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An analysis of the crash risk and likelihood of engaging in a distraction while driving using naturalistic, time-series data

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An analysis of the crash risk and likelihood of engaging in a distraction while driving using naturalistic, time-series data

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

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NOMENCLATURE

CRI	Crash Risk Index
CSV	Comma Separated Value
CTRE	Center for Transportation Research and Education
DAS	Data Acquisition System
DOT	Department of Transportation
GPS	Global Positioning System
ISU	Iowa State University
LOS	Level-of-Service
MAP-21	Moving Ahead for Progress in the 21st Century
mph	Miles per Hour
NDS	Naturalistic Driving Study
NHTSA	National Highway Traffic Safety Administration
RID	Roadway Information Database
SAFETEA-LU	Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users
SHRP2	Strategic Highway Research Program 2
TRB	Transportation Research Board
VTTI	Virginia Tech Transportation Institute

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DISCLAIMER

The findings and conclusions of this report are those of the author, Trevor Joseph Kirsch, and do not represent the views of the Virginia Tech Transportation Institute, the Transportation Research Board, or the National Academies.

ABSTRACT

Distracted driving has become a severe threat to traffic safety due in large part to the proliferation of in-vehicle smart technologies, the ubiquity of cell phones, and a general societal shift towards constant mobility and connectivity. Research has consistently demonstrated adverse consequences to engaging in a distracting secondary behavior while operating a motor vehicle. Much of the prior research in this area has leveraged data from traffic simulators and police-reported crash data, resulting in estimates as to the impacts of distraction on crash risk. However, research has been more limited under actual driving conditions and there remain important gaps with respect to how distracted driving and the associated crash risks vary across drivers and roadway environments.

This study addresses this gap by utilizing disaggregate time-series data from the second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) to conduct an in-depth investigation of various safety-focused aspects of distracted driving. The high resolution data were provided at 10 Hz resolution through a series of cameras and mechanical sensors. These operational data were integrated with geometric information from the companion Roadway Information Database (RID), as well as with data related to driver behavioral characteristics, risk perceptions, and risk-taking behavior from a series of participant surveys. Collectively, these sources resulted in a robust dataset of vehicle, roadway, weather, and driver behavioral parameters.

Various aspects of distracted driving were investigated as a part of this analysis, including the effects of distraction on driving performance. More specifically, the effects of various types of distraction on driver speed selection behavior was examined.

Additional analyses assessed how the prevalence of various types of distracting behaviors varied based upon driver characteristics, roadway geometry, traffic conditions, and environmental conditions. As a part of these investigations, a series of random effects linear and logistic regression models were estimated with the disaggregate time-series information. Risk models were also estimated to determine how various types of distractions impacted the likelihood of a crash or near-crash event. Ultimately, the results suggest that drivers generally adapt their behavior based upon the level of risk posed by various driving environments. These environmental factors, along with various driver-specific factors, were shown to influence speed selection, as well as proclivity for participating in various types of distracting behaviors. In turn, these distractions were found to exacerbate crash risks, with marked differences exhibited based upon the degree to which the distracting behaviors required drivers to direct their attention away from the primary driving task.

CHAPTER 1. INTRODUCTION

1.1 Background

Distracted driving is a multifaceted threat to traffic safety that has recently been expanded by factors such as the integration of within-vehicle smart technologies, cell phone ubiquity, and a general shift to a more mobile society. Distracted driving is any within-vehicle activity that diverts the attention of a motorist from their primary driving task (North Dakota Department of Transportation, 2017). Based on data from the Fatality Analysis Reporting System from the National Highway Traffic Safety Administration (NHTSA), more than 3,400 motor vehicle occupants were killed and an estimated 391,000 were injured in distracted driving crashes within the United States in 2015. Additionally, driver distraction was involved in 16 percent of all fatal crashes and 21 percent of all injury crashes that occurred in 2008 (NHTSA, 2009). In a 100-vehicle naturalistic driving study (NDS) conducted by NHTSA, more than 22 percent of both crashes and near-crashes were contributed to some type of within-vehicle distraction. Figure 1 depicts the total and fatal distraction crashes that occurred on all roadways within the United States between 2011 and 2015, according to NHTSA.

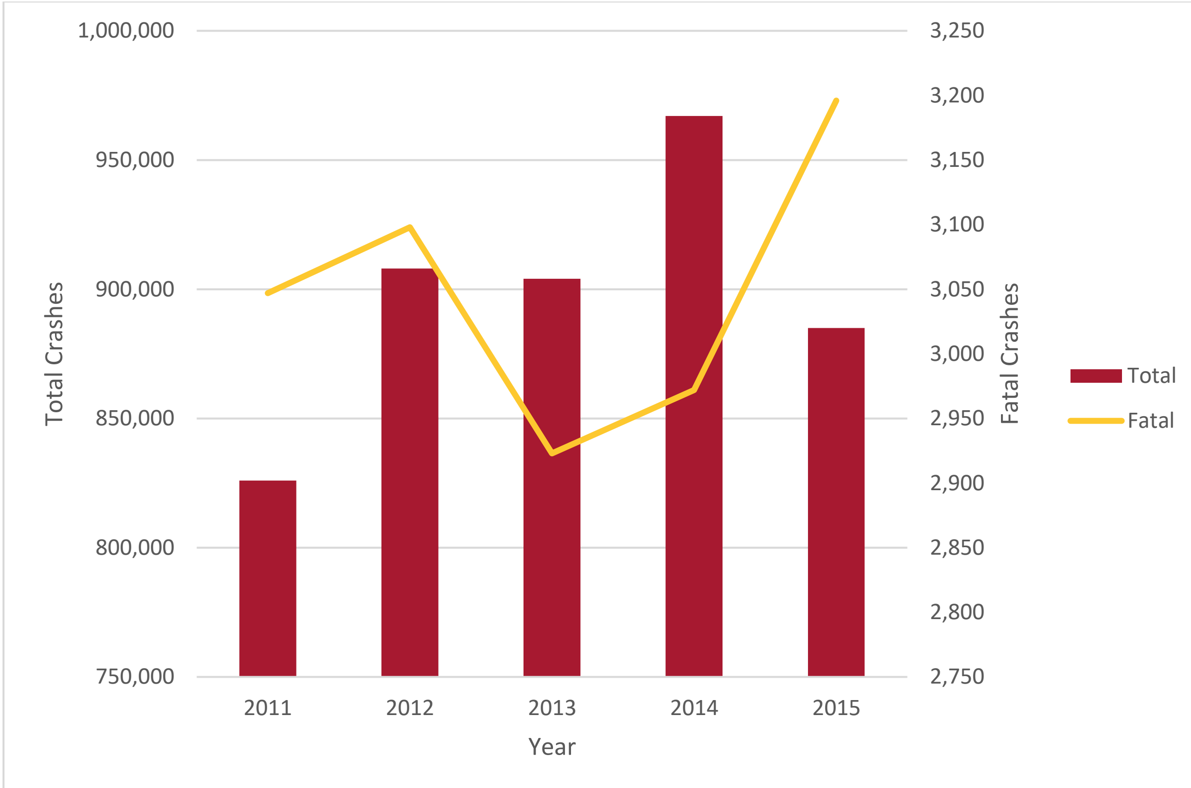

Figure 1. Total and Fatal Distraction Crashes between 2011 and 2015

There are a variety of tasks in which the driver may be involved that negate their attention to the roadway and the primary task of driving. Tasks that can lead to distracted driving are divided into the following three categories (United States Department of Transportation, 2013):

- Visual distraction – Any task that requires the driver to divert their attention from the road to visually obtain information
- Manual distraction – Any task that requires physical manipulation by the driver and encourages the driver to remove their hands from the steering wheel
- Cognitive distraction – Any task that requires a significant mental workload and causes the driver to actively think of something other than the driving task

Based on these classifications, some tasks considered commonplace by many motorists are distracting in nature, including interacting with the vehicle control panel, eating while operating a vehicle, and conversing with a passenger. Each of these is classified by the United States Department of Transportation (DOT) as a distracting act that may decrease the attention necessary to drive safely.

Whether the driver is aware that a secondary task is distracting or not, various performance metrics have been shown to be correlated with distracted driving. At an operational level, several studies have demonstrated that motorists consciously or subconsciously use compensatory behavior when engaging in a distracting behavior while driving to indirectly reduce their crash risk (Young and Regan, 2007). Some of these self-regulating behaviors include an intentional reduction in travel speed, an artificial increase in the lateral space between their car and the car in front of them, or knowingly shifting their attention between the primary driving task and a secondary distracting task rapidly in hopes that the brief moments of inattention will be insignificant in relation to their overall driving experience. For risky individuals, an acceptance of temporary driving degradation may occur (i.e. consciously checking mirrors and dashboard instruments less frequently than normal). This can arise from drivers temporarily modifying their normal driving behaviors and accepting a sub-optimal level of performance, or an unconscious shift of attention from the primary driving task to any type of distraction.

Based on these findings from research studies and trends in national-level databases, many transportation organizations have instituted public service announcements and campaigns that communicate the negative consequences of distracted driving to the public, such as “U Drive. U Text. U Pay”, “Phone in One Hand, Ticket in the Other”, and “One Text or Call Could Wreck It All" from the United States DOT (NHTSA, 2018). Figure 2 depicts one method through which these slogans are communicated to the traveling public. For example, the Iowa DOT uses variable message signs and "Message Mondays" to communicate safe driving habits to travelers. Despite these programs, the threat of distracted driving is commonly not considered by many motorists, mostly due to continued social norms and incorrect assumptions about distracted driving.

Figure 2. Iowa DOT Variable Message Sign (Iowa DOT, 2014)

One common type of distraction in modern transportation is the use of a cell phone while driving. Figure 3 contains a map of the United States that depicts the current statewide cell phone usage bans in each state based on information from the National Conference of State Legislature.

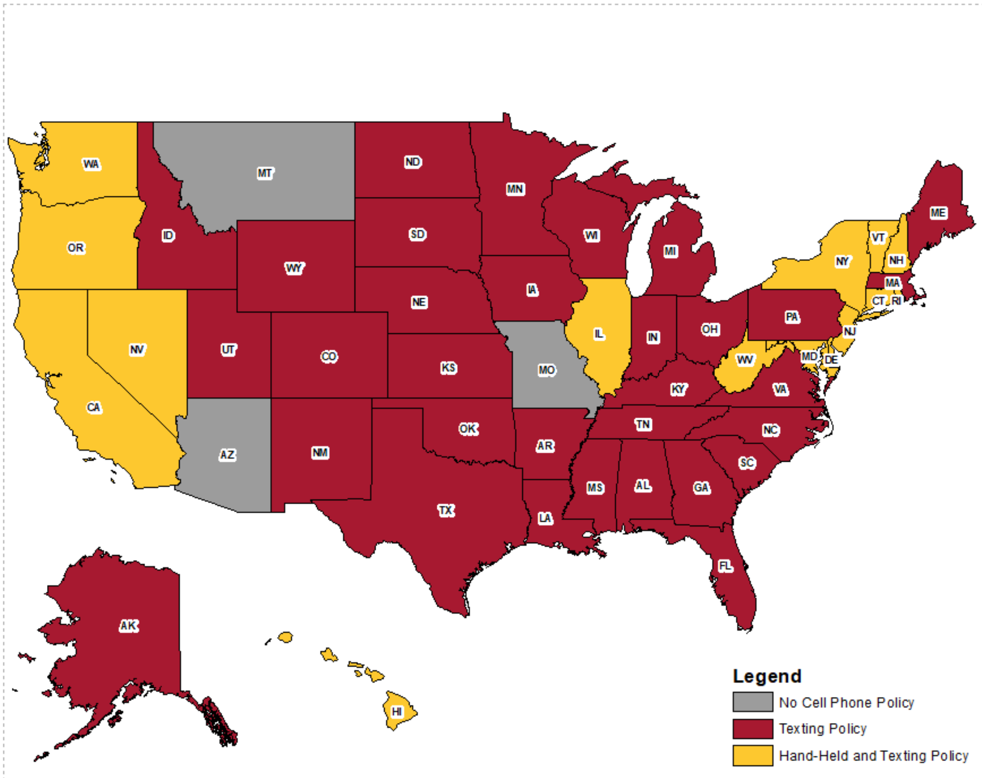

Figure 3. Current Statewide Cell Phone Usage Policies

Although many states have a law that prevents cellular phone usage while operating a motor vehicle, a study from NHTSA noted that 18 percent of all drivers have sent text messages or emails while driving under these regulations (Tison et al., 2011). Of those surveyed, more than half believed that using a cell phone while driving did not affect their individual driving performance, but when considering the same scenario as a passenger (i.e. riding as a passenger with a driver using their cell phone), 90 percent of the respondents noted they would feel “very unsafe” if a driver was using a handheld electronic device while driving. This overestimation of personal driving abilities and underestimating of distracted driving consequences generates an unsafe social norm, as 33 percent of young drivers (aged 18 to 24) believe that they can divert their attention from the roadway for 3 to 10 seconds before a secondary task becomes significantly dangerous. This belief, paired with recent estimates of severe underreporting associated with self-professing poor behavior (such as distraction), means that distracted driving is a critical issue in modern transportation safety (National Safety Council, 2013).

1.2 Research Objectives

The intent of this analysis was to determine the effect that driver distraction had on driver performance. This was completed using state-of-the-art data from the second Strategic Highway Research Program (SHRP2). The SHRP2 program funded the largest NDS to date that documented disaggregate driving behavior and corresponding operational characteristics every decisecond for more than five million trips. The information collected as a part of this program was recorded in real-time by a variety of sensors and video cameras outfitted to personal passenger vehicles over a four-year duration. A companion dataset of relevant roadway characteristics, known as the roadway information database (RID), was also developed to accurately determine the roadway characteristics and geometrics that were present on the roadways traveled by the participants during the data collection period. The RID contains geospatial information for over 25,000 miles of participant-traveled roadway.

Using this observational, time-series data of human behavior, the goal of this research was to measure the effect that driver distraction had on resultant roadway performance. This was done by leveraging the detailed information available from the NDS and the comprehensive RID. Ultimately, three specific research questions were addressed through the resultant analyses:

1. How did driver distraction affect the crash risk of motorists?
2. What type of risk-taking behaviors and human characteristics made drivers more likely to engage in distracted driving activities?

3. Under what roadway conditions were motorists more likely to engage in distracted driving activities?

The focus of this analysis was on freeways, which are designed to higher standards and require a significant amount of driver attention to navigate safely. The analysis began with a comparison of descriptive statistics related to vehicular speed selection under distracted and non-distracted conditions. Next, statistical models were developed that identified the underlying relationships between the variables of interest. A crash risk model, which considered the combination of crash and near-crash events, was also developed. Based on these findings, various conclusions and recommendations were discussed to reduce the likelihood of distracted driving in the future.

1.3 Thesis Structure

This document is organized into six individual sections. A brief description of each chapter is presented below:

Chapter 1: Introduction – The introduction provides aggregate statistics about the threat of distracted driving and outlines the various types of distracted driving that are present in modern transportation. The frequency of distracted driving is also presented to provide context as to how prevalent this behavior is while operating, as well as the risks that this dangerous behavior has on motorist safety.

Chapter 2: Literature Review – The literature review summarizes the state-of-the-art research that has focused on the safety and operational impacts of distracted driving. Various studies from the United States and abroad are considered to demonstrate the impact that distracted driving has on all vehicle operators worldwide. This section concludes with a brief review of the summarized research, as well as the identified gap within the existing distracted driving knowledge base, which this research attempts to fill.

Chapter 3: Data Description – The data description section discusses the SHRP2 program NDS in further detail than previous. The data collection procedure and types of information available through this program are also vividly described. Information about the companion RID database is presented.

Chapter 4: Methodology – The methodology section includes the type of analyses considered in this research. A brief overview of each statistical method and framework is also provided, as well as a discussion of why each method was selected for the analyses conducted.

Chapter 5: Results and Discussion – The results of the statistical analyses are presented in this section. Following the presentation of the statistical results, a discussion is provided that outlines the practical outcomes of the findings.

Chapter 6: Conclusions and Recommendations – The entire body of work is summarized in this section. A list of limitations is also included. Lastly, recommendations for future research are provided to assist with additional studies on this topic.

CHAPTER 2. LITERATURE REVIEW

2.1 Traffic Safety Impacts of Distracted Driving

Due to the rapid advancement of technology and within-vehicle communication systems, distracted driving has a much greater impact on traffic safety in modern transportation than ever before. Distracted driving includes a variety of roadway behaviors that can shift a driver's attention from the primary task of driving to a secondary task. Although distracted driving is commonly associated with the use of technologies such as cell phones, a variety of other distractions occur both inside and outside of the vehicle, including eating, conversing with passengers, and operating in-vehicle dashboard utilities (e.g., radio and navigation systems). These sources of distraction pose a significant public health risk across the United States. In 2015, 10 percent of fatal crashes, 15 percent of injury crashes, and 14 percent of all vehicular crashes were influenced by distracted driving (NHTSA, 2017). This resulted in more than 3,400 fatalities and an additional 391,000 injuries. Due to the prevalence of this issue, various national, state, and local transportation agencies have launched awareness campaigns to educate the public about the threats of distracted driving. Various studies have demonstrated that driver inattention is most prevalent for novice drivers, with nine percent of 15- to 19-year old operators driving while distracted during traffic crashes.

Distracted driving is not only a national issue, but also a threat to traffic safety internationally. Nearly 7,300 operators were fatally injured in single vehicle collisions in the European Union during 2015 (Adminaite et al., 2017). Of these fatalities, approximately 2,200 (31 percent) involved driver distraction. Of all the causal behaviors identified in the respective crash reports, distracted driving was the most prevalent. Additionally, younger drivers were again more likely to be involved in a collision when distracted. The novice motorists often engaged in inadequate swerving maneuvers or incorrectly assessed the traffic situation while distracted immediately before a crash.

Because distracted driving has been identified as a major threat to traffic safety, hundreds of research studies have been conducted to better understand the nature of those factors associated with driver inattention. As such, a publicly available database was created with the purpose of allowing researchers to form empirical questions related to distracted driving (Atchley et al., 2016). Fifty years of distracted driving research was included in the comprehensive database with the intent to aggregate results and inform traffic safety policy decisions. The sources of distraction as well as various driver performance measures were categorized from 342 individual studies. Ultimately, 81 percent of the analyses indicated that driver distractions degraded performance, while 16 percent noted no significant effect on performance parameters. A visual deception of this meta-analysis is available in Figure 4.

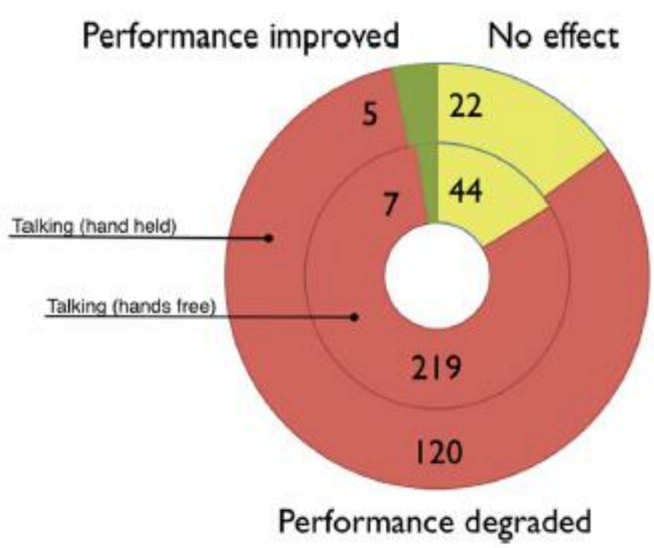

Figure 4. Performance Impacts of Hand-Held and Hands-Free Cell Phone Use while Driving (Atchely et al., 2016)

Note that the red category measured a negative driving performance due to cell phone use, while a yellow and green category indicated a neutral and positive effect, respectively. The frequencies listed for each category in Figure 4 indicated the number of variables utilized in the studies considered in the meta-analysis. A majority of the research focused solely on cell phone usage characteristics. From this subset of studies, driver texting resulted in the greatest performance degradation of all cell phone-related distractions.

Many agencies continue to promote educational campaigns to reduce the frequency and likelihood of distracted driving. Despite the identification of distracted driving as a dangerous behavior while driving, crashes due to distracted driving continue to increase annually. A task force was created to address this issue by combining experts in the fields of transportation, research, law enforcement, communications, health, legislation, behavior science, and policy to make recommendations that addressed the accepted social norms related to distracted driving (Oregon Department of Transportation, 2017). After eight months of deliberations, the task force made five recommendations to reduce distracted driving frequency and change identified norms, including the creation of a stricter cell phone use law and the implementation of a coordinated education and media campaign to better inform the public of the negative impacts of distracted driving. By focusing on the issue from a much broader context with a variety of industry experts, the recommendations were more holistic and achievable in nature.

2.1.1 Driver Behavior

Although distracted driving is commonly related to novice drivers and cell phone use, the threat to traffic safety includes the entire population of operators and more secondary behaviors than cell phone distraction alone. Research studied the likelihood of teenagers, young, middle-aged, and older adult drivers to engage in secondary tasks while operating a vehicle (Kidd and Buonarosa, 2017). The participants drove an instrumented sedan that included video cameras focused on the driver. Video clips were randomly sampled at speeds below 5 miles per hour (mph) and above 25 mph. Of the sampled clips, at least one secondary behavior was identified in 46 percent of the recorded trips. Of these identified distractions, 17 percent involved the driver conversing with a passenger, nine percent showed the operator grooming themselves, and six percent recorded a driver cell phone conversation. Based on the identified speed parameters, a distraction was 21 percent more likely to occur at speeds below 5 mph. The results from this analysis indicated that distracted driving is a human behavior that is evident among all operators, and a variety of tasks that seem commonplace to most drivers are actually distractions that impact resultant roadway performance.

Distracted driving is commonly related to human behavior factors. As such, various studies have correlated the frequency of distracted driving events and personality traits. A study of self-reported information on distracted driving tendencies and the perception of risk was conducted with 266 young adult drivers from academic institutions (Braitman and Braitman, 2017). The most commonly identified distracting behaviors were talking with passengers, eating and drinking, programming music, and using a Global Positioning System (GPS) navigation application while operating. Using a latent profile analysis, those individuals with the personality trait of extraversion were more likely to engage in distracting behaviors, even in high-risk situations (i.e. driving in inclement weather, traveling at high speeds, etc.). These drivers also rated their behaviors as moderately distracting, despite engaging in them, revealing that personality traits may be related to consistently higher frequencies of distracted driving. Further research, which focused on the correlations between parental and peer influences on distracted driving behavior, included a telephone survey of 403 adolescents and their parents (Carter et al., 2014). The survey used hierarchical multiple linear regression models and considered descriptive and injunctive social norms, including sociodemographics, sensation seeking characteristics, and risk perception. Interestingly, 92 percent of the surveyed adolescents admitted to regularly engaging in distracted driving behavior. Additionally, most individuals perceived that their parents and peers engage in distracted driving more frequently than themselves, which was not true.

2.1.2 Driver Performance

One of the greatest negative consequences of distracted driving is the impact on driver performance. Due to the distraction created by a secondary task, the performance of the operator is negatively impacted, which may result in a crash. Research explored the frequency and variation in driver errors while distracted (Young et al., 2012). Subjects operated an instrumented vehicle along an urban test route while performing a visually distracting task. Both driver video and vehicle data were collected. Upon classifying the errors, it was determined that the drivers who were distracted made significantly more errors than their non-distracted counterparts, although the nature of the errors did not differ substantially for the errors made while not distracted. These results suggested that the impact of distraction on driver performance may not be noticeable to the distracted individual, as new types of errors are not evident while engaging in a secondary task. More detailed research on driver performance was conducted using a driving simulator (Vieira and Larocca, 2016). The driving behavior of 17 individuals was documented by observing speed variations at select positions along a virtualized highway. A variety of secondary tasks were performed by the participants, as well as a baseline test with no distraction present. The analysis of the speed variations determined that distracted drivers performed worse than non-distracted drivers; distracted individuals did not recognize the beginning of a curve from the same distance as they did when they were not distracted. Also, the speed at which the subjects traversed curves was much greater while engaging in the secondary tasks. While performing baseline tests, the driving performance of the participants was noticeably enhanced, as drivers reached higher speeds during tangent sections of the roadway and lessened acceleration in the presence of curves, as the driving task had their undivided attention.

Based on previous research, driver performance while distracted is an issue that affects operators of all ages; however, this issue is exaggerated in middle-aged and elderly drivers due to brain aging and limited cognitive resources. A study of 51 middle-aged and 86 elderly drivers examined the distracted driving performance of these individuals in an instrumented vehicle while under a concurrent auditory-verbal processing load (Thompson et al., 2012). When compared to the baseline driving performance, the distractions were associated with reduced steering control in both age categories. Additionally, the elderly participants drove slower and showed decreased speed variability while distracted. This resulted in elderly drivers spending significantly more time holding the gas pedal steady while distracted, which is a threat to traffic safety. Lastly, 43 percent of middle-aged participants and 39 percent of elderly participants committed significantly more driving errors while distracted by a secondary task based on this research.

2.1.3 Driver Characteristics

Although distracted driving impacts all roadway users, a large portion of distracted driving research has focused on teen drivers. The reason for this focus is that younger drivers are quicker to implement new technologies in their lifestyles, which presents a tremendous opportunity for distraction while operating a vehicle. Additionally, current social norms have demonstrated that distracted driving (specifically cell phone use) is viewed as acceptable while driving among younger individuals. Research investigated these perceived social norms in an attempt to provide normative correctional information (Merrikhpour and Donmez, 2017). For the analysis, 40 teens were selected to perform a visual-manual secondary task while driving in a simulator. Various feedback conditions were applied, including: social norms, real-time, and no feedback as a baseline condition. Ultimately, social norms feedback reduced the off-road glance time and rate of long off-road glances among the participants. Additionally, this feedback type decreased brake response time. The results of this study indicated that by providing quantitative social norms to novice drivers, their actions can be corrected by proving that distracted driving is not common nor accepted among their parents or peers.

Although teen drivers may believe that distracted driving is acceptable based on false social norms, additional research has confirmed that drivers of all ages must be informed of the negative consequences related to distracted driving. To date, the relationship between executive control, age, and distracted driving has been under-researched. To address this, research focused on these parameters by collecting detailed information on weekly engagement in distracted driving behaviors from 59 participants (Pope et al., 2016). The operators ranged from young, middle, and older adults who self-reported executive difficulty as well as demographic information. Results from the analysis confirmed that distracted driving is a ubiquitous phenomenon. Older individuals were associated with fewer distracted driving behaviors; however, executive difficulty was associated with an increased frequency of distracted driving tendencies, regardless of age. These results indicated that drivers of all ages must be aware of the negative consequences of distracted driving.

2.2 Cell Phone Usage as a Secondary Task

Although a multitude of distractions are present while operating a motor vehicle, the ubiquity of cell phone ownership has quickly demonstrated to have negative impacts on traffic safety. Both talking and texting while using a cell phone have accounted for thousands of motor vehicle crashes each year. In order to estimate the frequency of cell phone-related distractions, a national survey of drivers examined the cell phone related-activities that 1,211 U.S citizens performed while driving (Gliklich et al., 2016). From this, a distracted driving survey score was calculated for each participant. A summation of these scores is provided in Figure 5.

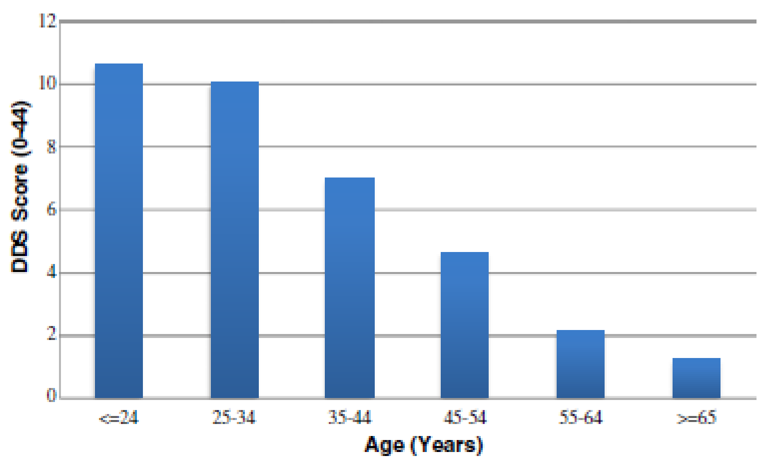

Figure 5. Mean Distracted Driving Survey Score by Age (Gliklich et al., 2016)

Based on the self-reported crash frequency, almost 60 percent of the respondents reported texting on a cell phone within the past 30 days of taking the survey. Of the surveyed behaviors, reading text messages (48 percent), viewing GPS navigation (43 percent), and writing text messages (33 percent) were the most frequent. The distracted driving survey scores were inversely correlated with age, indicating that younger drivers were more likely to engage in the distracting behavior. The distractions measured among the participants were also associated with the self-reported crash frequencies, indicating that more frequent engagement in distracting behaviors was correlated with more crashes.

An additional safety concern with the use of cell phones while operating a vehicle is the public perception of social norms (i.e. acceptability) and self-perception of risk among individuals. Despite the documented negative impacts of cell phone use while driving, many individuals believe that they are not personally impacted as much by the secondary behavior. Research investigated the proportion of drivers that engage in cell phone-related distractions (Prat et al., 2016). In total, 426 interviews among licensed drivers were performed. Although drivers in the survey were aware of a ban on all cell phone-based activities, almost 44 percent admitted to texting while operating. Additionally, 32 percent admitted to talking on their device while driving. Texting while driving was perceived by the participants as the most dangerous secondary activity that a driver could perform; however, descriptive norms further confirmed that motorists often engage in these types of distractions knowing the risk the task has on resultant traffic safety.

2.2.1 Driver Behavior

Human behavior is an integral part of distracted driving. As such, research has focused on the correlation between distracting activities and driver behavior. A man-machine framework was constructed in which vehicle and driver characteristics were related to cell phone use (Rajesh et al., 2016). A questionnaire presented to 1,203 drivers utilized a five-point Likert scale using a random sampling approach. The cell phone distraction model included human factors, vehicle characteristics, and driving conditions. Of the three categories of variables tested, the human factors characteristics had the greatest influence on cell phone-related distraction. Additionally, participants noted that cell phone usage while operating a motor vehicle was moderately risky, indicating that drivers knowingly engage in inappropriate and risky behavior while driving.

Another issue with cell phone use while driving is the assumed social norms demonstrated through human behavior research. Multiple research studies have documented that participants believe that cell phone use while driving is risky behavior and a threat to traffic safety, yet they engage in the secondary task themselves because they overestimate their own personal abilities. Research characterized the behavior of distracted driving among middle-aged adults through a 60-question survey (Engelberg et al., 2015). Based on the responses, a factor analysis was conducted. More than 65 percent of the adults reported texting while driving. Additionally, almost 25 percent of their time while driving on the freeway was spent using a cell phone for various tasks. A significant predictor of distraction frequency was the false behavior of perceiving oneself as capable of talking or texting while driving. Based on these results, further public education campaigns should be promoted to establish that cell phone usage is a distraction that impacts all drivers, regardless of assumed abilities.

2.2.2 Driver Performance

Distracted driving also has an adverse impact on speed selection. When operators are distracted by a secondary task, their attention is divided between driving the vehicle and interacting with the distraction. While this occurs, drivers tend to lower their speed and create a larger speed differential between themselves and surrounding vehicles. This creates an unsafe operating environment, as greater differences in vehicle speed increase the relative crash risk. An application of driver behavior adaptation theory noted the changes in speed selection of drivers distracted by cell phones (Oviedo-Trespalacios et al., 2016). The speed selection behavior was observed while drivers talked on a cell phone by holding it to their head or while using a hands-free device. The changes in driving behavior were recorded with a high-fidelity driving simulator. A system of seemingly unrelated equations were constructed for the analysis in order to account for the potential correlations between the phone use conditions. Significant predictors of speed adaptation included self-efficacy, attitude toward safety, and sensation seeking.

Speed selection is not only impacted by human behavior, but also by the surrounding environment. Research using an advanced driving simulator focused on the impact of road infrastructure and traffic complexity on speed adaptation while engaging in a secondary task (Oviedo-Trespalacios et al., 2017). For the analysis, 32 young operators drove on a simulated roadway while engaged in hand-held and hands-free conversations. The simulations included a variety of roadway and traffic compositions, including free flow traffic, urbanized roadways, heavy traffic, and suburban roadways. A decision tree was developed that considered the observed speed deviation from the posted speed limit. From this, generalized linear mixed models were created. The results indicated that drivers distracted by cell phone use selected a lower speed while operating along curved segments and during car-following tasks. Additionally, drivers who reported safe driving abilities while engaging in a cell phone-related distraction selected a lower speed than others while distracted, indicating that some operators are aware of the impacts that distraction can have on traffic safety.

Various other aspects of driver performance are impacted when distracted by a cell phone. Psychological impacts on driving performance have been successfully documented through distracted driving research. A study on the diminishing self-awareness of overall performance was conducted in which participants drove in a simulator under talking and no talking conditions (Sanbonmatsu et al, 2015). Driver errors were recorded during the simulation. Similar to previous research, drivers talking on cell phones committed more serious driving errors. Interestingly, participants talking on their cell phone rated their driving performance better than those who were not distracted, again indicating the impact of self-efficacy and an over assumption of one's abilities to multitask. The internal demand for limited neurological resources also generates poor driver performance due to distraction. A study involving a high-fidelity simulator and a single-task memory paradigm tested participants while determining the severity of this competition for mental resources (Watson et al., 2016). The research subjects were tested on driving performance only, mental capabilities only, and then the combination of both tasks. Results indicated that dividing the operator's attention between driving and distraction impaired the performance of both tasks.

The impacts of distraction are not only mental; quantitative performance measures have documented the physical impact of cell phone use on driving performance. Research has focused on vehicle-based performance attributes that change during talking and texting conditions (Choudhary and Velaga, 2016). The study examined the effects of simple and complex conversation, as well as simple and complex texting with various vehicle performance parameters. Characteristics of interest included lane position, lane departures, lateral acceleration, and steering wheel angle measurements. A driving simulator was utilized to collect the information from 100 licensed drivers of all ages. Repeated measures analysis of variance tests were constructed. All cell phone related distractions, except for simple conversation, resulted in an incorrect steering wheel change of at least ten degrees. This indicated that the physical driving performance of the operator was impacted by both of the cell phone use conditions (i.e. simple and complex texting), and the complex conversation condition. A ten degree change in the steering wheel angle may lead to unintended lane departures or head-on collisions with the opposite direction of travel, which is a major threat to traffic safety.

The negative traffic safety impact caused by cell phone distraction on driver performance is not only detrimental to the individual operator, but to surrounding vehicles as well. Various impacts on the operator, including lower speeds and lane deviations, cause a direct threat to traffic mobility. A study utilized a driving simulator to estimate the impact of driver distraction on traffic congestion (Stavrinos et al., 2013). The behavior of 75 teens and young adults was documented under various distractions, including talking and texting conditions. The simulation included a four-lane divided roadway under three separate LOS. Both a repeated measures analysis of variance and a generalized estimate equation Poisson model were used for analysis. Results from the study determined that more lane deviations and crashes occurred while the driver was texting. All sources of distraction had a significantly negative impact on traffic flow, as participants demonstrated greater speed variability, less lane changes, and lesser travel speeds.

2.2.3 Driver Characteristics

Although distracted driving affects all operators, a variety of research studies have focused exclusively on teenage drivers and cell phone use. This age demographic of novice operators is quick to adopt new technologies and implement them within their lifestyle, creating serious potential for distracted driving occurrences. Research determined that 57 percent of university students talk on their cell phone while driving (Gruyter et al., 2017). This increases to 62 percent when including those students who text while driving. Furthermore, those individuals who use a cell phone while driving were more likely than their peers to be involved in a crash. Because of these findings, additional public policy should be introduced to alert novice drivers of the threat to traffic safety caused by cell phone use.

As previously mentioned, a major issue with cell phone-related distractions is the false social norms and self-efficacy among operators. This is especially true among teenage drivers, who are constantly targeted by media campaigns that suggest a majority of their peers use their cell phone while driving. This overestimates the issue and creates a social norm that cell phone usage while operating is acceptable based on falsely reported behaviors. Research conducted by nine organizations and universities attempted to correct the social norms of collegiate drivers through educational programs (Hassani et al., 2016). A 30-minute, multi-media presentation about distracted driving was presented to 444 college students at 19 colleges and universities. To estimate the participants change in societal beliefs, surveys were given to the students before the workshop, immediately after the workshop, and three months after the workshop. Immediately following the workshop, all survey responses about distracted driving improved significantly. Additionally, 73 percent of the responses were favorable in the three month after survey, indicating that a majority of the distracted driving statistics and awareness information that was presented during the workshop were retained by the students.

Despite the research that has been conducted and the education campaigns that have focused on public perceptions, cell phone use while operating a motor vehicle is still a modern threat to traffic safety. Research conducted in 2012 attempted to gauge the current social norm of distracted driving among a sample of younger drivers (Atchley et al., 2012). The drivers were asked to read car crash scenarios and rate the responsibility of the driver. The crash situations included both drunk driving and distracted driving scenarios. The distraction scenarios involved cell phone use. Between both impairment conditions, drivers who were texting were considered to be the most responsible; however, novice participants assigned more fines and jail time to drunk drivers. This finding indicates again that younger drivers understand the threat that cell phone use has on traffic safety, but they often engage in the behavior themselves despite the risks. Results from the study indicate that social norms involving cell phone use have not yet been changed to the level that drunk driving has in modern society.

2.3 Usage of Naturalistic Driving Data

Although distracted driving research has historically been conducted with aggregate crash information, modern advancements in technology have been utilized to collect large amounts of disaggregate information. Often referred to as naturalistic driving data, this information includes detailed measurements of vehicle performance parameters, driver reaction times, and vehicle condition information. This information is collected through the use of unobtrusive data gathering equipment and without experimental control, resulting in a disaggregate approach to study driver behavior in a natural setting over a long period of time. This data provides great value to the field of transportation research as the interrelationship between drivers, vehicles, roadway characteristics, and conflict scenarios can be monitored in a natural environment while normal driving is occurring. This data is typically recorded with cameras and sensors that take observations frequently while the vehicle is in motion. This new technology and method of data collection has revolutionized the way distracted driving research can be conducted; however, this type of information is relatively new to the field of transportation and therefore has had minimal usage in the relevant literature. Despite this, a few research studies have used naturalistic driving data to estimate the various effects of distraction on operational parameters, including human behavior, driver performance, and crash risk.

2.3.1 Driver Behavior

Using naturalistic driving data, the behavior of adolescent drivers was monitored to determine the nature and prevalence of distracted driving behaviors (Foss and Goodwin, 2014). The vehicles of 52 high school students were equipped with unobtrusive data recorders for six months in order to obtain 20-second clips of video, audio, and vehicle kinematic information. The most common type of distracted behavior displayed by the high school students was cell phone use (6.7 percent), followed by adjusting vehicle controls (6.2 percent), and personal grooming (3.8 percent). Although most distracted behaviors were less frequent when adult passengers were present, conversation and horseplay were common when the passengers were near the same age as the novice driver. These situations (i.e. young drivers with young passengers) were correlated with looking away from the road, crash events, and rough (i.e. high g-force) driving. A visual depiction of the longest continuous glance away from the roadway as well as the total time spent looking away from the roadway are included in Figure 6. Note that the percent of clips variable in Figure 6 measures the frequency of the distraction occurring among all of the 20-second video and audio clips collected with the data recorders.

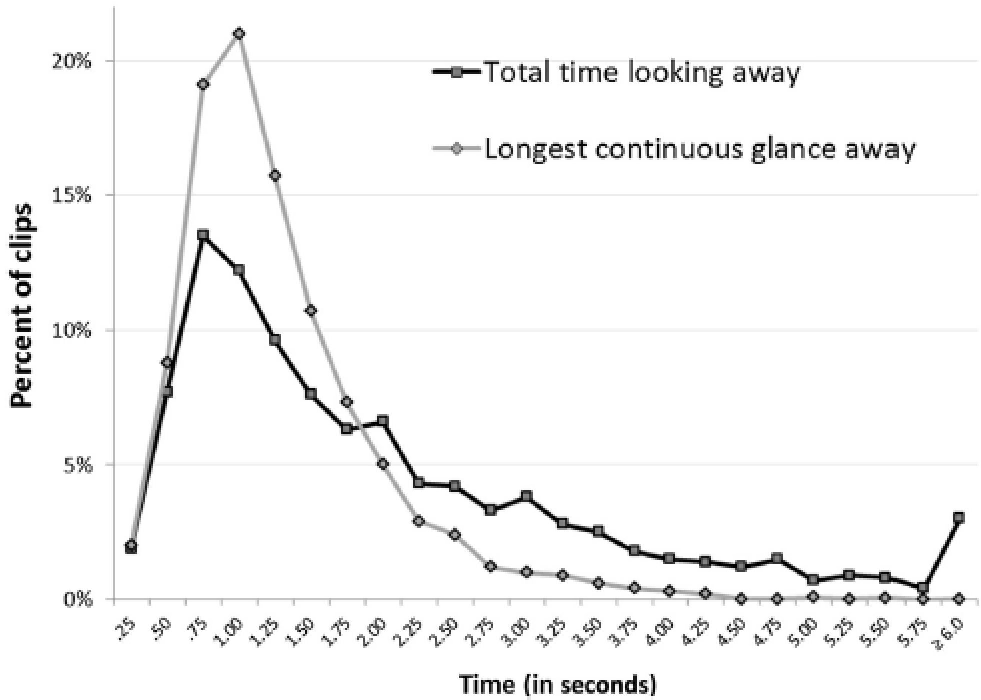

Figure 6. Comparison of Longest Continuous Glance and Total Time Looking Away from the Roadway (Foss and Goodwin, 2014)

2.3.2 Driver Performance

Due to the disaggregate nature of naturalistic driving data, it is possible to find correlations of greater fidelity between driver performance and distractions. Research was conducted in order to understand the association between distracted driving and driver performance in rear-end collisions on freeways (Gao, 2017). To quantitatively analyze this interaction, driver reaction time was selected as the indicator of crash risk. In total, 108 rear-end events were extracted and compared using both linear and causal models. The results determined that there was an association between driver distraction and reaction time. Furthermore, the presence of a distraction and the distraction duration were both positively associated with reaction time in a car-following situation.

2.3.3 Driver Characteristics

Naturalistic driving data has also been applied to crash risk research. A study focused on the effects of secondary tasks and behavior on both crashes and near-crashes at controlled and uncontrolled intersections (Ashley et al., 2017). Decision trees and multiple logistic regression models were generated to identify the secondary tasks and behavior characteristics that increased the likelihood of operators violating traffic laws. From the naturalistic driving data, the results determined that at both controlled and uncontrolled intersections, distracted driving increased the crash risk for drivers. Significant contributors to both crash and near-crash events were speeding, illegal passing, and distraction, all of which were related to human behavior characteristics. Additionally, crash risk also increased when operators were holding their cell phone, as determined by the analysis.

Crash risk has also been characterized by socioeconomic factors related to distracted driving. Using naturalistic data, a crash risk index (CRI) was created to estimate an operator's tendency to exhibit distracted driving behaviors (Ye, 2017). The CRI was developed using two components: the level of risk associated with performing specific secondary tasks and the likelihood of engagement in secondary tasks based on socioeconomic attributes. A logistic regression was performed with the two components to estimate CRI scores. Based on the results, the following secondary tasks were calculated as high risk: texting, holding a cell phone, personal grooming, and reaching for objects within the vehicle. Additionally, the socioeconomic attributes that were correlated with an increased likelihood of engaging in distracting activities were age, gender, personal annual miles traveled, marital status, income, and state of residence. Ultimately, a wide variety of significant results were identified that impacted the frequency of secondary task performance.

2.4 Recommendations

Because distracted driving is a modern threat to traffic safety, various countermeasures have been implemented to reduce the negative consequences of driver inattention. A technology transfer report was published by six universities to summarize the solutions that exist to counteract distracted driving (Peters and Stavrinos, 2017). Based on the conducted research, various approaches can be used to mitigate crashes due to driver inattention, including the installation of rumble strips and rumble stripes, appropriate signage, police-enforced texting stops, enhanced driver training programs, public information campaigns, and strict law enforcement. Among these countermeasures, the installation of rumble strips was the most common treatment implemented by various state DOTs to minimize the opportunity for roadway departures.

Besides infrastructure countermeasures, additional research has focused on providing various driving performance parameters that may be useful when conducting distracted driving research. As such, a meta-analysis of distracted driving research was conducted in that critical driving performance parameters were identified (Papantoniou et al., 2017). In total, 42 independent studies were examined. Each study involved a driving simulator that collected data on lateral control, longitudinal control, reaction time, gap acceptance, eye movement, and workload measures, among others. Each of the studies was published in a peer reviewed scientific journal and provided quantitative results. In a majority of the published papers, driver performance was measured based on a quantitative reduction in driver attention, driver behavior characteristics, or an increase in crash risk. The diversity of road and traffic characteristics considered was immense, ultimately leading to the simplistic recommendation of the driver performance measures.

CHAPTER 3. DATA SUMMARY

3.1 SHRP2 Program Overview

All the data utilized in this analysis were obtained as a part of the SHRP2 Implementation Assistance Program (IAP). The SHRP2 program was initially authorized in the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU). After legislative reform, the SAFETEA-LU act was replaced with the Moving Ahead for Progress in the 21st Century (MAP-21) act. The MAP-21 act continued the SHRP2 program and provided additional funding for this transportation initiative based on positive priori results. The SHRP2 program was initially established to determine strategic solutions to three key transportation issues that are commonly discussed in the United States: (1) improving highway safety, (2) reducing highway congestion, and (3) improving methods for renewable transportation infrastructure. The program was originally established in the National Cooperative Highway Research Program Report 510: Summary Report: Interim Planning for a Future Strategic Highway Research Program. An implementation strategy for the initiative was also outlined in the Transportation Research Board (TRB) Special Report 296: Implementing the Results of the Second Strategic Highway Research Program: Saving Lives, Reducing Congestion, and Improving Quality of Life.

The NDS conducted by the SHRP2 program is unique and revolutionary for the transportation industry because it is the largest NDS completed to date (Hamzeie, 2016). A NDS has two main advantages over traditional crash-based or operational-based analyses: (1) meticulously detailed and reviewable pre-crash information regarding the participant driver's behavior an instant before a crash occurs and (2) exposure information collected at a disaggregate level that measures the frequency and likelihood of driving behaviors and additional context of the contributing factors leading to a crash. Ultimately, the disaggregate nature of the NDS data allows for the analysis of human behavior while driving and the risk-taking tendencies of motorists, which was previously impossible to classify due to a lack of substantial information when using traditional data collection methods.

The use of driver behavior in crash modeling is critical when attempting to understand the effects of driver tendencies on resultant crash frequency and distraction likelihood. Traditional methods of analysis relied on police-reported crash information that was collected from the perspective of a non-crash individual. This individual was typically a responding police officer who considered the accounts of those involved in the crash, witnesses to the crash, and the evidence available through property damage to the vehicle(s) in question, among additional considerations (i.e. tire markings, weather conditions, animal presence, etc.). These after-the-crash investigations cannot accurately determine behavior before an accident because only aggregate information is available at the time of crash documentation, as well as the personal information provided by the vehicle occupants. Because of this, there is an inherent bias when using after-the-crash data as motorists would be less likely to report inappropriate behavior while driving, as additional charges may be associated with a crash caused due to poor operator behavior. Using NDS data, the detailed behavior of motorists was documented and confirmed in the instants immediately before a crash occurred. Driver impairment due to distraction, inattention, drowsiness, lack of judgement, or any additional human behavior characteristics was captured within the NDS framework and can be utilized in an analysis to determine future crash risk based on these disaggregate driver characteristics alone.

As mentioned previously, the SHRP2 program funded the largest NDS to date. The research project included observations from more than 2,600 participants. The in-vehicle observations were collected from these participants in six states across the United States. The number of vehicles included in the analysis per state were as follows (Campbell, 2012):

- Indiana – 150 vehicles
- Pennsylvania – 150 vehicles
- Florida – 441 vehicles
- New York – 441 vehicles
- North Carolina – 300 vehicles
- Washington – 409 vehicles

The participants were solicited through a variety of multi-media advertisements in each region. The participants were notified of the recruitment process through Craigslist posts, presentations, traditional mail flyers, internet-based mailings, and phone calls (Campbell, 2012). The study design ensured that there was an equal representation of both males and females, as well as all age categories, ranging from teenagers to elderly motorists. The technical coordination of the SHRP2 program NDS was performed by the Virginia Tech Transportation Institute (VTTI) (Campbell, 2012). Each interested participant was pre-screened before the research was conducted to ensure program eligibility. The eligibility for participation was based on the license status of the individual as well as the ownership of specific vehicle makes and models. Eligible vehicles included those that were of a recent model-year and were in good working condition (Campbell, 2012). Additionally, all vehicles in the analysis were passenger cars to ensure consistency between data collection instruments and to ease the installation process of the data collection units within the vehicle.

Given the disaggregate and detailed nature of the data collection procedure, the NDS maintained strict privacy rules and informed consent procedures to ensure that anonymity was maintained for all the solicited participants (Campbell, 2012). To collect the behavioral information, each solicited participant's vehicle was outfitted with a robust data acquisition system (DAS). A schematic of the DAS is provided in Figure 7.

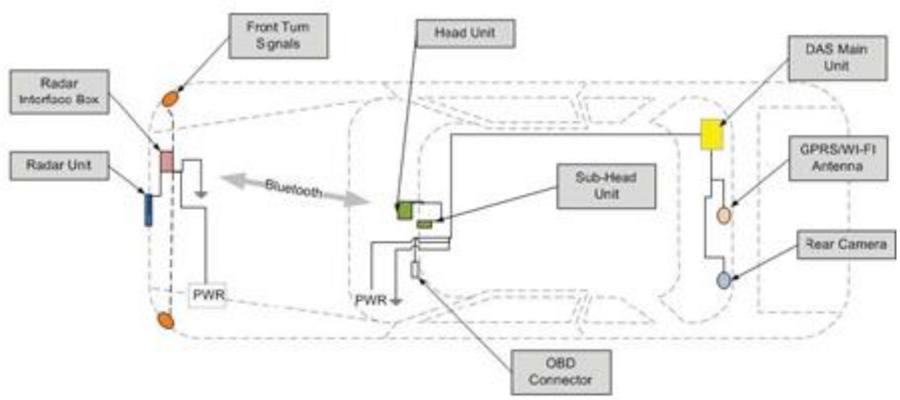

Figure 7. Schematic of SHRP2 DAS (FHWA, 2012)

The installation and testing of the DAS in each vehicle took approximately three hours to ensure that all instruments were connected correctly and recording the necessary information in real-time (Campbell, 2012). During this lengthy installation process, each driver was given a variety of personal assessment tests to complete at the testing facility. The tests measured a variety of driving-based skills and attributes, including executive function and cognition, visual perception, physical capabilities, personality traits, sleep patterns, medical records and conditions, and knowledge of proper conduct while operating a motor vehicle (Campbell, 2012). The physical tests for each motorist included a standard vision test, a test of grip strength, and a rapid-pace walking test. This information was collected to aid in the analysis of the risk-taking tendencies of the motorists.

Data were collected using the DAS and a portable hard drive onboard the participant's personal vehicle. This portable hard drive was removed from the vehicle biannually so the information could be downloaded to a secure system and the hard drive could be reissued with adequate storage for future data collection (Campbell, 2012). The NDS accumulated data from almost 2,600 participants. The DAS was developed by VTTI to collect the data necessary to support the objectives of the SHRP2 program. The combination of optical and mechanical instruments utilized to collect the information for the project was complex and included numerous sensors and tracking devices, including (Campbell, 2012):

- Forward radar sensor
- Four external video cameras
- Two internal video cameras
- Three vehicle accelerometers
- Passive alcohol sensor
- GPS
- Computer enhanced lane tracking technology

An image of one internal video camera and the passive alcohol sensor is depicted in Figure 8.

Figure 8. Interval Video Camera and Passive Alcohol Sensor (Campbell, 2012)

Additionally, other computer-based algorithms were included with the internal video cameras to accurately track subtle changes in driver behavior, such as eye movement and head positioning (Campbell, 2012). The tracking of more obvious changes in behavior, such as the utilization of a cell phone or eating while operating, was conducted by analyzing the internal video camera imagery after the data collection had completed. An example of the computer-based algorithm tracking the subtle changes in driver behavior is pictured in Figure 9.

Figure 9. Computer-Based Algorithm Tracking Subtle Changes in Driver Behavior (Campbell, 2012)

After installing the DAS and following the completion of the personal assessment tests, the solicited participants were released from the testing facilities with their customized personal vehicles. From their initial entry in the study to the completion of the data collection process, the participants traveled with their vehicles as they normally would have before enrolling in the NDS. The only additional task required by the participants was to return to the testing facility biannually so the data from the portable hard drive attached to their vehicle could be transferred to a secure network and the DAS could be briefly tested to ensure the instruments were recording accurate results (Campbell, 2012).

While the participants were operating their motor vehicles, the DAS continuously collected information during each trip taken by the operator. The central computer from that each device was attached recorded and encrypted all the information on the portable hard drive attached to their vehicle (Campbell, 2012). The four external video cameras were spaced and angled appropriately such that a wide field of view surrounding the vehicle was captured during each trip. Each of the four external cameras monitored the locations visible to the driver while sitting in the front seat; one camera was placed directly forward, two were angled out of the rear passenger windows, and one camera was facing directly backward. A visual depiction of this range of coverage is included in Figure 10.

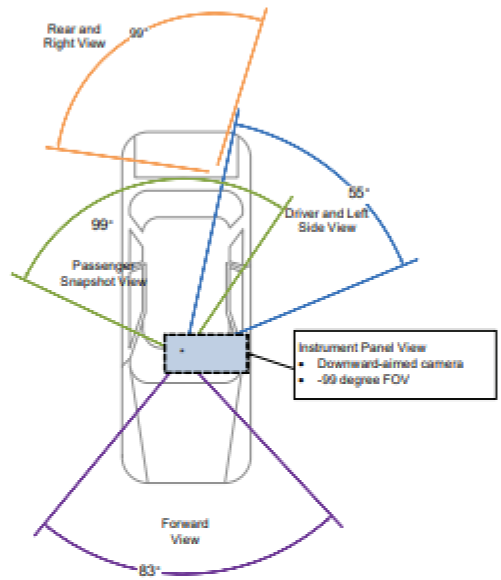

Figure 10. DAS Field of View (Campbell, 2012)

Furthermore, a Wi-Fi antenna was installed onboard the central computer in the vehicle to transmit the connectivity of each sensing unit. This way, participants could be contacted for any additional vehicular maintenance if a disconnection between any of the components was detected (Campbell, 2012). This process also accelerated the potential lapses in data collection that may have occurred between the required biannual visits to the testing facility.

Following the data collection period, all the recorded camera images were combined into a single frame for data reduction purposes, including the images from the four external cameras and the two internal cameras (Campbell, 2012). Of the two internal cameras, one was focused solely on the drivers face to track small behavioral shifts such as eye movements and head positioning, while the second was utilized to collect still images of the remaining interior of the vehicle to check for distractions not visible based on the driver's facial images. The second interior camera was also used to identify when rear-seated passengers were present in the vehicle (Campbell, 2012). The forward-facing camera imagery was analyzed independently to determine the traffic conditions (i.e. LOS) during the freeway trip event. After collection and quality assurance of the video files, these images were permanently blurred to protect the identities of the participants in the study. Ultimately, the data from each of the six NDS sites were encrypted and transferred to VTTI for further processing and quality control. After this procedure, the information was migrated to the NDS database, which has about 2 petabytes (2,000 terabytes) of information from the four-year data collection period (Campbell, 2012).

To assist in the analysis of human behavior and driver characteristics, the Iowa State University (ISU) Center for Transportation Research and Education (CTRE) developed an extensive database of roadway information and geometric characteristics in partnership with the SHRP2 program NDS. The collected information covered the entirety of the participant traveled network in the six study states. This robust dataset integrated aggregated information from the local state highway transportation agencies for the six study sites along with field collected measurements. The field collected data in the RID was captured using a data collection van that was outfitted with various instruments, sensors, and cameras to collect roadway measurements while traveling at the posted speed limits on the participant traveled routes. The roadway information collected by the van included:

- Number of lanes
- Lane type and width
- Grade
- Superelevation
- Beginning and ending points of horizontal curves
- Curve radius

- Paved shoulder presence and width
- Speed limit information and signage location
- Intersection locations and number of approaches
- Traffic control device locations

A picture of the data collection van in the process of collecting RID data is pictured in Figure 11.

Figure 11. RID Data Collection Van (Campbell, 2012)

This information was collected by the data collection van every second while the vehicle was in operation. The field data was verified through a quality assurance process. To determine which roadways to traverse for data collection, GPS traces of participant trips were provided to the ISU research faculty. Based on the results of these traces, the ISU CTRE van traveled along the same roadways to collect all the necessary roadway information and geometric characteristics of interest. Ultimately, about 12,000 miles of roadway information was measured to assist with the NDS.

Based on the available disaggregate human behavior data, the accompanying risk-taking characteristics from the required personal assessment tests, and the roadway geometrics collected from the participant traveled routes, the SHRP2 program NDS supports a comprehensive assessment of how driver performance is impacted by within-vehicle behavior, motorist attributes, and roadway characteristics. The primary benefit of this extensive data repository is the ability to determine those behaviors, characteristics, and geometrics with directly impact the driving performance of the motorist.

3.2 Data Preparation

For this analysis, time-series data were collected from all the freeway trip events completed by the solicited participants throughout the four-year NDS data collection period. The time-series data was recorded every decisecond by the onboard DAS installed on the participant's passenger cars. Because of this, there were multiple observations made during the same freeway trip event interval, which was completed by the same motorist.

The time-series freeway trip event data was provided in 30-second intervals for crash and near-crash events, meaning that 300 observations were available for each freeway trip event that involved any type of crash or near-crash (since a measurement was taken by the DAS every decisecond), while 21-second intervals (i.e. 210 observations) were provided for non-crash events. The crash events were reported by the NDS participants to the researchers, while near-crash events were identified based on the forward-facing video camera information. Additionally, the provided non-crash (i.e. control) events were randomly sampled freeway trip events that did not involve any type of crash. Each freeway trip event was given a unique identification number so proper data migration could occur when considering the information observed from the onboard DAS, the results of the personal assessment tests, and the RID data.

In this study, the effect of driver distraction on crash risk was analyzed. Additionally, the characteristics of drivers who were more likely to become distracted were considered in a separate analysis. Lastly, the effects of roadway parameters, such as characteristics and geometrics, were analyzed to determine their impact on the likelihood of driver distraction. To complete this analysis, the data were merged and analyzed based on the unique freeway trip event identifier previously mentioned to ensure accuracy among the three various data sources. All the video data for the NDS was analyzed and aggregated by VTTI. This included the review, analysis, and coding of the following human behavior aspects: the presence of distractions that occurred during the participant's freeway trip events, the time during which the participant was engaged and not engaged in such behavior, the answers to the personal assessment tests, and many other behavioral variables. This information was provided by VTTI to ensure that participant anonymity was maintained. Quality control procedures were also performed to ensure that the final dataset was accurate before the information was available to researchers.

To prepare the dataset for analysis, the freeway time-series information was first divided into two separate databases: distracted and non-distracted, with the latter providing baseline (i.e. control) data to allow for a comparison of differences in driving behavior. This was completed by separating the distracted freeway trip events and the non-distracted freeway trip events based on the VTTI coded driver behavior. Indicators were provided by VTTI to determine if the driver engaged in a distracting event during the freeway trip event. If a distraction occurred, the type of distraction was coded in the provided dataset, as was the time duration of the distraction. During the freeway trip event interval, each tenth of a second was given a corresponding identification value. Using both the unique freeway trip event indicator and the corresponding identification value of time, the interval during which the distraction event occurred was identified for further analysis purposes. After removing observations with missing data or data that could not be interpreted, the analysis datasets contained 497 participants who engaged in distracting behavior during their freeway trip events and 530 participants who did not engage in any distractions during their freeway trip events. This led to 20,571 observations in the distracted dataset, and 21,144 observations in the non-distracted dataset.

Due to the large size of the available information, separate comma separated value (CSV) spreadsheets were provided from VTTI for each individual freeway trip event. After freeway trip events were coded as distracted or non-distracted for the analysis, the CSVs for each respective category were separated into two folders. This was completed automatically by using a Python script and the unique freeway trip event identification number as discussed previously. The purpose of using the Python script to separate the files was to avoid any manual sorting techniques that may lead to human error. After separation, the resultant CSVs were still too disaggregated for analysis, as each freeway trip event was confined to an individual spreadsheet (i.e. each spreadsheet contained one freeway trip event, or 210-300 independent observations). To mitigate this issue, an R script was generated that automatically merged all the CSV files together based on their inclusion in their respective folders. This resulted in two complete datasets: one that contained all the observations for those freeway trip events during which a distraction occurred, and one that contained all the observations for those freeway trip events during which no distraction occurred. As previous, these will be referred to as the distracted and non-distracted datasets, respectively.

Following this aggregation, various statistics of interest were computed using the time-series information. For each freeway trip event, speed observations were aggregated to the nearest second. Since the speed component was essential when determining its impact on driver behavior, any freeway trip event that was missing this speed data was removed from the analysis. Next, each of the speed measurements was converted from kilometers per hour to mph, as the reported information was collected by the DAS in metric units.

Next, the speed limit information for the roadway was integrated from the RID database. From the data collection van, the speed limit of the roadway on which the participant was traveling was recorded every second. Any changes in speed limit were also identified during the data collection process, including transition and advisory speed limits due to variations in roadway geometry. Detailed quality assurance was also performed to ensure that speed limit changes were implemented in the dataset at the exact moment at which they occurred during the freeway trip event by using the appropriate identification value of time.

As mentioned previously, the front facing camera imagery was analyzed by VTTI researchers on a secure network to determine the exact timing of both crash and near-crash events. A crash event was denoted as any contact that a subject vehicle had with any object, whether fixed or moving (Hankey et al., 2016). This also included any non-premediated departures from the roadway. A near-crash event was any situation which required an evasive maneuver by the subject vehicle to avoid a crash (Hankey et al., 2016). Due to the similarity in the actions required by the motorist for these event types, both crash events and near-crash events were combined in the distracted and non-distracted datasets. Freeway trip events without a crash or near-crash event were classified as a non-crash (i.e. control) event for analysis comparison.

Besides the freeway trip event data that was collected, various demographic characteristics were obtained from the NDS participants through a series of surveys and interview questionnaires as mentioned previously. Before officially enrolling in the NDS, each of the participants completed a series of detailed personal assessment tests that collected various demographic information as well as tendencies and risk-taking behaviors, among other variables of interest. The participants answered a series of questions focused on their driving habits, how they performed under stressful situations, and measured their risk-taking likelihoods. The survey also documented any health impacts and medications or physical restrictions that may impair the participants from successfully enrolling in the NDS. This information was also integrated into the distracted and non-distracted datasets for each of the participants.

As mentioned previously, a comprehensive RID was developed by the ISU CTRE department to assist with the NDS. This database, which contained aggregate information about the roadways traveled by the solicited participants in all six states, was collected using a data collection van and included information about roadway geometries and characteristics. Specifically, the data maintained in the RID had variables related to alignment (i.e. tangent or curved surface), the number of lanes, lane width, and both left and right shoulder widths that were present during the freeway trip events. Ultimately, this information was matched with the freeway trip events for both the distracted and the non-distracted datasets. This information was included in the resultant analysis to determine the effects that roadway geometries and characteristics had on the likelihood of a driver to become distracted while operating a motor vehicle. Following the integration of the RID variables into both the distracted and non-distracted datasets, the two separate files were merged together with distraction-based binary indicators to create the dataset utilized for analysis.

The descriptive statistics of all of the variables utilized in the subsequent analyses are provided in Table 1, Table 2, Table 3, and Table 4. These tables contain the minimum, maximum, mean, and standard deviation of the time-series data, RID geometrics, driver characteristics, and driver behavioral survey results, respectively. The count in Table 1 and Table 2 represent the number of per-second observations included within the time-series data for each variable, with a maximum count of 41,715. The count in Table 3 and Table 4 represent the number of unit-specific observations derived from the time-series data, with a maximum count of 1,890. Note that various parameters were represented using binary indictors. These variables had a zero if the parameter was not present during that time, and a one if the parameter was present during that time.

Table 1. Descriptive Statistics of Time-Series Data

Variable	**Count**	**Min**	**Max**	**Mean**	**St. Dev.**
Driver selected speed (mph)	41,715	0	134.067	51.828	18.085
Speed limit (mph)	41,715	15	70	55.456	9.328
Crash or near-crash event	6,750	0	1	0.162	0.368
Distraction event	20,571	0	1	0.493	0.500
Distraction time	4,504	0	1	0.108	0.310
Instrument panel-related distraction	906	0	1	0.022	0.146
Hygiene-related distraction	1,029	0	1	0.025	0.155
Appearance-related distraction	135	0	1	0.003	0.057
Cell phone-related distraction	3,858	0	1	0.092	0.290
Passenger-related distraction	5,328	0	1	0.128	0.334
Consumption-related distraction	1,134	0	1	0.027	0.163
Smoking-related distraction	438	0	1	0.010	0.102
External distraction	2,187	0	1	0.052	0.223
Internal distraction	2,043	0	1	0.049	0.216
Activity-related distraction	3,513	0	1	0.084	0.278

The descriptive statistics for the driver-selected speed is included in Table 1. The measured travel speed of the driver was included in the time-series information, as well as the posted speed limit of the roadway. A binary indicator was included to represent the occurrence of a crash event. The “distraction event” variable was a summation of the disaggregate distraction categories in Table 1 and identified when any type of distraction occurred during a freeway trip event. The "distraction time" characteristic noted the exact moments during the freeway trip event that a distraction occurred, if present. Lastly, the disaggregate distraction categories in Table 1 are thoroughly explained in Table 6 in the Results and Discussion chapter of this study.

Table 2. Descriptive Statistics of RID Geometrics, Weather Conditions, and Traffic Congestion

Variable	**Count**	**Min**	**Max**	**Mean**	**St. Dev.**
Tangent lane type	28,628	0	1	0.686	0.464
Curve lane type	13,087	0	1	0.314	0.464
Lane width (ft.)	41,715	5.908	67.613	11.811	2.618
Average lane width (ft.)	41,715	7.625	46.475	11.810	1.833
Number of lanes	41,715	1	7	2.851	0.983
Average number of lanes	41,715	1	6	2.850	0.939
Left shoulder width (ft.)	41,715	0	43.258	4.609	3.537
Average left shoulder width (ft.)	41,715	0	21.878	4.609	3.242
Right shoulder width (ft.)	41,715	0	41.313	7.089	4.290
Average right shoulder width (ft.)	41,715	0	25.956	7.089	3.861
Degree of curvature (°)	41,715	0	90.946	0.676	1.936
Vertical grade (%)	41,715	-12.1	12.1	0.021	1.721
Clear weather conditions	37,479	0	1	0.898	0.302
Light rain weather conditions	1,461	0	1	0.035	0.184
Rainy weather conditions	2,253	0	1	0.054	0.226
Foggy weather conditions	366	0	1	0.009	0.093
Rainy and foggy weather conditions	93	0	1	0.002	0.047
Snowy weather conditions	63	0	1	0.002	0.039
Level-of-service A	19,197	0	1	0.460	0.498
Level-of-service B	15,498	0	1	0.372	0.483
Level-of-service C	4,062	0	1	0.097	0.296
Level-of-service D	1,866	0	1	0.045	0.207
Level-of-service E	936	0	1	0.022	0.148
Level-of-service F	156	0	1	0.004	0.061

Table 2 contains a summation of the RID geometrics, weather conditions, and traffic condition variables that were utilized in the analysis dataset. The "tangent lane type" and "curve lane type" variables were binary indicators that assumed a value of one when the horizontal alignment of interest was present (i.e. denoting when the freeway segment was tangent or curved). Note that a tangent segment is a roadway segment with a curve radius of 0°. The roadway geometrics of interest, including lane width, number of lanes, left shoulder width, and right shoulder width, were included at their per-second observation rate as well as averages over the duration of the freeway trip event. The "degree of curvature" variable was measured in degrees and had a value of zero along tangent segments. The "vertical grade" parameter was the collected percent grade from the data collection van. Lastly, the included weather and LOS parameters were binary indicators that were one when present during the freeway trip event and zero otherwise.

Table 3. Descriptive Statistics of Driver Characteristics

Variable	Count	Min	Max	Mean	St. Dev.
Female drivers	987	0	1	0.522	0.500
Male drivers	903	0	1	0.478	0.500
Driver age 16-19	76	0	1	0.040	0.196
Driver age 20-24	394	0	1	0.208	0.406
Driver age 25-29	250	0	1	0.132	0.339
Driver age 30-34	186	0	1	0.098	0.298
Driver age 35-39	103	0	1	0.054	0.227
Driver age 40-44	111	0	1	0.059	0.235
Driver age 45-49	127	0	1	0.067	0.250
Driver age 50-54	134	0	1	0.071	0.257
Driver age 55-59	142	0	1	0.075	0.264
Driver age 60-64	87	0	1	0.046	0.210
Driver age 65-69	114	0	1	0.060	0.238
Driver age 70-74	91	0	1	0.048	0.214
Driver age 75-89	75	0	1	0.040	0.195
Some high school education	20	0	1	0.011	0.102
High school diploma	128	0	1	0.068	0.251
Some education beyond high school	449	0	1	0.238	0.426
College degree	630	0	1	0.333	0.471
Some graduate school education	221	0	1	0.117	0.321
Advanced degree	442	0	1	0.234	0.423

Table 3. (continued)

Annual income under $29,000	218	0	1	0.115	0.319
Annual income between $30,000 and $39,999	180	0	1	0.095	0.294
Annual income between $40,000 and $49,999	192	0	1	0.102	0.302
Annual income between $50,000 and $69,999	364	0	1	0.193	0.394
Annual income between $70,000 and $99,999	352	0	1	0.186	0.389
Annual income between $100,000 and $149,999	396	0	1	0.210	0.407
Annual income more than $150,000	188	0	1	0.099	0.299
Average annual mileage less than 5,000 miles	75	0	1	0.040	0.195
Average annual mileage between 5,000 and 10,000 miles	337	0	1	0.178	0.383
Average annual mileage between 10,000 and 15,000 miles	695	0	1	0.368	0.482
Average annual mileage between 15,000 and 20,000 miles	331	0	1	0.175	0.380
Average annual mileage between 20,000 and 25,000 miles	175	0	1	0.093	0.290
Average annual mileage between 25,000 and 30,000 miles	129	0	1	0.068	0.252
Average annual mileage more than 30,000 miles	148	0	1	0.078	0.269
Zero violations within the last twelve months	1,225	0	1	0.648	0.478
One violation within the last twelve months	472	0	1	0.250	0.433
Two or more violations within the last twelve months	193	0	1	0.102	0.303
Zero crashes within the last twelve months	1,356	0	1	0.717	0.450
One crash within the last twelve months	428	0	1	0.226	0.419
Two or more crashes within the last twelve months	106	0	1	0.056	0.230

The descriptive statistics in Table 3 are all binary indicators that describe the various socioeconomic characteristics of the SHRP2 participants that were included in this analysis. There was slightly more females than males and the age distribution of the operators was skewed towards the younger age categories. Most drivers had a collegiate education and a median annual income value. The mileage variables represented the average annual mileage indicated by the driver before enrolling in the study. The average annual mileage category with the greatest frequency of observations was between 10,000 and 15,000. Lastly, the violation and crash parameters were a portion of the driver behavioral study in which the participant identified the number of violations and crashes they were involved in over the last twelve months before enrolling in the NDS. More than one-third (35 percent) of the operators had at least one ticketed violation, while 28 percent were involved in at least one crash or near-crash event.

Table 4. Descriptive Statistics of Driver Behavioral Survey Results

Variable	**Count**	**Min**	**Max**	**Mean**	**St. Dev.**
Driving abilities somewhat worse than the average driver	113	0	1	0.060	0.237
Driving abilities about the same as the average driver	573	0	1	0.303	0.460
Driving abilities somewhat better than the average driver	849	0	1	0.449	0.497
Driving abilities much better than the average driver	355	0	1	0.188	0.391
Never run red signals	1,110	0	1	0.587	0.492
Rarely run red signals	734	0	1	0.388	0.487
Sometimes run red signals	44	0	1	0.023	0.151
Often run red signals	2	0	1	0.001	0.033
Never take risks for fun	1,705	0	1	0.902	0.297
Rarely take risks for fun	145	0	1	0.077	0.266
Sometimes take risks for fun	40	0	1	0.021	0.144
Often take risks for fun	0	0	0	0.000	0.000
Never speed for fun	1,537	0	1	0.813	0.390
Rarely speed for fun	285	0	1	0.151	0.358
Sometimes speed for fun	60	0	1	0.032	0.175
Often speed for fun	8	0	1	0.004	0.065
Never tailgate	950	0	1	0.503	0.500
Rarely tailgate	726	0	1	0.384	0.486
Sometimes tailgate	191	0	1	0.101	0.301
Often tailgate	23	0	1	0.012	0.110
Never race drivers at green signal	847	0	1	0.448	0.497
Rarely race drivers at green signal	632	0	1	0.334	0.472
Sometimes race drivers at green signal	341	0	1	0.180	0.385
Often race drivers at green signal	70	0	1	0.037	0.189
Never accelerate at yellow signal	286	0	1	0.151	0.358
Rarely accelerate at yellow signal	967	0	1	0.512	0.500

Table 4. (continued)

Sometimes accelerate at yellow signal	576	0	1	0.305	0.460
Often accelerate at yellow signal	61	0	1	0.032	0.177
Never road rage	992	0	1	0.525	0.499
Rarely road rage	598	0	1	0.316	0.465
Sometimes road rage	280	0	1	0.148	0.355
Often road rage	20	0	1	0.011	0.102
Never race other drivers	1,797	0	1	0.951	0.216
Rarely race other drivers	86	0	1	0.046	0.208
Sometimes race other drivers	3	0	1	0.002	0.040
Often race other drivers	4	0	1	0.002	0.046
Never drive ten to twenty mph over the speed limit	393	0	1	0.208	0.406
Rarely drive ten to twenty mph over the speed limit	897	0	1	0.475	0.499
Sometimes drive ten to twenty mph over the speed limit	421	0	1	0.223	0.416
Often drive ten to twenty mph over the speed limit	179	0	1	0.095	0.293
Never drive more than twenty mph over the speed limit	1,427	0	1	0.755	0.430
Rarely drive more than twenty mph over the speed limit	386	0	1	0.204	0.403
Sometimes drive more than twenty mph over the speed limit	69	0	1	0.037	0.188
Often drive more than twenty mph over the speed limit	8	0	1	0.004	0.065
Never drive without wearing a seatbelt	1,699	0	1	0.899	0.301
Rarely drive without wearing a seatbelt	147	0	1	0.078	0.268
Sometimes drive without wearing a seatbelt	29	0	1	0.015	0.123
Often drive without wearing a seatbelt	15	0	1	0.008	0.089

The descriptive statistics for all of the included driver behavioral survey results are in Table 4. Note that these were also all binary indicators, similar to the characteristics included in Table 3. The parameters in Table 4 were the output of the written behavioral survey completed by all SHRP2 participants before enrolling in the program. For this portion of the survey, the participants were required to estimate how often they personally performed the behavior of interest. The options for each question were “never”, “rarely”, “sometimes”, or “often”. For this analysis, the operators who selected “never” or “rarely” were considered as non-risky motorists, as they had a lower frequency of poor roadway behavior in their past driving experiences. Conversely, operators who selected “sometimes” and “often” for the behaviors in question were considered as risky motorists, as they frequently exhibited poor roadway behavior in their past driving experiences.

The first four characteristics in Table 4 note a personal reflection on the driving abilities of the motorist. For this question, the driver rated their personal driving abilities compared to what they considered as the average driver. The remaining parameters in Table 4 followed the format described previously; the options for the frequency of engagement in each poor roadway behavior were “never”, “rarely”, “sometimes”, or “often”. The run red signals variables determined how frequently the operator ran red signals at intersections in their past driving experiences, while the risk for fun variable estimated if the driver enjoyed taking risks for fun while driving. The speed for fun characteristic determined the frequency the driver sped while driving for fun, while the tailgate, race drivers at green signals, accelerate at yellow signals, and road rage variables all measured the aggressiveness of the participant based on their prior driving experiences. The race other driver’s variable measured how frequently the motorist raced other drivers in the past. The two speeding parameters in Table 4 determined how often the participant traveled ten to twenty mph over the speed limit and how often they traveled more than twenty mph over the speed limit. Lastly, the seatbelt usage characteristic estimated the frequency of seatbelt non-usage while driving.

CHAPTER 4. METHODOLOGY

Based on the aggregate findings from the state-of-the-art literature review, the crash risk of motorists was likely to increase when engaged in a secondary task. There may also be some roadway features that are more conducive to distracted driving opportunities and increase the likelihood of a driver to engage in a distracting task. Lastly, some specific demographic characteristics or behavioral information may be correlated with the likelihood of drivers to engage in secondary tasks. To understand these relationships, detailed driver behavioral information from the SHRP2 program NDS and corresponding RID were integrated into a distracted dataset and a non-distracted dataset, as mentioned previously. These data were carefully merged together to create one cohesive dataset after generating two separate binary indicators: (1) an indicator that identified if a freeway trip event had a distraction occur at any time during the trip event, and (2) an indicator that identified the exact time during which the distraction was occurring. Using this information, the following questions of interest were addressed:

1. How did driver distraction affect the crash risk of motorists?

2. Under what roadway conditions were motorists more likely to engage in distracted driving activities?

3. What type of driver demographics and risk-taking behaviors made drivers more likely to engage in secondary tasks?

To examine these questions thoroughly, various regression models were estimated using the data from the SHRP2 program NDS. The details of each statistical method are described below.

4.1 Statistical Methods for Driver Performance Impacts

By using the collected travel speed from each driver during their respective freeway trip events, a variety of multivariate linear regression models were estimated with a variety of speed-related dependent variables. The statistical models were generated using the time series observations. To measure the effect that distractions had on driver performance, the driver selected speed was considered as the dependent variable for the analysis. Because this metric was continuous in nature (i.e. the available values were within a range of possible outcomes), a linear regression model was considered to examine the performance degradation of distracting behavior. A requirement of the linear regression framework was that an inherently linear relationship was available between the dependent variable (driver selected speed) and the various independent variables. The linear regression model for this analysis was modeled as follows (Zenina and Borisov, 2013):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \tag{1}$$

where Y was the dependent variable of interest (driver selected speed), X_1 through X_n were the independent variables, and β_0 through β_n were the estimated regression coefficients. A disturbance term (ε) was also included, the requirements of which were as follows (Karlaftis et al., 2010):

$$E[\varepsilon] = 0 \tag{2}$$

The variance of the disturbance term was independent across all observations as follows (Karlaftis et al., 2010):

$$VAR[\varepsilon] = \sigma^2 \tag{3}$$

This assumption, known as homoscedasticity, implied that the uncertainty in the model estimates was random across all observations and covariates in the analysis. This uncertainty included unobserved effects, measurement errors, and true random variation parameters.

Many independent variables were included to measure the effect that a variety of characteristics had on driver speed selection. To express this more effectively, a linear regression matrix notation was generated as follows:

$$Y_{n \times 1} = X_{n \times p}\beta_{p \times 1} + \varepsilon_{n \times 1} \tag{4}$$

where the X matrix was the size n x p. In this instance, n was the number of observations in the dataset, while p was the number of variables considered for each observation. A final assumption of the linear regression model was that the data from the population were randomly sampled. More explicitly, the probability that an observation was selected for analysis was unaffected by the additional observations within the sample.

An underlying issue with the time-series freeway trip event data utilized in this analysis was that there was likely a correlation in numerous parameters within each individual trip event given the repeated nature of the time-series data. In other words, all the observations of the driver characteristics, road segment geometrics, and weather conditions that were recorded during a singular freeway trip event would be related to one another as they are repeated throughout the time-series data. It was important to consider this correlation among freeway trip event observations, as some drivers may naturally tend to drive faster or slower than other drivers. This tendency may also be unique to each driver during periods of distraction. Failing to accommodate for these associations would lead to biased estimates and inaccuracies in the predictive independent variables. To account for this participant-specific correlation appropriately, a unique identifier was created to decipher each driver individually within the analysis dataset. This identifier was included in the resultant analyses to capture the effects of the unobserved tendencies between the SHRP2 participants. The inclusion of this identifier is commonly referred to as a random effects parameter.

4.2 Statistical Methods for the Effect of Roadway Characteristics, Weather Conditions, and Traffic Congestion

Roadway characteristics from the RID were also included in the statistical analyses. As mentioned previously, the roadway metrics were initially collected through a post hoc procedure by ISU CTRE at a one second interval with the usage of a data collection van. By using the GPS tracking information and the time identification factor previously discussed, the changes in roadway features were accurately migrated to the time-series framework.

Because this information was replicated to correspond with the time-series data, all of the roadway parameters of interest were also included in the linear regression model for analysis. The model also adequately considered the correlation between the drivers selected speed and the underlying tendencies of motorists to drive faster or slower than one another naturally by using a unique identifier for each freeway trip event. The unique identifier was a random effect parameter that ensured that the estimates for the roadway geometrics and characteristics were as accurate as possible, while considering the potential correlation between the multiple observations included for the same driver during the same freeway trip event.

4.3 Statistical Methods for the Likelihood of Distraction and Crash Risk

As mentioned previously, each of the participants in the NDS completed a series of demographic and behavioral surveys. A written driving test was also conducted that determined the participant’s level of traffic knowledge. This included a risk assessment test in which the participants characterized the level of risk they associated with various poor driving behaviors. An additional portion encouraged the participant to document their likelihood of engaging in such driving behaviors and approximate the number of times they exhibited these behaviors while driving on the roadway in the past year.

By linking the well documented distraction indictors from the time-series data to the participant survey results, those solicited participants who were distracted during their recorded freeway trip events were identified. Using this information, the demographic and characteristic attributes of these participants was compared to those individuals who did not engage in a secondary task during the study period. The intent of this analysis was to determine the various attributes that increased the likelihood of a motorist to engage in a distracting activity while driving.

To this end, logistic regression models were generated that examined the documented characteristics of the study participants. A logistic regression was an appropriate framework for the corresponding survey data as the dependent variable (i.e. engaging in a secondary task while driving) was dichotomous in nature. The purpose of the model was to describe the relationship between the binary dependent variable and the significant independent explanatory variables, which described the participant's demographic characteristics and risk-taking behaviors. The assumption of the logistic regression framework was that the significant explanatory variables directly influenced the outcome (or likelihood) of the dependent variable (i.e. engaging in a secondary task). The general form of the logistic regression model was a function of the covariates as follows:

$$Y_i = logit(P_i) = ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_K X_{K,i} \quad (5)$$

where the dependent term, Y_i, is the logistic transformation of P_i (Karlaftis et al., 2010). P_i was the probability of a freeway trip event involving a distracting behavior. $X_{1,i}$ through $X_{K,i}$ represented explanatory variables for each specific survey response, β_0

represented a constant term, and β_1 through β_K were the parameter estimates associated with the explanatory variables. Once these parameters were estimated, the probability that the outcome assumed a value of one was estimated as:

$$P_i = \frac{\exp(\beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_K X_{K,i})}{1 + \exp(\beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_K X_{K,i})} \tag{6}$$

A transformation of the logit model was utilized to estimate the resultant probability ratio, such that when the value of an explanatory variable increased by one additional unit, the probability ratio became:

$$\left(\frac{P_i}{1 - P_i}\right) = \left(\frac{P_i}{1 - P_i}\right) \text{ x } \exp(\beta_i) \tag{7}$$

This indicated that an increase in any independent variable X_i by one unit increased the odds of a freeway trip event involving a secondary behavior by a factor of e^{β_i}. It was also assumed within the logistic regression framework that the error terms were independently and identically distributed. Because each of the survey responses were repeated within the time-series database (i.e. demographic and behavioral survey answers were repeated every second for each freeway trip event), the previous unique identifier for each freeway trip event was considered as a random effects parameter to ensure that the model estimates were as accurate as possible. Without a random effects model, the repeated frequency of the survey information would result in biased estimates due to the nature of the repeated time-series data.

CHAPTER 5. RESULTS AND DISCUSSION

This chapter contains the results of the statistical analyses conducted for this study. Note that each of the model estimates in the upcoming tables were generated using a random effects framework; both the unique freeway trip event identifier and the unique participant identifier were included as random effects parameters. Various regression frameworks were considered to answer the three primary research questions, including linear and logistic regression models. Table 5 depicts the results of the random effects linear regression model for the driver selected speed during the freeway trip event.

Table 5. Random effects linear regression model for travel speed

Variable	Estimate	Std. Error	t-Value	Pr(>|t|)
Intercept	2.007	0.400	5.020	<0.001
Speed limit (mph)	0.837	0.008	100.530	<0.001
Average left shoulder width (ft.)	0.414	0.022	18.490	<0.001
Average right shoulder width (ft.)	0.764	0.021	35.716	<0.001
Degree of curvature (°)	-0.154	0.030	-5.085	<0.001
Light rain weather conditions (1 if yes; 0 otherwise)	-5.159	0.318	-16.222	<0.001
Rainy and foggy weather conditions (1 if yes; 0 otherwise)	-5.818	1.239	-4.695	<0.001
Level-of-service B (1 if yes; 0 otherwise)	-3.364	0.129	-26.020	<0.001
Level-of-service C (1 if yes; 0 otherwise)	-10.019	0.206	-48.661	<0.001
Level-of-service D (1 if yes; 0 otherwise)	-28.503	0.289	-98.485	<0.001
Level-of-service E (1 if yes; 0 otherwise)	-41.779	0.402	-103.903	<0.001
Level-of-service F (1 if yes; 0 otherwise)	-44.256	0.954	-46.383	<0.001
One violation within the last twelve months (1 if yes; 0 otherwise)	0.895	0.137	6.511	<0.001
Two or more violations within the last twelve months (1 if yes; 0 otherwise)	2.093	0.200	10.451	<0.001

Table 5. (continued)

Driving abilities much better than the average driver (1 if yes; 0 otherwise)	0.662	0.151	4.392	<0.001
Sometimes road rage (1 if yes; 0 otherwise)	1.465	0.168	8.733	<0.001
Often road rage (1 if yes; 0 otherwise)	2.227	0.548	4.065	<0.001
Often drive ten to twenty mph over the speed limit (1 if yes; 0 otherwise)	1.589	0.208	7.651	<0.001
Often drive more than twenty mph over the speed limit (1 if yes; 0 otherwise)	5.577	0.919	6.066	<0.001
Model Diagnostics				
Residual standard error	11.850			
Multiple R^2	0.571			
Adjusted R^2	0.570			
F statistic	3,078			
P value	<0.001			

Based on the results in Table 5, there were a variety of factors that decreased the travel speed selected by the driver during their freeway trip event. As the degree of curvature increased on the non-tangent sections of traversed freeway, the selected travel speed decreased. For a seven degree increase in horizontal curvature, the resultant travel speed was reduced by about one mph. Additionally, adverse weather conditions resulted in lower travel speeds, as shown in previous naturalistic research (Hamzeie et al., 2017). Each LOS indicator was included in the linear regression model in Table 5. Using LOS A as a baseline, each reduction in LOS resulted in a subsequent reduction in travel speed. This result was intuitive as a reduction in LOS is directly correlated with traffic density, which prevents the efficient flow of vehicles through a corridor and thus lowers individual operator speeds. The speed reductions noted in Table 5 were much more severe than those estimated in the *Highway Capacity Manual* for each individual LOS condition (TRB, 2010).

Conversely, several variables in Table 5 demonstrated an estimated increase in travel speeds. As expected, an increase in the posted speed limit resulted in faster travel speeds. This result has been determined in previous research studies (Highway Loss Data Institute, 2008). In terms of roadway geometrics, an increase in both the left shoulder width and the right shoulder width along the traveled freeway route increased the travel speed. In other words, as the width of the overall roadway increased, drivers felt more comfortable traveling at a faster speed. The increases in speed in Table 5 were within the range of those predicted by the *Highway Capacity Manual* formulas (0.4 mph to 1.1 mph) for a similar route type (TRB, 2010). When considering driver behaviors and characteristics, risky drivers with poor roadway behavior traveled at faster speeds during their freeway trip events. For example, drivers with one violation within the last twelve months traveled 0.90 mph faster than their counterparts who had no violations within the last twelve months, while motorists with two or more violations within the last twelve months traveled more than two mph faster than the baseline condition. Additionally, people who stated that they thought their driving abilities were much better than the average driver traveled 0.66 mph faster than other motorists. These results also indicated that risky drivers and those with poor roadway behavior traveled faster than those drivers who are non-risky in nature.

Regarding the effect of distractions on driving performance, Table 6 below identifies the types of distractions that occurred during all freeway trip events within the analysis dataset. Because these distraction categories individually were infrequent and most were related to other categories, aggregated categories were created for further analysis. The types of distraction vary greatly, ranging from cell phone usage to eating without utensils;

however, similar distractions were grouped together from the disaggregate categories and aggregated based on the type of action performed within the vehicle.

Table 6. Disaggregate and aggregate distraction categories

Disaggregate Categories	**Count**	**Aggregate Categories**	**Count**
Adjusting/monitoring climate control	105	Instrument Panel	906
Adjusting/monitoring radio	531	Instrument Panel	
Inserting/retrieving CD (or similar)	21	Instrument Panel	
Adjusting/monitoring other devices integral to vehicle	249	Instrument Panel	
Applying make-up	21	Hygiene	1,029
Biting nails/cuticles	315	Hygiene	
Brushing/flossing teeth	30	Hygiene	
Combing/brushing/fixing hair	198	Hygiene	
Shaving	21	Hygiene	
Other personal hygiene	444	Hygiene	
Removing/adjusting clothing	72	Appearance	135
Removing/adjusting jewelry	42	Appearance	
Removing/inserting/adjusting contact lenses or glasses	21	Appearance	
Cell phone, Locating/reaching/answering	153	Cell Phone	3,828
Cell phone, Dialing hand-held	72	Cell Phone	
Cell phone, Dialing hands-free using voice-activated software	21	Cell Phone	
Cell phone, Talking/listening, hand-held	1,581	Cell Phone	
Cell phone, Holding	684	Cell Phone	
Cell phone, Texting	978	Cell Phone	
Cell phone, Browsing	318	Cell Phone	
Tablet, Operating	21	Cell Phone	
Reading	30	Cell Phone	
Passenger in adjacent seat-interaction	4,743	Passenger	5,328
Passenger in rear seat-interaction	324	Passenger	
Child in adjacent seat-interaction	84	Passenger	
Child in rear seat-interaction	126	Passenger	
Pet in vehicle	51	Passenger	
Drinking from open container	84	Consumption	1,134
Drinking with lid and straw	231	Consumption	
Drinking with lid, no straw	105	Consumption	
Drinking with straw, no lid	0	Consumption	

Table 6. (continued)

Eating with utensils	42	Consumption	
Eating without utensils	672	Consumption	
Lighting cigar/cigarette	21	Smoking	
Smoking cigar/cigarette	396	Smoking	438
Extinguishing cigar/cigarette	21	Smoking	
Distracted by construction	21	External	
Looking at animal	30	External	
Looking at pedestrian	21	External	2,187
Looking at an object external to the vehicle	126	External	
Other external distraction	1,989	External	
Reaching for food-related or drinking-related item	189	Internal	
Reaching for personal body-related item	21	Internal	
Reaching for object, other	153	Internal	2,043
Moving object in vehicle	360	Internal	
Object in vehicle, other	447	Internal	
Other non-specific internal eye glance	873	Internal	
Dancing	357	Activity	3,543
Talking/singing, audience unknown	3,156	Activity	

Table 7 contains the results of the random effects logistic regression model for any type of distraction included in the analysis. To accomplish this, a binary indicator was created that identified when any of the distractions in Table 6 occurred during a freeway trip event. Therefore, the results in Table 7 reflect the conditions and types of individuals who were likely to engage in a distracting event.

Table 7. Random effects logistic regression model for any distraction

Variable	**Estimate**	**Std. Error**	**z-Value**	**Pr(>|z|)**
Intercept	0.662	0.081	8.180	<0.001
Clear weather conditions (1 if yes; 0 otherwise)	0.279	0.035	8.063	<0.001
Foggy weather conditions (1 if yes; 0 otherwise)	-0.545	0.119	-4.563	<0.001

Table 7. (continued)

Level-of-service A (1 if yes; 0 otherwise)	0.184	0.020	9.225	<0.001
Female drivers (1 if yes; 0 otherwise)	0.181	0.020	9.056	<0.001
Advanced degree (1 if yes; 0 otherwise)	-0.315	0.024	-13.299	<0.001
Two or more violations within the last twelve months (1 if yes; 0 otherwise)	0.455	0.033	13.595	<0.001
Two or more crashes within the last twelve months (1 if yes; 0 otherwise)	-0.311	0.044	-7.146	<0.001
Never drive without wearing a seatbelt (1 if yes; 0 otherwise)	-1.125	0.075	-15.093	<0.001
Rarely drive without wearing a seatbelt (1 if yes; 0 otherwise)	-0.714	0.082	-8.672	<0.001
Modal Diagnostics				
Null deviance	57,821			
Residual deviance	56,729			
AIC	56,749			
Fisher scoring iterations	4			

Based on the statistical estimates in Table 7, both weather factors and driver behaviors and characteristics had a significant impact on the likelihood of engaging in any type of distracting activity. While driving in foggy conditions, the likelihood of a driver to engage in a distracting secondary behavior was reduced by 42 percent. Conversely, driving during clear weather conditions increased the probability of engaging in a distraction by 32 percent. Furthermore, drivers with advanced degrees (i.e. any type of graduate degree) were less likely to engage in a distraction while operating a motor vehicle. Drivers who reported being involved in two or more crashes in the previous twelve months seemed to drive more cautiously, as their likelihood of engaging in a distraction was also reduced based on the statistical estimates. After being involved in multiple crashes, drivers may experience a significant shift in their behavior while driving, which may cause them to be more cautious and take less risks during their trip events. Lastly, non-risky drivers were associated with a decreased probability of distraction. This trend in human behavior was similar to the previous results in Table 5; non-risky drivers were less likely to engage in any type of secondary task while driving.

There were also various traffic conditions and behavioral characteristics that increased the likelihood of a driver to perform a distracting activity. Distractions were more likely to occur during optimal LOS conditions. This finding was intuitive as less traffic is on the roadway under LOS A conditions, which may have resulted in the operators feeling more comfortable while driving and ultimately engaging in a distracting activity under conditions in which they felt were less risky. When considering the gender of the operator, female drivers were more likely to engage in a distracting behavior. Lastly, those drivers who noted that they had two or more violations within the last twelve months were 58 percent more likely to engage in a distracting secondary task. This finding presents an interesting result when compared to the crash event estimates in Table 7. Based on the statistical results, those drivers who were repeatedly cited for driving violations (i.e. risky drivers) were likely to continue exhibiting poor driving behavior, while those that were involved in multiple crash events were less likely to engage in a distracting activity.

Table 8 depicts the results of the random effects logistic regression model for distractions related to the instrument panel. As noted in Table 6, instrument panel distractions were classified as the following actions:

- Adjusting or monitoring climate control
- Adjusting or monitoring the radio
- Inserting or retrieving a CD (or similar)
- Adjusting or monitoring other devices that are integral to the vehicle

Ultimately, distractions caused by the instrument panel were those in which the operator dedicated a portion of their attention to the headboard and front instrument cluster of the vehicle rather than the primary driving task.

Table 8. Random effects logistic regression model for instrument panel distraction

Variable	**Estimate**	**Std. Error**	**z-Value**	**Pr(>|z|)**
Intercept	-2.042	0.200	-10.199	<0.001
Speed limit (mph)	-0.045	0.004	-10.837	<0.001
Average right shoulder width (ft.)	0.079	0.010	7.984	<0.001
Average annual mileage more than 30,000 miles (1 if yes; 0 otherwise)	0.755	0.100	7.528	<0.001
Two or more violations within the last twelve months (1 if yes; 0 otherwise)	1.062	0.082	12.960	<0.001
Two or more crashes within the last twelve months (1 if yes; 0 otherwise)	-1.275	0.223	-5.706	<0.001
Driving abilities much better than the average driver (1 if yes; 0 otherwise)	0.729	0.078	9.403	<0.001
Never race drivers at green signal (1 if yes; 0 otherwise)	-0.589	0.076	-7.720	<0.001
Never accelerate at yellow signal (1 if yes; 0 otherwise)	-0.711	0.136	-5.243	<0.001
Often drive ten to twenty mph over the speed limit (1 if yes; 0 otherwise)	0.366	0.095	3.845	<0.001

Table 8. (continued)

Modal Diagnostics	
Null deviance	8,731
Residual deviance	8,166
AIC	8,186
Fisher scoring iterations	7

Based on the statistical estimates in Table 8, the likelihood of engaging in an instrument panel-related distraction decreased by four percent for every one mph increase in the posted speed limit. In other words, as the speed limit of the roadway increased, drivers were less likely to engage in an instrument panel-related distraction. Similar to the results in Table 7, drivers who were involved in two or more crashes were less likely to engage in instrument panel-related distractions. As determined previously, the involvement of an operator in several crashes within a twelve month time period may have increased their caution while driving, which resulted in a reduced probability of engaging in risky behaviors. This hypothesis was also supported by the negative estimates for non-risky drivers in Table 8.

The estimates provided in Table 8 captured a variety of roadway and behavioral attributes that increased the probability of engaging in an instrument panel-related distraction. As the right shoulder width increased, the likelihood of a motorist to engage in an instrument panel-related distraction also increased. For every one foot increase in the right shoulder width, the likelihood of being involved in an instrument panel-related distraction increased by eight percent. This result was intuitive as the drivers may have become more comfortable when the total roadway width increased. This increase in comfort allowed the operators to engage in instrument panel-related distractions more frequently. Also, the drivers who traveled the most among the sampled participants (based on their reported average annual mileage) were more likely to engage in an instrument panel-related distraction. This characteristic may be a proxy for an increase in driving experience. This increase in experience may be associated with an increase in comfort and thus a greater likelihood of engaging in a secondary task. As previous, those operators with two or more violations had a significant increase in their probability of distraction engagement. Risky drivers were also more likely to engage in instrument panel-related distractions. Lastly, those drivers who reported their driving abilities were much better than the average driver were 107 percent more likely to engage in an instrument panel-related distraction while driving. This finding reflects the social norm issue discussed in the relevant safety literature; modern operators believe that most other drivers are engaging in distracting activities, when the actual sample of distracted motorists is much less than socially perceived.

Table 9 contains the results of the random effects logistic regression model for distractions related to hygiene. As noted in Table 6, hygiene distractions were classified as the following actions:

- Applying make-up
- Biting nails or cuticles
- Brushing or flossing teeth
- Combing, brushing, or fixing hair
- Shaving
- Any other personal hygiene actions

Distractions related to hygiene were those in which the driver shifted their focus from the primary task of driving to an appearance-focused task that involved touching their face or removing their hands from the steering wheel for an appearance-focused reason.

Table 9. Random effects logistic regression model for hygiene distraction

Variable	Estimate	Std. Error	z-Value	Pr(>|z|)
Intercept	-5.794	0.226	-25.587	<0.001
Clear weather conditions (1 if yes; 0 otherwise)	1.663	0.221	7.514	<0.001
Level-of-service A (1 if yes; 0 otherwise)	0.667	0.065	10.231	<0.001
Female drivers (1 if yes; 0 otherwise)	0.473	0.065	7.233	<0.001
One crash within the last twelve months (1 if yes; 0 otherwise)	-0.769	0.094	-8.170	<0.001
Often accelerate at yellow signal (1 if yes; 0 otherwise)	0.960	0.127	7.544	<0.001
Modal Diagnostics				
Null deviance	9,651			
Residual deviance	9,288			
AIC	9,300			
Fisher scoring iterations	8			

After considering all of the time-series, roadway, and behavioral information, only one characteristic was associated with a reduction in the probability of engaging in a hygiene-related distraction. Drivers who were involved in one crash within the past twelve months were 54 percent less likely to be engaged in a secondary task. This result was similar to the previous trends estimated for motorists who were involved in crash events.

A majority of the significant variables were correlated with an increase in poor roadway behavior. As previous, a lack of adverse weather may have allowed drivers to feel more comfortable and engage in distracting activities. Based on the statistical estimates in Table 9, drivers were 428 percent more likely to engage in a hygiene-related distraction during clear weather conditions, as compared to adverse weather conditions. As previous, a better LOS resulted in an increased probability of engaging in a hygiene-related distraction. Also, females were more likely than their male counterparts to perform a hygiene-related distraction. Lastly, risky drivers were more likely to be involved in a hygiene-related distraction during their freeway trip events.

Table 10 depicts the statistical estimates of the random effects logistic regression model for distractions related to cell phone use. As noted in Table 6, cell phone distractions were classified as the following actions:

- Locating, reaching, or answering a cell phone
- Dialing a cell phone, either using the device interface or hands-free with voice activated software
- Talking or listening with a cell phone
- Holding a cell phone
- Texting on a cell phone
- Browsing on a cell phone
- Operating a tablet
- Reading a book

Ultimately, distractions caused by cell phones were classified as any type of interaction with a mobile electronic device while the operator was driving along the freeway.

Table 10. Random effects logistic regression model for cell phone distraction

Variable	**Estimate**	**Std. Error**	**z-Value**	**Pr(>|z|)**
Intercept	-1.735	0.075	-23.167	<0.001
Driver selected speed (mph)	-0.020	0.001	-22.052	<0.001
Tangent lane type (1 if yes; 0 otherwise)	0.301	0.039	7.662	<0.001
Female drivers (1 if yes; 0 otherwise)	0.542	0.036	15.184	<0.001
Two or more violations within the last twelve months (1 if yes; 0 otherwise)	1.040	0.044	23.517	<0.001

Table 10. (continued)

Never drive without wearing a seatbelt (1 if yes; 0 otherwise)	-0.303	0.051	-5.894	<0.001
Modal Diagnostics				
Null deviance	25,717			
Residual deviance	24,435			
AIC	24,447			
Fisher scoring iterations	5			

A multitude of parameters impacted the likelihood of engaging in a cell phone-related distraction while operating a motor vehicle. As the travel speed increased, the likelihood of engaging in a cell phone-related distraction decreased. Specifically, for every one mph increase in travel speed, the probability of engaging in a cell phone-related distraction decreased by two percent. This result was intuitive as traveling at faster speeds requires greater control and attention from the driver. Also, non-risky motorists were correlated with a decrease in the likelihood of engaging in a cell phone distraction.

Similar to the previous disaggregate distraction models, female drivers and drivers with two or more violations in the last twelve months were more likely to engage in a cell phone-related distraction while driving. Regarding the curvature of the roadway surface, traveling on tangent segments resulted in a greater likelihood of cell phone usage, in comparison to curved segments. This result was unsurprising as less attention is required to navigate along a tangent segment in comparison to a curved segment. Because of this, motorists were more likely to dedicate some of their attention to a distracting activity on tangent sections of the roadway when less vehicular control is required.

Table 11 below contains the results of the random effects logistic regression model for distractions related to passenger interactions. As noted in Table 6, passenger distractions were classified as the following:

- Interacting with a passenger in an adjacent seat
- Interacting with a passenger in the rear seats
- Interacting with a child in an adjacent seat
- Interacting with a child in the rear seats
- Interacting with a pet in the vehicle

Each of these interactions was combined as one type of distraction since the level of engagement between the operator and the passenger was similar in nature.

Table 11. Random effects logistic regression model for passenger distraction

Variable	**Estimate**	**Std. Error**	**z-Value**	**Pr(>|z|)**
Intercept	-1.987	0.034	-57.997	<0.001
Degree of curvature (°)	-0.061	0.012	-5.168	<0.001
Level-of-service A (1 if yes; 0 otherwise)	0.591	0.030	19.731	<0.001
Two or more violations within the last twelve months (1 if yes; 0 otherwise)	0.214	0.047	4.599	<0.001
Two or more crashes within the last twelve months (1 if yes; 0 otherwise)	-0.867	0.087	-9.909	<0.001
Often run red signals (1 if yes; 0 otherwise)	2.150	0.290	7.425	<0.001
Never drive more than twenty mph over the speed limit (1 if yes; 0 otherwise)	-0.260	0.034	-7.675	<0.001
Modal Diagnostics				
Null deviance	31,873			
Residual deviance	31,208			

Table 11. (continued)

AIC	31,222
Fisher scoring iterations	5

Various attributes were associated with a decrease in the likelihood of a motorist to engage in a passenger-related distraction. As the degree of curvature increased (on curved segments), the probability of a passenger-related distraction deceased. As previously mentioned, more attention is required to successfully navigate curved roadway segments. Because of this, the likelihood of distraction decreased as the curvature of the roadway increased. As identified previously, motorists involved in two or more crashes within the past twelve months seemed to adjust their behavior and operate in a less risky manner. These motorists were 58 percent less likely to engage in a passenger-related distraction in comparison to motorists who were involved in less than two crashes within the previous twelve months. Similarly, non-risky motorists were less likely to perform passenger-related distractions.

Conversely, drivers were more likely to engage in a passenger-related distraction under ideal LOS conditions (i.e. LOS A). This result was similar to other types of distractions examined in this analysis. Similarly, those drivers who were cited for two or more violations within the last twelve months were 24 percent more likely to engage in a passenger-related distraction. Lastly, risky motorists were significantly more likely to engage in a passenger-related distraction. Operators that exhibited risky behavior were 758 percent more likely than non-risky motorists to engage in a distracting secondary task related to passenger interactions.

Table 12 depicts the results of the random effects logistic regression model for distractions related to food and drink consumption while driving. As noted in Table 6, the consumption of food and drink was classified as follows:

- Drinking from an open cup
- Drinking from a cup with a straw and a lid
- Drinking from a cup with a straw and no lid
- Drinking from a cup with a lid and no straw
- Eating with utensils
- Eating without utensils

These categories of distractions were aggregated together as consumption-related distractions because each involved the process of eating food or drinking a beverage while driving.

Table 12. Random effects logistic regression model for consumption distraction

Variable	**Estimate**	**Std. Error**	**z-Value**	**Pr(>|z|)**
Intercept	-6.948	0.264	-26.337	<0.001
Average lane width (ft.)	0.089	0.011	8.088	<0.001
Clear weather conditions (1 if yes; 0 otherwise)	1.698	0.221	7.674	<0.001
Level-of-service A (1 if yes; 0 otherwise)	0.946	0.067	14.135	<0.001
Level-of-service F (1 if yes; 0 otherwise)	2.260	0.243	9.290	<0.001
Female drivers (1 if yes; 0 otherwise)	0.339	0.062	5.441	<0.001
Advanced degree (1 if yes; 0 otherwise)	-0.328	0.079	-4.143	<0.001
Average annual mileage more than 30,000 miles (1 if yes; 0 otherwise)	0.741	0.088	8.457	<0.001

Table 12. (continued)

Two or more crashes within the last twelve months (1 if yes; 0 otherwise)	-1.190	0.223	-5.341	<0.001
Driving abilities somewhat worse than the average driver (1 if yes; 0 otherwise)	-0.779	0.179	-4.340	<0.001
Often tailgate (1 if yes; 0 otherwise)	1.157	0.255	4.545	<0.001
Model Diagnostics				
Null deviance	10,413			
Residual deviance	9,826			
AIC	9,848			
Fisher scoring iterations	8			

Most of the examined variables increased the likelihood of engaging in consumption-related distraction; however, a few driver behaviors and characteristics were associated with a decrease in the probability of engaging in the secondary task of interest. As demonstrated previously, motorists with an advanced degree were less likely to consume food or drinks while driving during their freeway trips. Additionally, a similar trend in safer driving was demonstrated by the operators involved in two or more crashes within the previous twelve months. Interestingly, motorists who considered themselves worse than the average driver were also less likely to engage in consumption-related distractions. This finding supports the hypothesis that some unconfident operators may not engage in tasks that they know are distracting to maintain their attention to the driving task.

Based on the statistical estimates in Table 12, an increase in the lane width on the freeway was correlated with an increase in the probability of engaging in a consumption-related distraction. As demonstrated with other types of distractions, a lack of adverse weather conditions was also conducive to consumption distractions. Interestingly, both LOS

A and LOS F were significantly associated with the distraction type of interest; however, the magnitudes of both estimates varied greatly. Under ideal traffic conditions (i.e. LOS A), the likelihood of engaging in a consumption-related distraction was 158 percent, while this increased significantly to 858 percent for LOS F conditions. These findings represent two vastly different traffic conditions; however, both were conducive for food and drink consumption. Under LOS A conditions, operators may feel more comfortable eating, drinking, and driving because they have more available space around them due to a lack of traffic. In LOS F conditions, traffic is often progressing slowly under stop-and-go queuing conditions, meaning that drivers may think it is an appropriate time to engage in consumption-related distractions while not in motion. As previous, female operators were more likely to engage in this type of distraction than their male counterparts. Also, motorists with the most travel experience (i.e. greatest average annual mileage) were more likely to consume food and drinks while driving. Lastly, risky individuals were 218 percent more likely to engage in a consumption-related distraction than their non-risky counterparts.

Table 13 contains the results of the random effects logistic regression model for distractions related to smoking. As noted in Table 6, smoking distractions were classified as follows:

- Lighting a cigar or cigarette
- Smoking a cigar or cigarette
- Extinguishing a cigar or cigarette

These three categories of distraction were aggregated together as each of them was directly related to the act of smoking cigars or cigarettes while driving.

Table 13. Random effects logistic regression model for smoking distraction

Variable	**Estimate**	**Std. Error**	**z-Value**	**Pr(>|z|)**
Intercept	-3.960	0.194	-20.458	<0.001
Average number of lanes	-0.394	0.064	-6.178	<0.001
Level-of-service A (1 if yes; 0 otherwise)	0.429	0.104	4.125	<0.001
Two or more crashes within the last twelve months (1 if yes; 0 otherwise)	0.835	0.166	5.033	<0.001
Often drive without wearing a seatbelt (1 if yes; 0 otherwise)	3.519	0.148	23.735	<0.001
Model Diagnostics				
Null deviance	4,863			
Residual deviance	4,441			
AIC	4,451			
Fisher scoring iterations	8			

Of all the variables considered, only the average number of lanes was associated with a decrease in the probability of engaging in a smoking-related distraction. For every one lane increase, the probability of the driver to perform a smoking-related distraction decreased by 33 percent. This finding was intuitive as an increase in the number of travel lanes is typically correlated with an increase in traffic and complexity while driving. Because of this increased complexity, additional concentration is required to drive safely, which may have resulted in the reduced probability to engage in the distraction category of interest.

Similar to previous findings, a more efficient LOS resulted in an increased likelihood of performing a smoking-related secondary task. Under LOS A conditions, the likelihood of a motorist to engage in a smoking-related distraction was 54 percent compared to all other traffic conditions. Interestingly, the opposite trend was determined for motorists involved in two or more crashes within the last twelve months, when compared to other types of distractions. For smoking-related distractions, individuals were more likely to perform the secondary task of interest despite being involved in multiple previous crash events. This finding indicated that smoking may not be treated as a serious threat to traffic safety and may be seen as a commonplace task while operating for most drivers. Lastly, risky drivers were more likely to perform a smoking-related distraction than non-risky drivers.

Table 14 depicts the results of the random effects logistic regression model for distractions that were external to the vehicle. As noted in Table 6, external distractions were classified as follows:

- Distracted by roadside construction
- Looking at an animal outside of the vehicle
- Looking at a pedestrian outside of the vehicle
- Looking at an object outside of the vehicle
- Any other significant glance outside of the vehicle

Table 14. Random effects logistic regression model for external distraction

Variable	**Estimate**	**Std. Error**	**z-Value**	**Pr(>|z|)**
Intercept	-2.932	0.158	-18.602	<0.001
Speed limit (mph)	-0.009	0.002	-3.796	<0.001
Clear weather conditions (1 if yes; 0 otherwise)	0.628	0.094	6.671	<0.001
Female drivers (1 if yes; 0 otherwise)	-0.349	0.045	-7.670	<0.001
Average annual mileage less than 5,000 miles (1 if yes; 0 otherwise)	0.842	0.080	10.480	<0.001
Sometimes take risks for fun (1 if yes; 0 otherwise)	0.991	0.098	10.068	<0.001
Often drive more than twenty mph over the speed limit (1 if yes; 0 otherwise)	1.974	0.180	10.976	<0.001

Table 14. (continued)

Model Diagnostics	
Null deviance	17,153
Residual deviance	16,734
AIC	16,748
Fisher scoring iterations	6

Based on the model estimates in Table 14, the posted speed limit of the roadway had a slight effect on the probability of the driver to engage in an external distraction. For every one mph increase in the posted speed limit, the probability of performing an external distraction decreased by one percent. This finding was similar to other types of distractions. As the speed limit of the roadway increases, the complexity and attention required to successfully navigate the freeway safely also increases, which may restrain the driver from diverting their attention to an external object outside of the vehicle. Also, female operators were less likely to engage in an external distraction in comparison to male operators.

Conversely, there were additional factors that were correlated with an increase in the probability of an external distraction. As determined in previous models, a lack of adverse weather conditions was associated with an increased probability of external distraction occurrence. External glances were 87 percent more likely to occur during clear weather conditions in comparison to any type of adverse weather. Drivers may be more comfortable driving in clear conditions; therefore, they may feel that performing external distractions is not a significant threat to their safety due to this increased comfort. Various behavioral characteristics were also significant in Table 14. Motorists with less driving experience (i.e. the lowest amount of reported average annual mileage) were more likely to engage in an external distraction. Additionally, risky operators were also more likely to perform an external distraction. This finding was similar to many other types of distraction categories identified previously.

Table 15 contains the statistical estimates of the random effects logistic regression model for distractions related to actions within the vehicle (i.e. internal distractions). As noted in Table 6, internal distractions were classified as follows:

- Reaching for a food or drink item
- Reaching for a personal item
- Reaching for an object
- Moving an object within the vehicle
- Any other object movement within the vehicle

Ultimately, these distraction categories were combined as the actions for the driver were similar: the operator shifts their focus from the primary driving task to a secondary task that requires them to move or retrieve an object within their vehicle.

Table 15. Random effects logistic regression model for internal distraction

Variable	**Estimate**	**Std. Error**	**z-Value**	**Pr(>|z|)**
Intercept	-2.615	0.077	-34.005	<0.001
Average number of lanes	-0.116	0.025	-4.550	<0.001
Female drivers (1 if yes; 0 otherwise)	-0.357	0.047	-7.621	<0.001
Driving abilities somewhat worse than the average driver (1 if yes; 0 otherwise)	0.965	0.076	12.657	<0.001
Often accelerate at yellow signal (1 if yes; 0 otherwise)	0.708	0.092	7.684	<0.001
Often drive more than twenty mph over the speed limit (1 if yes; 0 otherwise)	2.071	0.170	12.173	<0.001
Model Diagnostics				
Null deviance	16,309			
Residual deviance	15,880			

Table 15. (continued)

AIC	15,892
Fisher scoring iterations	6

Similar trends between variables were established in Table 15. As the number of lanes increased, the probability of the driver to perform an internal distraction decreased. Furthermore, female drivers were 30 percent less likely to engage in an internal distraction in comparison to their male counterparts. Alternatively, motorists who rated their own driving abilities as worse than the average driver were more likely to engage in an internal distraction. As determined in previous models, risky operators were more likely to perform an internal distraction while driving.

Table 16 depicts the results of the random effects logistic regression model for distractions related to within-vehicle activities. As noted in Table 6, activity-related distractions were classified as follows:

- Dancing
- Talking without an audience
- Singing without an audience

These distraction categories were aggregated together as they were performed by the driver without the presence of a passenger and distracted the motorists mentally from the primary task of driving.

Table 16. Random effects logistic regression model for activity distraction

Variable	**Estimate**	**Std. Error**	**z-Value**	**Pr(>|z|)**
Intercept	-3.178	0.079	-40.477	<0.001
Degree of curvature (°)	0.026	0.007	3.830	<0.001
Clear weather conditions (1 if yes; 0 otherwise)	0.716	0.077	9.331	<0.001

Table 16. (continued)

Female drivers (1 if yes; 0 otherwise)	0.185	0.036	5.189	<0.001
Advanced degree (1 if yes; 0 otherwise)	-0.269	0.045	-5.996	<0.001
Sometimes road rage (1 if yes; 0 otherwise)	0.287	0.046	6.198	<0.001
Often road rage (1 if yes; 0 otherwise)	1.220	0.110	11.045	<0.001
Model Diagnostics				
Null deviance	24,107			
Residual deviance	23,785			
AIC	23,799			
Fisher scoring iterations	5			

Based on the results presented in Table 16, only one driver characteristic was associated with a decreased probability of engaging in an activity-related distraction. Motorists with an advanced degree were 24 percent less likely to perform an activity-related distraction than drivers with any other education level. Despite this finding, other correlations were similar to previously established trends among other types of distractions. An increase in the degree of curvature for non-tangent freeway sections was associated with an increase in the probability of performing an activity-related distraction. This finding was interesting as an increase in the degree of curvature requires additional driver attention; however, the results of this analysis indicated that motorists were more likely to perform an activity-related distraction on sharper curves. Based on this result, motorists may not associate dancing, talking, or singing as distracting behaviors. As previous, clear weather conditions resulted in an increased probability of activity-related distractions. Females were also more likely to engage in an activity-related distraction when compared to male operators. Finally, risky individuals were more likely to dance, talk, or sing while driving. Interestingly, the likelihood of distraction increased as the frequency of this risky behavior increased, as noted by the estimates in Table 16.

Table 17 contains the results of the random effects logistic regression model for crash risk during the freeway trip events. Using the forward facing video camera imagery, various crash categories were recorded by VTTI, including crash events and near-crash events. As mentioned previously, a near-crash is any event in which an evasive maneuver must be performed to prevent a crash from occurring. These two categories were aggregated together for the analysis of crash risk. Table 17 contains the results of the statistical analysis.

Table 17. Random effects logistic regression model for crash risk

Variable	**Estimate**	**Std. Error**	**z-Value**	**Pr(>|z|)**
Intercept	-2.178	0.054	-40.030	<0.001
Hygiene-related distraction (1 if yes; 0 otherwise)	0.707	0.080	8.804	<0.001
Cell phone-related distraction (1 if yes; 0 otherwise)	1.152	0.040	28.829	<0.001
Internal distraction (1 if yes; 0 otherwise)	1.391	0.050	27.687	<0.001
Activity-related distraction (1 if yes; 0 otherwise)	0.492	0.046	10.595	<0.001
Average number of lanes	0.248	0.014	17.619	<0.001
Female drivers (1 if yes; 0 otherwise)	-0.163	0.028	-5.890	<0.001
Never tailgate (1 if yes; 0 otherwise)	-0.124	0.029	-4.335	<0.001
Never race drivers at green signal (1 if yes; 0 otherwise)	-0.572	0.036	-16.103	<0.001
Rarely race drivers at green signal (1 if yes; 0 otherwise)	-0.398	0.036	-11.131	<0.001
Often road rage (1 if yes; 0 otherwise)	1.124	0.098	11.511	<0.001

Model Diagnostics	
Null deviance	36,931
Residual deviance	34,743
AIC	34,765
Fisher scoring iterations	4

From the estimates in Table 17, there were various driver behaviors and characteristics that decreased the probability of being involved in a crash event. Female drivers were less likely to be involved in a crash than their male counterparts. Furthermore, a similar trend was present between risky and non-risky drivers. Non-risky motorists were less likely to be crash involved, while risky operators were more likely to be involved in a crash event. These results reflected the trend established in Table 5; non-risky drivers traveled with caution and safety-focused roadway behavior, while risky drivers traveled faster and were at a greater risk of being involved in a crash event.

Numerous other estimates in Table 17 also demonstrated an increase in crash risk, including various types of distractions and roadway characteristics. As the number of lanes increased, the probability of being in a crash event also increased. For every one lane increase in the roadway, the crash risk increased by 28 percent. Furthermore, four types of aggregate distraction categories were correlated with an increase in crash risk. Both hygiene-related and activity-related distractions were found to increase the crash risk while operating. However, the estimates for cell phone-related and internal distractions had a much greater effect on the resultant crash risk. A cell phone-related distraction while driving was determined to increase the crash risk by 216 percent, while an internal distraction increased the crash risk by 302 percent.

CHAPTER 6. CONCLUSIONS

This study provides significant insights into the influence of distractions on driver speed selection and crash risk. Various analyses were conducted which leveraged high-fidelity time-series data from the second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS). Relationships were identified between various roadway, traffic, and behavioral characteristics and the prevalence of various types of distracting behaviors. An aggregate summary of the findings from this study follows, including a discussion on how these results can be used to help inform policy, design, and future research efforts.

6.1 Driver Performance Findings

Various roadway, weather, and traffic characteristics were correlated with driver speed selection. An increase in the degree of curvature of a roadway segment reduced the driver selected speed, though these reductions were quite small, which is likely due in part to the fact that this analysis focused on freeway facilities where the curves are generally designed to radii significantly above the minimum values recommended by the American Association of State Highway and Transportation Officials (AASHTO). Driver speeds were also found to be reduced under adverse weather conditions and during congested traffic conditions. Compared to free-flow conditions (i.e. level-of-service (LOS) A), driver speeds decreased significantly with each decreasing LOS. This is noteworthy as the LOS was determined based upon a video review by the Virginia Tech Transportation Institute (VTTI) staff and, as such, it was unclear how well the mathematical speed-density relationship would align with empirical data from the Highway Capacity Manual (HCM). Interestingly, these results were very well in line with what would be expected in the HCM.

Roadway geometrics and driver behavioral characteristics also exacerbated driver travel speed. Travel speeds were shown to consistently increase in magnitude with each interval increase in the posted speed limit, though these increases were slightly lower in magnitude than the actual increase in the posted limit. Speeds were also slightly faster on segments with greater shoulder widths. In terms of driver characteristics, participants with a prior history of traffic violations tended to travel at higher speeds on freeway segments, as did drivers who often performed other potentially high-risk maneuvers (e.g., running red lights, racing other motorists, etc.). The latter result is particularly concerning and reinforces prior research, which suggests a high-risk subset of drivers is responsible for a disproportionate number of traffic crashes and fatalities and that this group has generally not been affected by targeted education and enforcement programs.

Interestingly, the involvement of a motorist in a distracting activity while driving was found to have no significant effect on the selected travel speed. Although engaging in a secondary task while driving divides the operator's attention between the primary driving task and the distracting secondary task, the travel speed of the motorist was not adjusted during this process. This may be due to the variety of automatic speed management controls (i.e. cruise control technologies) that are available in modern vehicles. Recall that all vehicles utilized in the SHRP2 program NDS were recent model years to facilitate the installation of the required sensors and cameras. Because on this criterion, it is possible that most of the vehicles in the analysis had cruise control capabilities which the driver utilized during their freeway trip event.

6.2 Distraction Likelihood Findings

The following characteristics and behaviors were correlated with a reduction in secondary behavior while driving: adverse weather conditions, higher educational attainment (i.e. obtaining an advanced degree), being involved in two or more crashes within the last twelve months, and non-risky behaviors. Conversely, distracting behavior was more likely under clear weather conditions (as opposed to adverse weather conditions) and efficient traffic progression (i.e. LOS A). Likewise, female operators and motorists with two or more violations were more likely to perform any type of distracting task while driving. These trends were similar to those defined within the disaggregate distraction analyses that were presented in detail in the previous section. Additionally, drivers who frequently engaged in risky behavior while driving were more likely to travel faster and engage in more distractions than non-risky operators. In this study, driver risk-taking behaviors and levels of risk perception were quantified through the consideration of proxy survey variables (i.e. the frequency of a motorist's prior engagements in various poor behavior activities).

6.3 Crash Risk Findings

A crash risk model was also investigated to determine which factors were likely to increase or decrease the likelihood of a crash or near-crash event based on the time-series data. From the analysis, female drivers and non-risky operators were less likely to be crash involved. In contrast, an increase in the number of lanes on the freeway increased the likelihood of being involved in a crash event. This finding was a proxy for an increase in vehicular exposure, as an increase in the number of lanes is typically associated with an increase in the amount of traffic and congestion. With more traffic present, crash and near-crash events are more likely to occur. Additionally, risky drivers were more likely to be crash involved. Based on prior travel speed and aggregate distraction findings concerning risky drivers, it was not surprising that individuals with these characteristics were correlated with a significant increase in crash risk.

The developed crash risk model also considered all ten disaggregate distraction types to estimate the distractions that had the greatest probability of increasing crash risk. From the analysis, the following distraction types were associated with an increase in crash risk:

- Hygiene-related distractions
- Cell phone-related distractions
- Internal distractions
- Activity-related distractions

Of these, internal distractions increased crash risk the most. Recall that internal distractions involved the operator reaching for or moving an item of interest in their vehicle while driving. Drivers may not consider this action as a distraction that affects their overall roadway performance; however, the results of this analysis indicated that these actions increased their crash risk by more than 300 percent.

6.4 Limitations and Future Research

Although a thorough analysis was performed with the time-series information, there were limitations to the analysis that impacted the results of this study. Because the recorded disaggregate information contained personably identifiable characteristics, pre-coded and anonymous information was released by VTTI to protect the identities of the research participants. During this data reduction process, quality assurance and quality control measures were performed; however, this aggregation of the data removed potential factors of interest from the analysis, such as detailed driver ethnicity information and passenger presence, among others. Likewise, the entire analysis focused on travel information collected from participants driving on freeway segments. Additional data from other facility types is available, which would provide an interesting dynamic for future research. Lastly, including both acceleration and deceleration information recorded throughout the freeway trip events may provide interesting relationships between the distracted and non-distracted motorists, as rapid changes in acceleration or deceleration are expected by the distracted motorists as their attention shifts between the primary driving task and the distracting secondary task while driving.

6.5 Practical Applications

As demonstrated by the relationships discovered in this analysis, there are correlations between driver behaviors, characteristics, and involvement in distracting activities while driving. Although the results of this study focus on the likelihood of performing a secondary task and the crash risk associated with various driving distractions, further research could use these relationships to generate effective policies and procedures to be used by law enforcement officers for identifying and ticketing distracted motorists. From this analysis, risky drivers were more likely to engage in a variety of distraction categories, as well as travel faster and have a greater crash risk than their non-risky counterparts. To combat the negative roadway performance impacts that occur due to distracted driving, these relationships could be further developed into training programs for law enforcement officers, which educate them on the types of motorists who are more likely to engage in distracting secondary behavior while driving.

Additionally, the results of these analyses demonstrated that cell phone usage while driving creates a significant threat to traffic safety, as crash risk was increased by more than 200 percent. Despite this, not all states have restrictions on cell phone usage while driving, as shown in Figure 3. Based on the results of this analysis, it is highly recommended that each state consider legislation which results in a statewide ban on handheld cell phone usage for all drivers. This ban should include any type of cell phone-related distractions, including talking, texting, and browsing while driving.

Although many automobile and cell phone manufacturers are currently working on integrating their technologies together to create a seamless user experience, the results of this analysis suggest that this integration should be tailored more towards reducing the number of distractions available to the driver. For example, automobile and cell phone manufacturers should limit the amount of interaction required by the driver to use these technologies. This includes the use of device interfaces as well as voice activated commands, as both provide opportunities of distraction for the motorist. To limit the opportunities for distraction, the automobile and cell phone industries should work towards limiting device interactions with the driver while the vehicle is in motion. This would reduce the frequency of distractions available while driving to only emergency situations and remove some distracting elements that are currently available in modern vehicles, such as GPS interactions, cell phone voice commands, and integrated music control, among others.

It is also important for safety-focused transportation agencies to consider the results of this analysis, specifically the types of distractions that were determined to increase crash risk. As demonstrated by the comprehensive literature review, several types of distracting behaviors may not be considered distracting by most motorists. Although cell phone usage is the focus of many distracted driving campaigns and the subject of modern media coverage, there are many other types of distracted driving behaviors which reduce roadway safety. By creating public awareness campaigns that broaden the focus of distracted driving to all types of distractions, including visual, manual, and cognitive activities, public education may be able to reduce the severe threat that distracted driving has on traffic safety.

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