of Violation = 1 (1 if yes, 0 otherwise)	118	0	1	0.242	0.428
Number of Violation = 2 or more (1 if yes, 0 otherwise)	84	0	1	0.172	0.377
Driver impairments: none (1 if yes, 0 otherwise)	473	0	1	0.969	0.173
Driver impairments: others (1 if yes, 0 otherwise)	15	0	1	0.031	0.173
Traffic					
Business industrial (1 if yes, 0 otherwise)	239	0	1	0.454	0.498
Bypass divided highway with traffic signals (1 if yes, 0 otherwise)	18	0	1	0.034	0.181
Interstate bypass divided highway with no traffic signals (1 if yes, 0 otherwise)	39	0	1	0.074	0.261
Moderate Residential (1 if yes, 0 otherwise)	143	0	1	0.271	0.445
Others, church, urban, school (1 if yes, 0 otherwise)	86	0	1	0.176	0.381
Divided median strip or barrier (1 if yes, 0 otherwise)	145	0	1	0.278	0.442
Other traffic flow (1 if yes, 0 otherwise)	377	0	1	0.773	0.419
LOS A (1 if yes, 0 otherwise)	283	0	1	0.490	0.500
LOS B (1 if yes, 0 otherwise)	180	0	1	0.312	0.463
LOS C, D, E, and F (1 if yes, 0 otherwise)	94	0	1	0.193	0.394
Traffic control any (1 if yes, 0 otherwise)	278	0	1	0.420	0.493
No traffic control (1 if yes, 0 otherwise)	383	0	1	0.579	0.493
Surface dry (1 if yes, 0 otherwise)	416	0	1	0.85	0.358
Surface others (1 if yes, 0 otherwise)	74	0	1	0.15	0.358
Number of travel lanes = 2 or 3 (1 if yes, 0 otherwise)	342	0	1	0.701	0.458
Number of travel lanes others (1 if yes, 0 otherwise)	227	0	1	0.465	0.499
Speed (mph)	488	0	62.75	25.54	11.18

The traffic flow was divided into two parts divided median strip or barrier, and other traffic flow (not divided, one-way traffic, no lanes i.e. no marked lane of travel e.g., driveways). The presence of divided median was there in 64 percent of the high-speed events, while for low-speed it was present in only 28 percent of events. As expected, traffic controls are more likely to present in low-speed (42 percent) environments as compared to high-speed (22 percent).

6.3 Statistical methodology

As noted previously for the speed-related analysis the overall data was divided into low-speed and high-speed environments by median speed. These are timeseries data that has speed at every event-second and the cumulative seconds of driver distraction with its type. To develop vehicles' speed profiles, several variables of interest are considered such as cumulative number of seconds for which drivers were distracted by a particular secondary task; driver and roadway characteristics in an event. As the dependent variable was the speed of the vehicle, linear regression model is considered for modeling purposes. Speed was also shown to exhibit linear relationships with several independent variables of interest, making linear regression an appropriate empirical framework for analyzing these data.

The nature of the study design is that each driver had one safety critical event and four baseline events, and each event has 20 seconds of detailed observations before precipitating event (with few exceptions, due to missing observations). This raises the concerns of correlation due to unobserved factors that are unique to each event and each driver. Failure to account for these correlations may result in biased or inefficient parameter estimates. To account for these issues a two-way random effects linear regression model is estimated (Greene, 2012), which takes the following form:

$$y_{it} = \beta X_{it} + u_i + w_t + \varepsilon_{it} \tag{6}$$

$$u_i \sim N(0, \sigma_u^2)$$

$$w_t \sim N(0, \sigma_w^2)$$

$$\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$$

where y_{it} is the speed of driver i at time t that ranges from 1 to 20 seconds, and β and X_{it} are vectors of estimable parameters and explanatory variables (e.g., cumulative number of seconds for which secondary task was present, demographic details of drivers and traffic flow/roadway conditions), u_i is a random effect that captures unobserved event-level effects (this term retains the same value for an event), w_t is a similar random effect for each driver in the dataset (this term retains the same value for a driver), and ε_{it} is the traditional idiosyncratic error term. Both u_i and w_t allow the constant term to vary across event-driver. When examining the model results, positive coefficients reflect variables associated with an increase in vehicles' speed, while negative coefficients indicate a decrease in vehicle speed.

6.4 Results and discussion

The results of two-way random effects models to examine the differences in driver speed selection between low-speed and high-speed environments are shown in Table 6.6. Before the detailed statistical analyses, drivers' speed selection with respect to various secondary tasks was investigated through data visualization using data from both environments. Subsequently, separate models were estimated for low-speed and high-speed conditions using a forward-selection approach. Variables were retained in the model if they were logically defensible and demonstrated a relationship with speed that was practically and/or statistically significant. Whenever, a new variable was added to the model, diagnostics were evaluated including collinearity measures, as well as the sign and direction of those variables already included in the model.

In general, all types of secondary tasks showed negative relationships with drivers' speed selection in high-speed environments. This is an interesting result and may be an indication of risk compensation behavior as noted by several prior studies (Li et al., 2020; Oviedo-Trespalacios et al., 2016; K. Young et al., 2003). However, in low-speed environments, most of the secondary tasks are correlated with higher speeds, which may be simply due to driver inattention or require further investigation. This trend of drivers' speed selection with cumulative seconds of engagement in secondary tasks in both environments can be seen in Figure 6.1.

In examining the model results, the impacts of any distractions on speeds tend to be relatively small when considering one-second intervals. Further, as there was significant variability in the duration of the distractions by type, to provide further clarity as to the effects of each distraction type, these effects on average speed are multiplied by the average duration of distraction (obtained from Table 6.2 and Table 6.3). To this end, Figure 6.2 illustrates 95 percent confidence intervals of the impact of an average duration of distraction on speeds in both environments.

It can be seen that external distractions (e.g., looking at pedestrian, animal or construction, not related to driving) tended to have larger effects on vehicles' speed in both environments on a per-second basis. This leads to a total speed reduction of 1.2 to 1.5 mph for an average duration of looking external in both environments. These results were similar to a driving simulator study that found looking at advertisements reduces the driving speed (Chattington et al., 2009). But for internal distractions (e.g., looking at passenger, or searching for a device/object), these effects turned out to be insignificant in both environments, showing that there is difference between internal and external distractions.

Consumption-related activities like eating/drinking tend to decrease the speed in both environments. Yet, the rate of speed reduction is greater in high-speed settings. An average episode of eating/drinking in high-speed environment reduces the speed by 6 mph, whereas in low-speed it reduces by 1.8 mph only. Some naturalistic studies have found that these distractions do not affect speed (Sayer et al., 2005; Schneidereit et al., 2017) but do increase steering variance (Sayer et al., 2005). Personal hygiene (e.g., grooming, biting nails, combing etc.) related distractions are a combination of visual, manual, and cognitive distractions. These were found to significantly increase the speed in low-speed environments by 2 mph for an average episode. This is similar to a naturalistic study that showed these distractions tend to degrade the driver performance (Stutts et al., 2005).

Reaching/manipulating an object increased speeds in low-speed environments by 3.5 mph and decreased speeds in high-speed environments by 2 mph on average. Such type of distractions are concerning as they take drivers' eyes away from the road and hands away from the steering wheel at the same time, which reduces the driving performance. These results are consistent with literature that showed interacting with a vehicle's entertainment system reduced speeds by 4 mph (Horberry et al., 2006). Adjusting in-vehicle devices tends to negatively affect driver's speed in high-speed environments by 1 mph on average. This effect was not significant in low-speed settings. A similar study observed that adjusting/monitoring radio or climate change was associated with a reduction in speed for events with high initial speed (Schneidereit et al., 2017). Dancing and singing related distractions tend to increase the speed in low-speed environment by 2.2 mph and decrease it in high-speed by 0.8 mph for an average episode of distraction.

Talking to passengers increased speeds by 1.8 mph in low-speed settings and decreased speeds by 1.2 mph in high-speed environments. This aligns with the existing literature that suggests conversing with a passenger was associated with exceeding speed limits and increasing traffic violations (Ross et al., 2016; Toxopeus et al., 2011). However, the magnitude of speed change in conversing with passenger is less as compared to talking on cell phone. This may be attributed to the shared responsibility of monitoring the environment among passengers and drivers (Arvin & Khattak, 2020).

Table 6.6 Drivers' Speed Selection Linear Regression Model for Low-speed and High-speed Environments

	Below Median (Low-speed environment)			Above Median (High-speed environment)		
	Coeff.	S. E.	P-value	Coeff.	S. E.	P-value
Intercept	23.730	2.860	<0.001***	38.749	2.356	<0.001***
No distraction (baseline)						
Cumulative Adjusting devices/Center stack controls/Others (s)	0.067	0.072	0.353	-0.208	0.064	0.001**
Cumulative Dance/Sing/Talk to self (s)	0.218	0.032	<0.001***	-0.076	0.027	0.005**
Cumulative Eating and Drinking (s)	-0.138	0.084	0.100	-0.491	0.047	<0.001***
Cumulative Holding Object (s)	0.005	0.034	0.889	-0.236	0.033	<0.001***
Cumulative Looking External (s)	-0.402	0.094	<0.001***	-0.392	0.084	<0.001***
Cumulative Looking Internal (s)	0.013	0.260	0.961	-0.006	0.092	0.946
Cumulative Personal Hygiene (s)	0.328	0.073	<0.001***	-0.012	0.064	0.851
Cumulative Reaching/Manipulating an object/Reading/Writing (s)	0.393	0.032	<0.001***	-0.197	0.030	<0.001***
Cumulative Talk to Passenger (s)	0.130	0.028	<0.001***	-0.097	0.023	<0.001***
Cumulative Talking Handheld (s)	0.193	0.039	<0.001***	-0.303	0.034	<0.001***
Age 50+ (baseline)						
Age 16 to 19 (1 if yes, 0 otherwise)	0.312	1.345	0.817	3.290	1.371	0.017*
Age 20 to 24 (1 if yes, 0 otherwise)	0.543	1.334	0.684	3.686	1.194	0.002**
Age 25 to 49 (1 if yes, 0 otherwise)	-0.903	1.485	0.544	2.447	1.386	0.080 .
Number of violations = 0 (baseline)						
Number of violations = 1 (1 if yes, 0 otherwise)	-0.827	1.178	0.484	0.520	1.104	0.638
Number of violations = 2 or more (1 if yes, 0 otherwise)	-0.629	1.336	0.638	1.961	1.106	0.079 .
Driver impaired (1 if yes, 0 otherwise)	-1.087	2.627	0.679	-4.216	2.058	0.041*
Locality others, urban, school, church (baseline)						
Business industrial (1 if yes, 0 otherwise)	-2.753	0.573	<0.001***	-2.606	0.502	<0.001***
Bypass divided highway with traffic signals (1 if yes, 0 otherwise)	-1.034	1.191	0.385	-1.130	0.693	0.103
Interstate bypass divided highway with no traffic signals (1 if yes, 0 otherwise)	3.840	1.369	0.005**	6.748	0.650	<0.001***
Moderate Residential (1 if yes, 0 otherwise)	-1.292	0.569	0.023*	-3.460	0.638	<0.001***
Traffic control device absent (baseline)						
Traffic control device present (1 if yes, 0 otherwise)	-3.886	0.184	<0.001***	-3.145	0.207	<0.001***
Level of service (C, D, E and F) (baseline)						
LOS A Free flow (1 if yes, 0 otherwise)	3.086	0.527	<0.001***	3.014	0.485	<0.001***
LOS B Flow with some restrictions (1 if yes, 0 otherwise)	2.952	0.450	<0.001***	2.238	0.420	<0.001***

Table 6.6 (cont'd)

Traffic flow Undivided and others (baseline)						
Traffic flow Divided median strip or barrier (1 if yes, 0 otherwise)	2.633	0.400	<0.001***	6.659	0.386	<0.001***
Event ID (intercept) Variance	91.555			73.053		
Subject ID (intercept) Variance	4.741			7.068		
Error	28.616			18.499		
AIC	61447.18			58769.92		
BIC	61647.88			58971.29		
R-sq.	0.717			0.871		
With random effects						
Log-likelihood	-30696.59			-29356.96		
Without random effects						
Log-likelihood	-36133.58			-35684.91		
LR-test	10874***			12656***		

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Talking handheld on a cell phone is a manual and cognitive task; however, the workload depends on the complexity of conversation. This secondary task tends to increase the driving speed in low-speed environment by 3.5 mph and decrease it in high-speed environment by 6 mph. Such a huge reduction in speed is sufficient to increase the likelihood of safety critical events. Numerous studies investigated the impact of cell phone handheld and found that the drivers tend to lower their speed to compensate for the risk due to cell phone talking (K. Young et al., 2003; Oviedo-Trespalacios et al., 2017a).

Distractions tended to be associated with lower vehicles speeds in high-speed settings and higher speeds in low-speed environments. In either case, the resultant speed differentials created by drivers engaged in secondary tasks provides a potential explanation for the higher number of safety critical events that are associated with distractions.

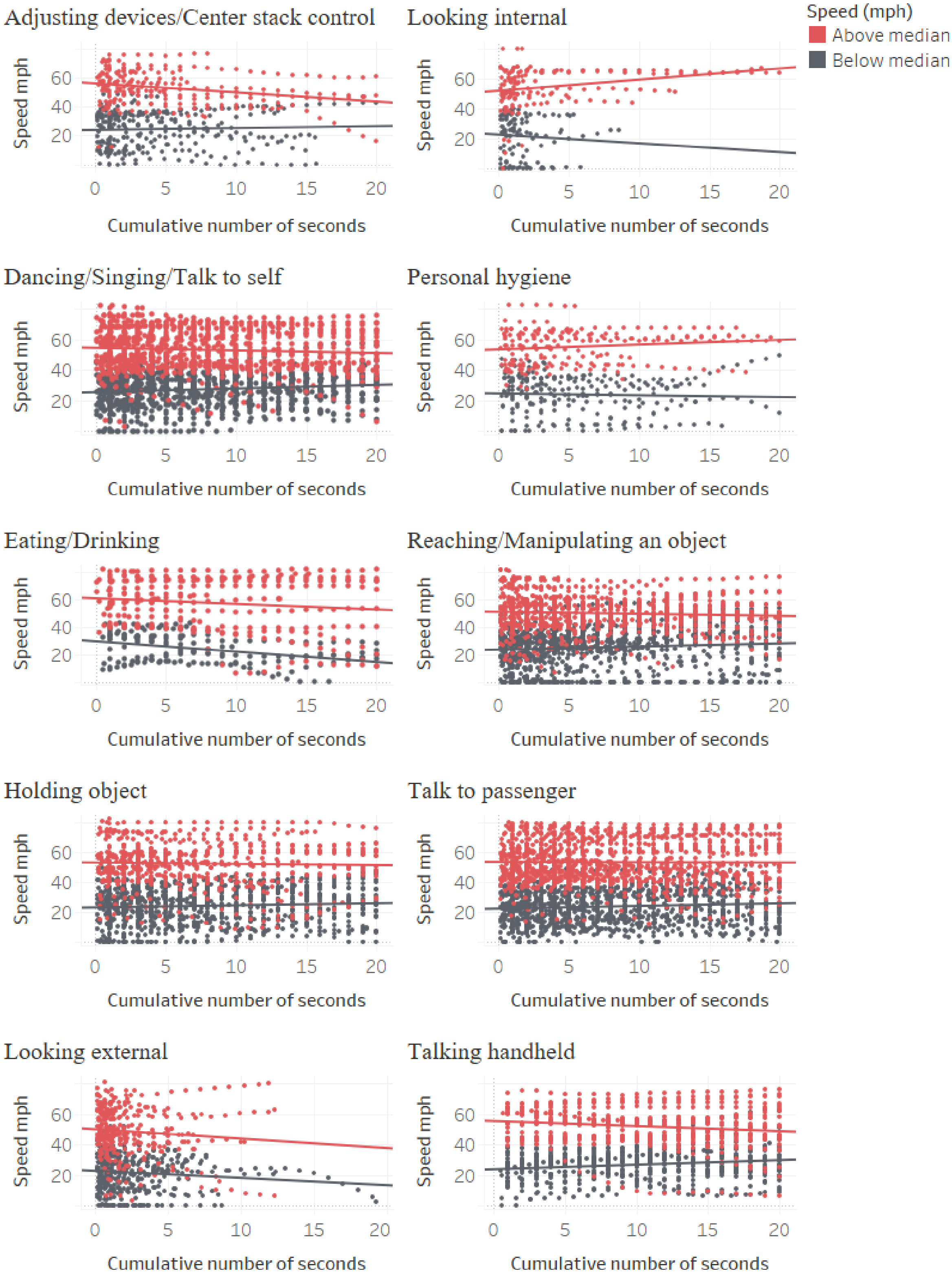

Figure 6.1 Distribution of Driving Speed Over Cumulative Time Spent in Secondary Task

Beyond distractions, there are many factors that affect driver speed selection. Certain driver characteristics such as age, number of traffic violations, and driver impairment were also considered in the model. All the driver characteristics had no significant impact on driver speed selection in low-speed environment. This could be attributed to the lower posted speed limits, more vehicle to vehicle interaction, and more restrictive nature of low-speed environments, which does not allow for higher variability in speeds among different driver characteristics. For high-speed environments, drivers of age 16-24 years tend to drive approximately 3.3 mph higher than the old age drivers (50+ years). Interestingly, in high-speed environments impaired drivers tend to drive slowly as compared to unimpaired drivers; and the drivers with two or more traffic violations tend to have higher speeds than those with no traffic violations. Such findings were not observed for low-speed environments. Lastly, business industrial locations tend to reduce the speed as compared to other localities in both environments. Functional classification of the roadway and traffic flow conditions were found to influence the speed.

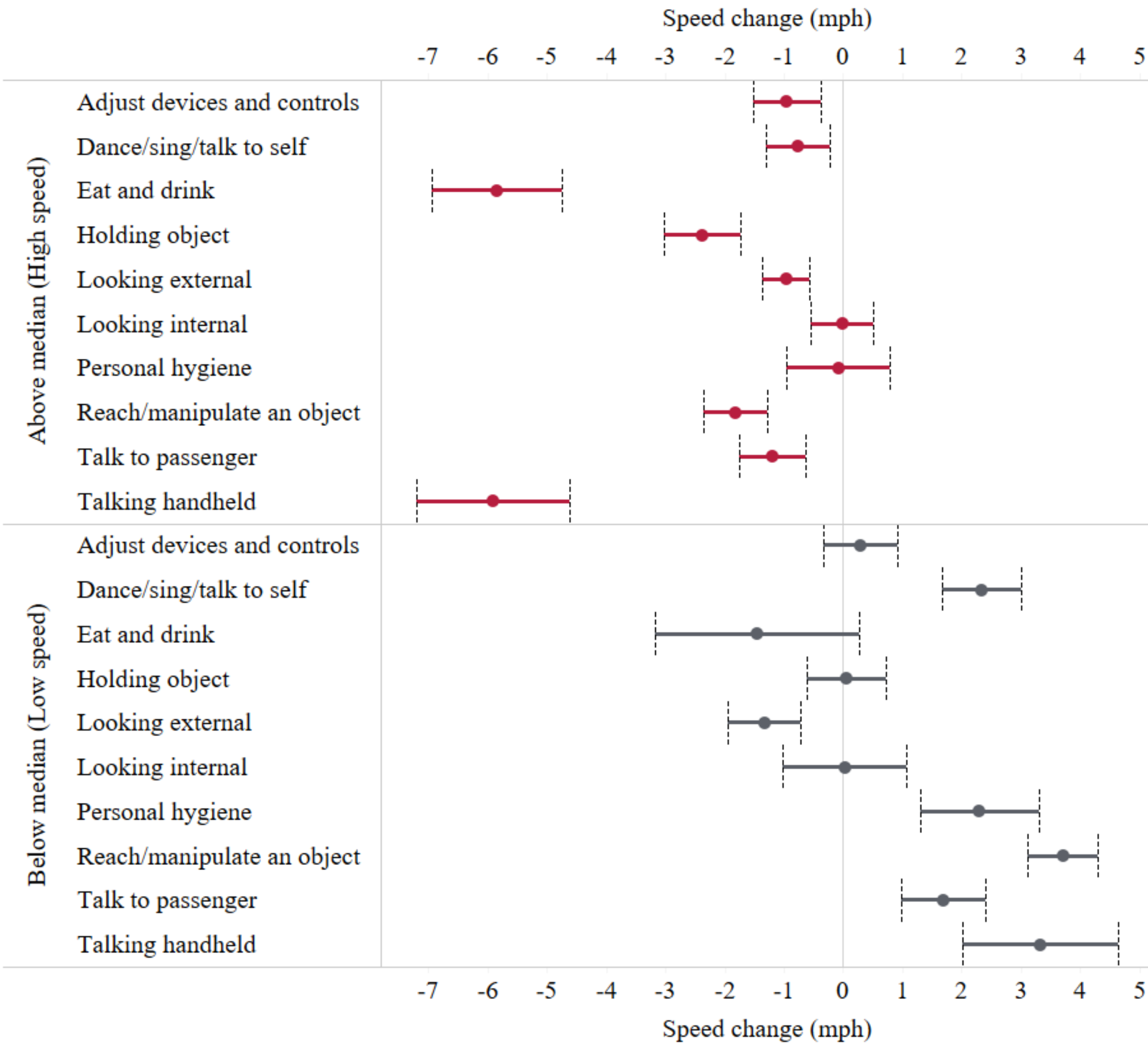

Figure 6.2 Upper and Lower Confidence Limit of Speed Change for Average Duration of Secondary Task in Both Environments

7. CONCLUSIONS

This study utilized standard SHRP 2 naturalistic driving data and NEST timeseries data to provide insights regarding- 1.) driver distraction and near-crash risk in two-lane highways and freeways 2.) distraction duration and its relationship with crash and near-crash risks. 3.) driver distraction and speed selection in low-speed and high-speed environments. The following sections provide the conclusions for each of the study objectives and recommendations from the overall study.

7.1 Assessing near-crash risk in freeways vs two-lane highways

Mixed effects logistic regression models were estimated to discern how the risks of near-crash events varied by distraction type while controlling for other pertinent factors of interest. This study gives a comparison on how the near-crash risk varies on two-lane highways and freeways with different types of distractions. Due to the different nature of both roadway facilities, these have to be studied differently and as expected the near-crash risk was different for various secondary tasks on both the facilities. This comparison of near-crash risk between the roadway facilities with driver distraction was missing in the prior studies.

In general, the same factors tended to increase the risks of near-crash events on both facility types. However, the magnitude of these differences in risk varied significantly, with the impacts typically being more pronounced on two-lane facilities where there was more frequent interaction between the subject drivers and other vehicles. Overall, the secondary tasks that created the most pronounced risks were those that introduced a combination of cognitive, visual, and manual distractions. For example, drivers who used cell phones were subject to higher risks and these risks tended to be most pronounced when both visual and manual distractions were involved. Likewise, risks tended to be highest when drivers reached for other objects inside the vehicle, engaged in personal hygiene-related activities, or focused on activities occurring outside of the driving environment.

7.2 Duration of distraction and occurrence of near-crash and crash

Logistic regression models were estimated to understand how the risks of occurrence of near-crash and crash varied by types and duration of distractions. This comparison of the occurrence of near-crash vs crash by distraction types and duration was missing in prior studies. In general, the results show that the duration of distraction tends to increase the likelihood of both near-crashes and crashes, and there were no significant differences in the occurrence of both the events. For both near-crash and crash the risks were more pronounced for those tasks that are a combination of visual and manual distractions or require longer gaze, such as reaching or manipulating an object, adjusting center stack control and external distractions. Lastly, similar type of roadway infrastructures and conditions tend to increase or decrease the likelihood of crashes and near-crashes.

7.3 Drivers' speed selection in low-speed vs high-speed environment

Mixed effects linear regression models were developed to analyze the speed profile of distracted drivers. This analysis provides a comparison on the impact of various types of distraction categories on speed selection of drivers in low-speed vs. high-speed environment. In general, the results of this study show that in high-speed environments, engagement in any type of secondary task tended to decrease the speeds, while mixed findings were observed in low-speed environments. It was interesting to note that the same type of secondary tasks showed opposing relationships with respect to vehicle's speeds between low-speed and high-speed environments.

Overall, for both the environments, the secondary tasks that influence the speed to a large degree were a combination of visual, manual, and cognitive distractions i.e., eating/drinking, cell phone talking handheld and reaching/manipulating an object. Interestingly, external distractions (e.g., looking at pedestrian, animals, construction etc.) have negative effect on speed in both the environments, while internal looks/glances were not found to affect the speed in both environments.

7.4 Recommendations and future work

The results of this study provide further motivation for stricter laws against distracted driving. Some studies showed that drivers believe that their driving performances are unaffected by the secondary tasks (Science Daily, 2012) and they are capable of multi-tasking; however, only few percent of the population can actually do so (American Safety Council, 2021). Some researchers argued that the lack of understanding of the self-regulatory behavior of drivers has made it challenging to accurately estimate the crash risk associated with driver distraction (Funkhouser & Sayer, 2012). This lack of knowledge has made it tough to form policies and countermeasures against distracted driving. However, attempts have been made to educate the drivers regarding the threats related to distracted driving through public awareness campaigns and outreach programs. It is important to acknowledge that 24 states in the U. S. have banned handheld cell phone use, and 48 have banned texting (IIHS, 2022). Along with these, other laws implicitly address the issues of secondary tasks e.g., reckless driving law that is highest in Oregon $6,250 and lowest in Kentucky, Mississippi, New Mexico and Ohio, which is $100 (Comoreanu, 2018). Attempts should be made to make these laws uniform so that this problem can be tackled across all states.

The study results also provide motivation for stronger legislation to curb distracted driving broadly (i.e., beyond cell phone use), as well as for the development and implementation of educational programs, outreach campaigns, and targeted enforcement. There are various examples of such programs, including Distracted Driving Awareness Month, the "U Drive. U Text. U Pay" campaign, and "Phone in One Hand Ticket in the Other" (APG News, 2018; NHTSA, 2022a; NSC, 2022). Again, these existing programs focus largely on cell phone use, but campaigns focused on distraction deserve broader consideration.

Such programs would be important elements of a larger safe systems approach to traffic safety, a key component of which is "safe road users" (i.e., promoting safe and responsible driving behavior through education, awareness, and enforcement). It is important to note that, while distractions had negative impacts on both road types, the likelihood of crash and near-crash events was significantly lower on high-speed roads and roads with median dividers. In general, such roads are more forgiving and better able to account for driving errors. This aligns with another component of the safe systems approach (i.e., "safe roads"), which advocates to design roads in ways that can accommodate such errors (GHSA, 2021). This also calls for modified roadway infrastructure such as rumble strips, tactile lane markings, and high visibility crosswalk etc.

Lastly, the SHRP 2 NDS data provides opportunities to investigate a wide range of fundamental research questions related to distracted driving. Future research should aim to answer the questions like- how the crash risk due to distraction varies at intersection versus non-intersection locations; how the likelihood of getting engaged in distraction varies w.r.t contexts/driving environments irrespective of the occurrence of safety critical events; and how the duration of distraction varies with driving environments. Further, driver distraction at signalized intersections is also an issue and its relationship with start-up lost time and dilemma zone is not explored yet. Answers to these questions are needed to formulate policies and countermeasures against distracted driving, as such, future should aim to answer these questions.

REFERENCES

REFERENCES

AAA Foundation for Traffic Safety. (2016). *2015 Traffic Safety Culture Index*. Retrieved March 8, 2021, from https://aaafoundation.org/wp-content/uploads/2016/02/2015TrafficSafetyCultureIndexReport.pdf

American Safety Council. (2021). *The Science Behind Distracted Driving*. Retrieved March 8, 2021, from https://blog.americansafetycouncil.com/the-science-behind-distracted-driving-2/

APG News. (2018, April 4). Phone in one hand, ticket in the other. *APG News Serving the People of Aberdeen Proving Ground, Md.* https://apgnews.com/community-news/phone-one-hand-ticket/

Arvin, R., & Khattak, A. J. (2020). Driving impairments and duration of distractions: Assessing crash risk by harnessing microscopic naturalistic driving data. *Accident Analysis & Prevention*, *146*, 105733. https://doi.org/10.1016/j.aap.2020.105733

Asbridge, M., Brubacher, J. R., & Chan, H. (2013). Cell phone use and traffic crash risk: A culpability analysis. *International Journal of Epidemiology*, *42*(1), 259–267. https://doi.org/10.1093/ije/dys180

Atwood, J., Guo, F., Fitch, G., & Dingus, T. (2018). The driver-level crash risk associated with daily cellphone use and cellphone use while driving. *Accident Analysis & Prevention*, *119*, 149–154. https://doi.org/10.1016/j.aap.2018.07.007

Bakiri, S., Galéra, C., Lagarde, E., Laborey, M., Contrand, B., Ribéreau-Gayon, R., Salmi, L.-R., Gabaude, C., Fort, A., & Maury, B. (2013). Distraction and driving: Results from a case–control responsibility study of traffic crash injured drivers interviewed at the emergency room. *Accident Analysis & Prevention*, *59*, 588–592.

Bendak, S., & Al-Saleh, K. (2010). The role of roadside advertising signs in distracting drivers. *International Journal of Industrial Ergonomics*, *40*(3), 233–236. https://doi.org/10.1016/j.ergon.2009.12.001

Bocanegra, J., Hickman, J. S., Hanowski, R. J., Olson, R. L., & Truck, V. T. T. Institute. C. F. (2009). *Driver Distraction in Commercial Vehicle Operations*. https://doi.org/10.21949/1502647

Brown, I. D., Simmonds, & Tickner, A. H. (1969). Interference between concurrent tasks of driving and telephoning. *Journal of Applied Psychology*. https://trid.trb.org/view/107747

Brumfield, R., & Pulugurtha, S. S. (2011). *Public Roads—When Distracted Road Users Cross Paths , November/December 2011—FHWA-HRT-12-001*. Retrieved July 7, 2021, from https://www.fhwa.dot.gov/publications/publicroads/11novdec/01.cfm

Campbell, K. L. (2012). The SHRP2 Naturalistic Driving Study: Addressing Driver performance and Behavior in Traffic Safety. *TR NEWS 282.*

Chan, M., & Singhal, A. (2013). The emotional side of cognitive distraction: Implications for road safety. *Accident Analysis & Prevention*, *50*, 147–154. https://doi.org/10.1016/j.aap.2012.04.004

Chan, M., & Singhal, A. (2015). Emotion matters: Implications for distracted driving. *Safety Science*, *72*, 302–309. https://doi.org/10.1016/j.ssci.2014.10.002

Chattington, M., Reed, N., Basacik, D., & Flint, A. (2009). *Investigating Driver Distraction: The Effects of Video and Static Advertising*. Transportation Research Laboratory.

Choudhary, P., Imprialou, M., Velaga, N. R., & Choudhary, A. (2018). Impacts of speed variations on freeway crashes by severity and vehicle type. *Accident Analysis & Prevention*, *121*, 213–222. https://doi.org/10.1016/j.aap.2018.09.015

Choudhary, P., & Velaga, N. R. (2017a). Analysis of vehicle-based lateral performance measures during distracted driving due to phone use. *Transportation Research Part F: Traffic Psychology and Behaviour*, *44*, 120–133. https://doi.org/10.1016/j.trf.2016.11.002

Choudhary, P., & Velaga, N. R. (2017b). Modelling driver distraction effects due to mobile phone use on reaction time. *Transportation Research Part C: Emerging Technologies*, *77*, 351–365. https://doi.org/10.1016/j.trc.2017.02.007

Comoreanu, A. (2018). *Strictest And Most Lenient States on Speeding and Reckless Driving*. WalletHub. Retrieved on June 20, 2021 from: https://wallethub.com/edu/strictest-and-most-lenient-states-on-speeding/14211

Crundall, D., Van Loon, E., & Underwood, G. (2006). Attraction and distraction of attention with roadside advertisements. *Accident Analysis & Prevention*, *38*(4), 671–677. https://doi.org/10.1016/j.aap.2005.12.012

CTRE. (2021). *SHRP 2 – Roadway Information Database*. Center for Transportation Research and Education. https://ctre.iastate.edu/shrp2-rid/

De Gruyter, C., Truong, L. T., & Nguyen, H. T. T. (2017). Who’s calling? Social networks and mobile phone use among motorcyclists. *Accident Analysis & Prevention*, *103*, 143–147. https://doi.org/10.1016/j.aap.2017.04.010

Dingus, T. A., Guo, F., Lee, S., Antin, J. F., Perez, M., Buchanan-King, M., & Hankey, J. (2016). Driver crash risk factors and prevalence evaluation using naturalistic driving data. *Proceedings of the National Academy of Sciences*, *113*(10), 2636–2641.

Dingus, T. A., Klauer, S. G., Neale, V. L., Petersen, A., Lee, S. E., Sudweeks, J., Perez, M. A., Hankey, J., Ramsey, D., & Gupta, S. (2006). *The 100-Car Naturalistic Driving Study. Phase 2: Results of the 100-Car Field Experiment*. United States Department of Transportation. National Highway Traffic Safety Administration.

Divekar, G., Pradhan, A. K., Pollatsek, A., & Fisher, D. L. (2012). Effect of External Distractions: Behavior and Vehicle Control of Novice and Experienced Drivers Evaluated. *Transportation Research Record*, *2321*(1), 15–22. https://doi.org/10.3141/2321-03

Dumitru, A. I., Girbacia, T., Boboc, R. G., Postelnicu, C.-C., & Mogan, G.-L. (2018). Effects of smartphone based advanced driver assistance system on distracted driving behavior: A simulator study. *Computers in Human Behavior*, *83*, 1–7. https://doi.org/10.1016/j.chb.2018.01.011

European Road Safety Observatory. (2018). Driver Distraction 2018. Retrieved April 5, 2021, from https://ec.europa.eu/transport/road_safety/sites/roadsafety/files/pdf/ersosynthesis2018-driverdistraction.pdf

Federal Highway Administration. (2019). Highway Statistics 2017. Annual Vehicle Distance Traveled in Miles and Related Data by Highway Category and Vehicle Type. Retrived on June 20, 2019 from https://www.fhwa.dot.gov/policyinformation/statistics/2017/vm1.cfm

Foss, R. D., & Goodwin, A. H. (2014). Distracted Driver Behaviors and Distracting Conditions Among Adolescent Drivers: Findings From a Naturalistic Driving Study. *Journal of Adolescent Health*, *54*(5, Supplement), S50–S60. https://doi.org/10.1016/j.jadohealth.2014.01.005

Funkhouser, D., & Sayer, J. (2012). Naturalistic Census of Cell Phone Use. *Transportation Research Record*, *2321*(1), 1–6. https://doi.org/10.3141/2321-01

Gershon, P., Sita, K. R., Zhu, C., Ehsani, J. P., Klauer, S. G., Dingus, T. A., & Simons-Morton, B. G. (2019). Distracted Driving, Visual Inattention, and Crash Risk Among Teenage Drivers. *American Journal of Preventive Medicine*, *56*(4), 494–500. https://doi.org/10.1016/j.amepre.2018.11.024

Gershon, P., Zhu, C., Klauer, S. G., Dingus, T., & Simons-Morton, B. (2017). Teens' distracted driving behavior: Prevalence and predictors. *Journal of Safety Research*, *63*, 157–161. https://doi.org/10.1016/j.jsr.2017.10.002

Governors Highway Safety Association. (2021). *Distracted Driving*. Retrieved on March 20, 2021. https://www.ghsa.org/state-laws/issues/distracted%20driving

Gliklich, E., Guo, R., & Bergmark, R. W. (2016). Texting while driving: A study of 1211 U.S. adults with the Distracted Driving Survey. *Preventive Medicine Reports*, *4*, 486–489. https://doi.org/10.1016/j.pmedr.2016.09.003

Goodwin, A. (2015). *Countermeasures That Work: A Highway Safety Countermeasure Guide For State Highway Safety Offices*. Eighth Edition. United States Department of Transportation. National Highway Traffic Safety Administration.

Greene, W. H. (2012). *Solutions and Applications Manual. Econometric Analysis* (Sixth Edition).

Guo, F. (2019). Statistical Methods for Naturalistic Driving Studies. *Annual Review of Statistics and Its Application*, *6*(1), 309–328. https://doi.org/10.1146/annurev-statistics-030718-105153

Guo, F., Klauer, S. G., Fang, Y., Hankey, J. M., Antin, J. F., Perez, M. A., Lee, S. E., & Dingus, T. A. (2017). The effects of age on crash risk associated with driver distraction. *International Journal of Epidemiology*, *46*(1), 258–265. https://doi.org/10.1093/ije/dyw234

Hamzeie, R., Savolainen, P. T., & Gates, T. J. (2017). Driver speed selection and crash risk: Insights from the naturalistic driving study. *Journal of Safety Research*, *63*, 187–194. https://doi.org/10.1016/j.jsr.2017.10.007

Hankey, J. M., Perez, M. A., & McClafferty, J. A. (2016). Description of the SHRP2 Naturalistic Database and the Crash, Near-Crash, and Baseline Datasets. The Strategic Highway Research Program 2. Transportation Research Board.

Haque, M. M., Oviedo-Trespalacios, O., Debnath, A. K., & Washington, S. (2016). Gap Acceptance Behavior of Mobile Phone–Distracted Drivers at Roundabouts. *Transportation Research Record*, *2602*(1), 43–51. https://doi.org/10.3141/2602-06

Haque, Md. M., & Washington, S. (2014). A parametric duration model of the reaction times of drivers distracted by mobile phone conversations. *Accident Analysis & Prevention*, *62*, 42–53. https://doi.org/10.1016/j.aap.2013.09.010

Hedlund, J., & Compton, R. (2005). Graduated driver licensing research in 2004 and 2005. *Journal of Safety Research*, *36*(2), 109–119. https://doi.org/10.1016/j.jsr.2005.02.001

Hedlund, J., Shults, R. A., & Compton, R. (2003). What we know, what we don’t know, and what we need to know about graduated driver licensing. *Journal of Safety Research*, *34*(1), 107–115. https://doi.org/10.1016/S0022-4375(00)0865

Hickman, J. S., Hanowski, R. J., & Bocanegra, J. (2010). *Distraction in Commercial Trucks and Buses: Assessing Prevalence and Risk in Conjunction with Crashes and Near-Crashes*. United States Department of Transportation. Federal Motor Carrier Safety Administration.

Highway Capacity Manual, Sixth Edition: A Guide for Multimodal Mobility Analysis. (2016). Transportation Research Board. https://www.trb.org/Main/Blurbs/175169.aspx

Ho, G., Scialfa, C. T., Caird, J. K., & Graw, T. (2001). Visual Search for Traffic Signs: The Effects of Clutter, Luminance, and Aging. *Human Factors*, *43*(2), 194–207. https://doi.org/10.1518/001872001775900922

Horberry, T., Anderson, J., Regan, M. A., Triggs, T. J., & Brown, J. (2006). Driver distraction: The effects of concurrent in-vehicle tasks, road environment complexity and age on driving performance. *Accident Analysis & Prevention*, *38*(1), 185–191. https://doi.org/10.1016/j.aap.2005.09.007

Huisingh, C., Griffin, R., & Jr, G. M. (2015). The Prevalence of Distraction Among Passenger Vehicle Drivers: A Roadside Observational Approach. *Traffic Injury Prevention*, *16*(2), 140–146. https://doi.org/10.1080/15389588.2014.916797

Huisingh, C., Owsley, C., Levitan, E. B., Irvin, M. R., MacLennan, P., & McGwin, G. (2019). Distracted Driving and Risk of Crash or Near-Crash Involvement Among Older Drivers Using Naturalistic Driving Data With a Case-Crossover Study Design. *The Journals of Gerontology: Series A*, *74*(4), 550–555. https://doi.org/10.1093/gerona/gly119

Hurwitz, J. B., & Wheatley, D. J. (2002). Using Driver Performance Measures to Estimate Workload. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *46*(22), 1804–1808. https://doi.org/10.1177/154193120204602206

IIHS. (2022). *Distracted driving*. IIHS-HLDI Crash Testing and Highway Safety. https://www.iihs.org/topics/distracted-driving

InSight SHRP2 NDS. (2021). *SHRP2 NDS Data Access*. Retrived on Dec 19, 2021 from https://insight.shrp2nds.us/home/index

Kentucky Farm Bureau. (2017). *Distracted driving has been around longer than you think*. Retrieved on June 6, 2021 from https://www.kyfb.com/insurance/lifes-blueprints/distracted-driving-has-been-around-longer-than-you-think/

Kidd, D. G., Tison, J., Chaudhary, N. K., McCartt, A. T., & Casanova-Powell, T. D. (2016). The influence of roadway situation, other contextual factors, and driver characteristics on the prevalence of driver secondary behaviors. *Transportation Research Part F: Traffic Psychology and Behaviour*, *41*, 1–9. https://doi.org/10.1016/j.trf.2016.06.004

Kircher, K., Patten, C., & Ahlström, C. (2011). *Mobile telephones and other communication devices and their impact on traffic safety*. Vti. Sweden.

Kirsch, T. (2018). An analysis of the crash risk and likelihood of engaging in a distraction while driving using naturalistic, time-series data. *Graduate Theses and Dissertations*. https://doi.org/10.31274/etd-180810-6022

Klauer, S. G., Dingus, T. A., Neale, V. L., Sudweeks, J. D., & Ramsey, D. J. (2006). The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data. United States Department of Transportation. National Traffic Safety Administration.

Klauer, S. G., Feng, G., Jeremy, S., & Thomas, D. (2010). *An Analysis of Driver Inattention Using a Case-Crossover Approach on 100-Car Data: Final Report.* DOT HS 811 344. https://doi.org/10.1037/e729232011-001

Li, X., Oviedo-Trespalacios, O., & Rakotonirainy, A. (2020). Drivers' gap acceptance behaviours at intersections: A driving simulator study to understand the impact of mobile phone visual-manual interactions. *Accident Analysis & Prevention*, *138*, 105486. https://doi.org/10.1016/j.aap.2020.105486

McEvoy, S. P., Stevenson, M. R., & Woodward, M. (2006). The impact of driver distraction on road safety: Results from a representative survey in two Australian states. *Injury Prevention*, *12*(4), 242–247. https://doi.org/10.1136/ip.2006.012336

McEvoy, S. P., Stevenson, M. R., & Woodward, M. (2007). The contribution of passengers versus mobile phone use to motor vehicle crashes resulting in hospital attendance by the driver. *Accident Analysis & Prevention*, *39*(6), 1170–1176. https://doi.org/10.1016/j.aap.2007.03.004

National Highway Traffic Administration. (2018). Road Safety. Retrived on June 20, 2019 from https://www.nhtsa.gov/road-safety

NHTSA. (2018b). *Traffic Safety Facts. Distracted Driving 2016* (DOT HS 812 517). National Highway Traffic Safety Administration. U.S. Department of Transportation.

National Highway Traffic Administration. (2021). *Distracted Driving 2019*. Traffic Safety Facts Research Note. DOT HS 813 111. United States Department of Transportation.

NHTSA. (2022a). *Distracted Driving | U Drive. U Text. U Pay. | NHTSA* [Text]. National Highway Traffic Safety Administration. https://www.nhtsa.gov/events/distracted-driving-u-drive-u-text-u-pay

NHTSA. (2022b). *Traffic Safety Facts. Distracted Driving 2020* (DOT HS 813309; p. 7). National Highway Traffic Safety Administration. U.S. Department of Transportation.

National Highway Traffic Administration. (2013). Safety in Numbers. Vol 1 (1). United States Department of Transportation.

National Highway Traffic Administration. (2020). *Distracted Driving 2018*. Traffic Safety Facts. Retrieved February 9, 2021, from https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812926

NSC. (2022). *Everything You Need for Distracted Driving Awareness Month*. National Safety Council. https://www.nsc.org/pages/ddam/ddam-materials

Obeidat, M. S., Rababa, M. M., & Tyfour, W. R. (2021). Effects of vehicle's human machine interface devices on driving distractions. *Theoretical Issues in Ergonomics Science*, *0*(0), 1–21. https://doi.org/10.1080/1463922X.2021.1975171

Oviedo-Trespalacios, O., Haque, M. M., King, M., & Washington, S. (2017a). Self-regulation of driving speed among distracted drivers: An application of driver behavioral adaptation theory. *Traffic Injury Prevention*, *18*(6), 599–605. https://doi.org/10.1080/15389588.2017.1278628

Oviedo-Trespalacios, O., Haque, Md. M., King, M., & Washington, S. (2016). Understanding the impacts of mobile phone distraction on driving performance: A systematic review. *Transportation Research Part C: Emerging Technologies*, *72*, 360–380. https://doi.org/10.1016/j.trc.2016.10.006

Oviedo-Trespalacios, O., Haque, Md. M., King, M., & Washington, S. (2017b). Effects of road infrastructure and traffic complexity in speed adaptation behaviour of distracted drivers. *Accident Analysis & Prevention*, *101*, 67–77. https://doi.org/10.1016/j.aap.2017.01.018

Owens, J. M., Dingus, T. A., Guo, F., Fang, Y., Perez, M., & McClafferty, J. (2018). Crash risk of cell phone use while driving: A case-crossover analysis of naturalistic driving data. Retrieved April 15, 2021, from https://aaafoundation.org/wp-content/uploads/2018/01/CellPhoneCrashRisk_FINAL.pdf

Owens, J. M., Angell, L., Hankey, J. M., Foley, J., & Ebe, K. (2015). Creation of the Naturalistic Engagement in Secondary Tasks (NEST) distracted driving dataset. *Journal of Safety Research*, *54*, 33.e29-36. https://doi.org/10.1016/j.jsr.2015.07.001

Owens, J. M., Angell, L., Hankey, J., McClafferty. (2016). *User Guide and Data Dictionary: Naturalistic engagement in secondary tasks (NEST) dataset*. Virginia Tech Transportation Institute.

Owens, J. M., McLaughlin, S. B., & Sudweeks, J. (2011). Driver performance while text messaging using handheld and in-vehicle systems. *Accident Analysis & Prevention*, *43*(3), 939–947. https://doi.org/10.1016/j.aap.2010.11.019

Prat, F., Gras, M. E., Planes, M., Font-Mayolas, S., & Sullman, M. J. M. (2017). Driving distractions: An insight gained from roadside interviews on their prevalence and factors associated with driver distraction. *Transportation Research Part F: Traffic Psychology and Behaviour, 45*, 194–207.

Ranney, T. (2008). *Driver Distraction: A Review of the Current State-of-Knowledge.* DOT HS 810 787. United States Departement of Transportation. Natioanl Traffic Safety Administration.

Redelmeier, D. A., & Tibshirani, R. J. (1997). Association between Cellular-Telephone Calls and Motor Vehicle Collisions. *New England Journal of Medicine*, *336*(7), 453–458. https://doi.org/10.1056/NEJM199702133360701

Regan, M. A., Lee, J. D., & Young, K. (2008). *Driver Distraction: Theory, Effects, and Mitigation*. CRC Press.

Young, K. & Regan, M. (2007). *Driver distraction: A review of the literature. In: I.J. Faulks, M. Regan, M. Stevenson, J. Brown, A. Porter & J.D. Irwin (Eds.).* Distracted driving. Sydney, NSW: Australasian College of Road Safety. Pages 379-405.

Ross, V., Jongen, E. M. M., Brijs, K., Brijs, T., & Wets, G. (2016). Investigating risky, distracting, and protective peer passenger effects in a dual process framework. *Accident Analysis & Prevention*, *93*, 217–225. https://doi.org/10.1016/j.aap.2016.05.007

Rupp, M. A., Gentzler, M. D., & Smither, J. A. (2016). Driving under the influence of distraction: Examining dissociations between risk perception and engagement in distracted driving. *Accident Analysis & Prevention*, *97*, 220–230. https://doi.org/10.1016/j.aap.2016.09.003

Saifuzzaman, M., Haque, Md. M., Zheng, Z., & Washington, S. (2015). Impact of mobile phone use on car-following behaviour of young drivers. *Accident Analysis & Prevention*, *82*, 10–19. https://doi.org/10.1016/j.aap.2015.05.001

Sangster, J., Rakha, H., & Du, J. (2013). Application of Naturalistic Driving Data to Modeling of Driver Car-Following Behavior. *Transportation Research Record*, *2390*(1), 20–33. https://doi.org/10.3141/2390-03

Sayer, J. R., Devonshire, J. M., & Flannagan, C. A. (2005). *The Effects of Secondary Tasks on Naturalistic Driving Performance*. Report No. UMTRI-2005-29. University of Michigan.

Schneidereit, T., Petzoldt, T., Keinath, A., & Krems, J. F. (2017). Using SHRP 2 naturalistic driving data to assess drivers' speed choice while being engaged in different secondary tasks. *Journal of Safety Research*, *62*, 33–42. https://doi.org/10.1016/j.jsr.2017.04.004

Science Daily. (2012). *Distracted drivers think of themselves as good drivers, research suggests*. ScienceDaily. https://www.sciencedaily.com/releases/2012/05/120510095812.htm

Senders, J. W., Kristofferson, A. B., Levison, W. H., Dietrich, C. W., Ward, J. L., & Beranek, B. (1967). The Attentional Demand of Automobile Driving.

Simons-Morton, B. G., Guo, F., Klauer, S. G., Ehsani, J. P., & Pradhan, A. K. (2014). Keep Your Eyes on the Road: Young Driver Crash Risk Increases According to Duration of Distraction. *Journal of Adolescent Health*, *54*(5, Supplement), S61–S67. https://doi.org/10.1016/j.jadohealth.2013.11.021

Stavrinos, D., Jones, J. L., Garner, A. A., Griffin, R., Franklin, C. A., Ball, D., Welburn, S. C., Ball, K. K., Sisiopiku, V. P., & Fine, P. R. (2013). Impact of distracted driving on safety and traffic flow. *Accident Analysis & Prevention*, *61*, 63–70.

Stutts, J. C., Feaganes, J., Reinfurt, D., Rodgman, E., Hamlett, C., Gish, K., & Staplin, L. (2005). Driver's exposure to distractions in their natural driving environment. *Accident Analysis & Prevention*, *37*(6), 1093–1101. https://doi.org/10.1016/j.aap.2005.06.007

Stutts, J. C., Feaganes, J., Rodgman, E., Hamlett, C., Reinfurt, D., Gish, K., Mercadante, M., & Staplin, L. (2003). The Causes and Consequences of Distraction in Everyday Driving. 47th *Annual Proceedings Association for the Advancement of Automotive Medicine*, 235–251.

Stutts, J. C., Reinfurt, D. W., Staplin, L., & Rodgman, E. A. (2001). The Role of Driver Distraction in Traffic Crashes. *AAA Foundation for Traffic Safety*. https://doi.org/10.1037/e363942004-001

Stutts, J. C., Reinfurt, D. W., Staplin, L., & Rodgman, E. A. (2015). The Role of Driver Distraction in Traffic Crashes. McGrath Auto Blog. http://www.mcgrathautoblog.com/automotive-news/the-history-of-distracted-driving-and-how-to-end-it/

Sullman, M. J. M. (2012). An observational study of driver distraction in England. *Transportation Research Part F: Traffic Psychology and Behaviour*, *15*(3), 272–278. https://doi.org/10.1016/j.trf.2012.01.001

Sween, M., Ceschi, A., Tommasi, F., Sartori, R., & Weller, J. (2017). Who is a Distracted Driver? Associations between Mobile Phone Use while Driving, Domain-Specific Risk Taking, and Personality. *Risk Analysis*, *37*(11), 2119–2131. https://doi.org/10.1111/risa.12773

Toxopeus, R., Ramkhalawansingh, R., & Trick, L. (2011). The Influence of Passenger-Driver Interaction on Young Drivers. *Proceedings of the 6th International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design : Driving Assessment 2011*, 66–72. https://doi.org/10.17077/drivingassessment.1379

Trivedi, N., Haynie, D., Bible, J., Liu, D., & Simons-Morton, B. (2017). Cell phone use while driving: Prospective association with emerging adult use. *Accident Analysis & Prevention*, *106*, 450–455.

Vegega, M., Jones, B., & Monk, C. (2013). Understanding the effects of distracted driving and developing strategies to reduce resulting deaths and injuries: a report to Congress (No. DOT HS 812 053). United States Department of Transportation. National Highway Traffic Safety Administration.

Virginia Tech. (2021). *Researchers determine driver risks using large-scale, crash-only naturalistic database*. Retrieved on June 15, 2021 from https://www.vtnews.vt.edu/content/vtnews_vt_edu/en/articles/2016/02/022316-vtti-researchdistraction.html

World Health Organization. (2020). Road traffic injuries. Retrieved on March 20, 2021 from https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries

Wilson, F. A., & Stimpson, J. P. (2010). Trends in Fatalities From Distracted Driving in the United States, 1999 to 2008. *American Journal of Public Health*, *100*(11), 2213–2219. https://doi.org/10.2105/AJPH.2009.187179

Wu, J., & Xu, H. (2018). The influence of road familiarity on distracted driving activities and driving operation using naturalistic driving study data. *Transportation Research Part F: Traffic Psychology and Behaviour*, *52*, 75–85.

Xu, C., Liu, P., Wang, W., & Li, Z. (2012). Evaluation of the impacts of traffic states on crash risks on freeways. *Accident Analysis & Prevention*, *47*, 162–171. https://doi.org/10.1016/j.aap.2012.01.020

Yang, K., Wang, X., & Yu, R. (2018). A Bayesian dynamic updating approach for urban expressway real-time crash risk evaluation. *Transportation Research Part C: Emerging Technologies*, *96*, 192–207. https://doi.org/10.1016/j.trc.2018.09.020

Ye, M., Osman, O. A., & Ishak, S. (2017). Accounting for Driver Distraction and Socioeconomic Characteristics in a Crash Risk Index: Naturalistic Driving Study. *Transportation Research Record*, *2659*(1), 204–211. https://doi.org/10.3141/2659-22

Young, K. L., & Lenné, M. G. (2010). Driver engagement in distracting activities and the strategies used to minimise risk. *Safety Science*, *48*(3), 326–332. https://doi.org/10.1016/j.ssci.2009.10.008

Young, K. L., & Salmon, P. M. (2012). Examining the relationship between driver distraction and driving errors: A discussion of theory, studies and methods. *Safety Science*, *50*(2), 165–174. https://doi.org/10.1016/j.ssci.2011.07.008

Young, K. L., Salmon, P. M., & Cornelissen, M. (2013). Distraction-induced driving error: An on-road examination of the errors made by distracted and undistracted drivers. *Accident Analysis & Prevention*, *58*, 218–225. https://doi.org/10.1016/j.aap.2012.06.001

Young, K., Regan, M., & Hammer, M. (2003). *Driver Distraction: A Review of the Literature*. Report No. 206. Monash University Accident Research Centre.