Exploration of Naturalistic Driving Data: Development of Distracted Driver Behaviour Models

by

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Abstract

Distraction is detrimental to traffic safety. This thesis provides insights into distracted driving behaviours through two research objectives explored on naturalistic driving data: 1) distraction engagement behaviours and visual attention allocation as a function of varying environmental demands, and 2) engagement in multiple types of secondary tasks. For this purpose, Naturalistic Engagement in Secondary Tasks (NEST) dataset was utilized. Through inferential statistics, it was shown that higher visual difficulty in the driving environment is associated with a decreased likelihood of distraction engagement, and a decrease in non-forward glances with the likelihood of longer glances (> 2s) being reduced to a larger extent compared to shorter ones (> 1.6s). Drivers 35 and older have reduced rates of non-forward glances compared to younger drivers. Moreover, the results demonstrate that engagement in multiple secondary task types is prevalent, and is more likely to occur in safety-critical as opposed to non-safety critical situations (baselines).

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List of Abbreviations

CI – Confidence Interval

NEST – Naturalistic Engagement in Secondary Tasks

NHTSA – National Highway Traffic Safety Administration

NDS – Naturalistic Driving Study

OR – Odds Ratio

SCE – Safety Critical Event

SHRP2 – Second Strategic Highway Research Program

Chapter 1

1 Introduction

Driver distraction is a major cause of fatalities and injuries in motor vehicle crashes and has been defined as misallocation of attention from driving related components to a non-driving task or to an information source (Smiley, 2005). The National Highway Traffic Safety Administration's (NHTSA) 2015 annual crash data attributes 3,477 crash-related fatalities (10% of all fatal crashes) and 391,000 crash-related injuries (15% of injury crashes) to driver distraction (National Center for Statistics and Analysis, 2017). In terms of driving performance and crash risk, distracted driving has been shown to degrade lateral and longitudinal vehicle control, to delay responses to hazards, to elevate workload, and to increase crash risk (Dingus et al., 2016; Horberry, Anderson, Regan, Triggs, & Brown, 2006; Strayer & Johnston, 2001).

Distracted driving has been studied extensively over the past two to three decades given its prevalence in crash records (Regan, Lee, & Young, 2009). In the past, the primary method for studying driver distraction was through either a driving simulator or an instrumented vehicle under controlled conditions (Caird, Willness, Steel, & Scialfa, 2008; Regan et al., 2009). Although these types of studies provide valuable insights into the effects of distraction on driving performance, they do not capture how drivers actually engage in distractions in the real world. A great portion of past experiments investigated driver distraction through secondary tasks imposed on the drivers at a given period of time, and generally did not employ self-paced secondary tasks (Caird, Johnston, Willness, Asbridge, & Steel, 2014; Caird et al., 2008). While there are some examples of controlled studies that used self-paced secondary tasks, these studies still presented a task to the participants that they should engage in, and thus did not capture the decision making processes involved in distraction engagement (e.g., deciding to text on a cell phone). A crash study by Beanland et al. (2013) found 70% of distraction-related crashes in Australia to involve a distraction in which the driver was voluntarily engaged. Therefore, the contrived settings of an experiment appear to capture only a part of the story. It is likely that artificially simulated distraction tasks can lead the drivers to perform differently than they usually do in a real-world situation for several reasons. First, the experimenter controls when and where a secondary task will arise, which does not mimic the real-world task initiation time/location or the pace of task completion. Second, as the experimenter is present during data collection, the participant responses may be biased due to the awareness of being under direct observation.

Besides the issues associated with the realism and the pacing of the secondary tasks used, driving simulator experiments have other validity issues. For example, simulators do not impose any crash risks that drivers normally face in real-world driving, including when they engage in distractions. The driving scenarios created within the simulation environment also are limited in how much they can capture the variety of environmental uncertainties that are present in real-world driving. Even with on-road instrumented vehicle studies, the roads chosen are generally controlled and are of limited variety and thus do not represent a broad spectrum of driving conditions. For these reasons, controlled studies in both simulators and instrumented vehicles do not entail a high level of ecological validity.

In addition to experimental methods, driver behaviour is also often studied by means of self-reported questionnaires and interviews (Lansdown, 2006; Sullman & Baas, 2004; Young & Lenné, 2010). These types of studies use surveys and interview-like discussions to gather driver behaviour data by asking the participants to self-evaluate and categorize themselves into one of multiple categories (e.g., distraction engagement frequency and number of fines). These studies are crucial for identifying factors that influence drivers' decision to engage in a secondary task; however, self-reporting bias is a concern in these studies (af Wåhlberg, Dorn, & Kline, 2011), for example due to the limitation of questionnaires in providing detailed contextual information.

The growing interest in understanding the natural driving behaviour of road users has resulted in the development of new research methods to capture naturalistic driving data. Naturalistic Driving Studies (NDS) are being leveraged to better understand the way drivers interact with the roadway, the vehicle, and environmental factors. In these studies, participating vehicles are equipped with onboard advanced data-acquisition devices including cameras and various sensors that continuously monitor driving behavior, vehicle maneuvers, and external conditions for an extended period of time while participants drive their vehicles naturally. The increase in computing power of unobtrusive in-vehicle technologies (i.e., cameras, sensors, data acquisition system) capable of collecting, storing, and processing increasing amounts of real-time data, as well as the improvements in storing capacities, data-mining, and image processing have made NDS technically feasible. An important feature of NDS is the opportunity to gain insights into drivers' behaviour in both normal and safety-critical situations. These insights can improve the knowledge about traffic safety from the perspective of driver behaviour and crash causation. Naturalistic driving research is the most realistic approach that fills a void in the conventional driving safety research methods by providing extensive details of the complex traffic system (i.e., drivers' behaviour, their driving performance, and the immediate driving conditions) and provides a unique opportunity to investigate the interrelationships between the driver, the vehicle, and the driving environment. Although NDS is valuable for studying natural distraction behaviour together with the prevalence of distractions in the real-world driving, these studies are uncontrolled, and their coding methodology may introduce biases as well. For example, the driver glance data is mainly coded as directional rather than contextual which can result in mislabels of the gaze locations in some situations. Further, the description of a driving situation and behaviour depends highly on the data reductionists' perspective and judgement.

The overall aim of this thesis was to explore the relationship between distracted driving behaviours and environmental demands using real-world (naturalistic) driving data. This thesis utilized the Naturalistic Engagement in Secondary Tasks (NEST) dataset designed explicitly to capture driver distraction engagement (Owens, Angell, Hankey, Foley, & Ebe, 2015). This dataset was created from the largest naturalistic driving study ever conducted to date— the U.S. Second Strategic Highway Research Program (SHRP2) (Dingus et al., 2016).

1.1 Research Objectives

1.1.1 Objective I: Driver Distraction Engagement and Glance Behaviour

Although driver distraction increases crash risk, drivers are often capable of dividing their attention between secondary tasks and driving without any, or with minor consequences, to driving performance and safety. The lack of negative consequences can in part be explained by findings from earlier naturalistic studies, which suggest that drivers exhibit self-regulating behaviors regarding distraction engagement: e.g., being more likely to initiate cell-phone conversations and visual-manual phone tasks when stopped compared to driving at high speeds

(Funkhouser & Sayer, 2012; Tivesten & Dozza, 2015). Risk-reducing adaptive behaviors have also been observed in simulator studies on driver distraction. For instance, when distracted by a cell-phone conversation, drivers have been observed to be less likely to overtake slower vehicles (Charlton, 2009) and to change lanes (Cooper, Vladisavljevic, Medeiros-Ward, Martin, & Strayer, 2009), and more likely to reduce their speed to a larger extent when driving on curves (Oviedo-Trespalacios, Haque, King, & Washington, 2017). Although prior research has found a variety of adaptive behaviors about cell-phone tasks, to the best of our knowledge, no naturalistic research to date investigated whether and how environmental demands affect driver engagement in distractions in general. Visual attention adaptation has been studied in general in on-road studies (Räsänen & Summala, 1998; Shinar, 2008; Tijerina, Barickman, & Mazzae, 2004), and during visual-manual phone tasks in a naturalistic study (Tivesten & Dozza, 2014). The results suggest that drivers modify their visual attention allocation based on expectancies (Räsänen & Summala, 1998; Tijerina et al., 2004) and driving demands (Shinar, 2008; Tivesten & Dozza, 2014). Although prior naturalistic research found visual attention adaptation behaviours during visual-manual phone tasks, how the environmental demands affect drivers' general visual attention allocation behaviours has not yet been examined. Therefore, the first research objective in this thesis aimed to investigate whether and how drivers adapt, based on environmental demands, their secondary task engagement and visual attention allocation away from the forward scene (direction of travel).

To capture environmental demand, this thesis focused on two constructs: visual and motor control difficulty. Visual difficulty was used to describe the density of static and dynamic elements of the driving scene that the driver needs to observe and track (i.e., traffic signs, vehicles, pedestrians, cyclists, intersections) together with the visibility level. Motor control difficulty was used to describe the lateral and longitudinal vehicle control demands imposed on the driver by the environment and was built from NEST variables related to the road alignment and surface condition (e.g., road curvature is expected to increase lateral control demand, road surface being wet is expected to increase longitudinal control demand). Objective 1 analysed environmental demand separately through visual and motor control difficulty constructs, given that previous research have identified adaptive behaviours due to both visual (Räsänen & Summala, 1998; Tijerina et al., 2004) and manual (Parnell, Stanton, & Plant, 2018a) demands.

1.1.2 Objective II: Driver Engagement in Multiple Tasks

As mentioned earlier, the detrimental effects of driver distraction on traffic safety has been extensively researched on crash records and in controlled studies. There has also been analysis on naturalistic driving data investigating crash risks associated with different distraction types. Recent analysis on SHRP2 data indicate that hand-held cell-phone dialing (Odds Ratio, OR = 12.2), reading/writing (OR = 9.9), and reaching for a non-cell phone object (OR = 9.1) are associated with the highest crash risks amongst various secondary activities (Dingus et al., 2016). Furthermore, supported by the findings of earlier naturalistic studies (Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006), visual-manual secondary activities are the most detrimental to crash risk compared to other types of secondary activities.

It should be noted that most studies on driver distraction, if not all, focused exclusively on the effects associated with one type of secondary task compared to no secondary task (i.e., model driving or baseline) or another task. Early descriptive analysis on the NEST dataset suggests that drivers may be engaging in more than one type of secondary task in relatively short periods of time (i.e., within 10s) (Domeyer et al., 2016), potentially being exposed to increased demands brought on by multi-tasking and task-switching. The authors of this early analysis found that the majority of distraction-affected safety-critical events (SCE: crashes/near-crashes) and baseline (model driving) epochs reported in NEST include more than one type of secondary task, suggesting that engagement in multiple types of secondary tasks do occur. This finding raises questions about the overall prevalence of this phenomenon. Although most crash risk studies to date reported the effects associated with one type of secondary task, it appears that these effects may be confounded by the presence of other secondary tasks. Therefore, in addition to studying how environmental demands affect engagement in distractions in general, this thesis also investigated the prevalence of engagement in multiple types of secondary tasks. The aim of this research objective was to investigate and compare the prevalence of engagement in single vs. multiple types of secondary tasks in distraction-affected SCEs (crashes/near-crashes) and baselines (model driving) reported in the NEST dataset. Contextual factors such as environmental demand (visual difficulty and motor control difficulty) and vehicle speed were also considered as it was expected that the overall driving context would also affect whether drivers engaged in multiple types of secondary tasks. In contrast to Objective 1, the environmental demand associated with the overall driving context in Objective 2 was captured through a combination of both constructs: visual and motor control difficulty. Analysis on the separate constructs was conducted initially but the separate analysis did not provide further insights and hence the two constructs were collapsed together.

1.2 Thesis Outline

This rest of this thesis is organized in the following way:

Chapter 2 provides the background literature and the motivation to investigate the following two research objectives: 1) distraction engagement behaviours and visual attention allocation as a function of varying environmental demands, and 2) prevalence of engagement in multiple types of secondary tasks within different environmental demands.

Chapter 3 provides a detailed explanation of the NEST dataset including a historical perspective on naturalistic driving studies.

Chapter 4 presents the methods used for examining research objective 1 (Driver Distraction Engagement and Glance Behaviour) and the associated statistical results.

Chapter 5 presents the methods used for examining research objective 2 (Driver Engagement in Multiple Tasks) and the associated statistical results.

Chapter 6 concludes the findings of the research, focusing on the two key research objectives, and includes a discussion of the implication of findings for future research into traffic safety.

1.3 Summary of Contributions

There are several important areas where this thesis makes an original contribution to traffic safety research.

Objective 1: Findings have shown that secondary task engagement and glance behaviors change with varying environmental demands. It appears that drivers adapt their engagement in secondary activities in a risk reducing direction. Namely, the likelihood of secondary task engagement was found to be lower in higher visual difficulty situations compared to lower difficulty ones. Driving conditions with higher visual difficulty also were associated with a lower percent time looking non-forward, a lower frequency of non-forward glances, as well as a lower likelihood of exhibiting long non-forward glances. An increase in speed was associated with a decrease in the likelihood of engagement in higher motor control difficulty situations but not in lower ones. Thus, drivers modulate their secondary task engagement based on environmental demands; their speed also plays a role.

The following publications were generated from the findings of Objective 1:

Risteska, M., Donmez, B., & Chen, H. Y. W. (1st review received June 2018; revise and resubmit). The effect of driving demands on secondary task engagement and glance behaviors. *Safety Science*.

Risteska, M., Chakraborty, J., & Donmez, B. (2018). Predicting environmental demand and secondary task engagement using vehicle kinematics from naturalistic driving data. In *Proceedings of the 10th International ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications*, Toronto, ON. (37% acceptance rate)

Objective 2: Engagement in multiple types of secondary tasks was observed in 52% of the distraction-affected SCEs and 31% of the baselines involving secondary task engagement. Moreover, engagement in multiple types of secondary tasks was significantly more likely (as opposed to engagement in a single secondary task) during SCEs compared to baselines. Overall, it appears that engagement in multiple secondary task types is prevalent in both distraction-affected SCEs and baselines, but is more likely in SCEs than baselines. As mentioned earlier, most crash risk studies to date reported the effects associated with one type of secondary task when it appears that in reality these effects may be confounded by the presence of other secondary tasks.

The following journal paper was published based on the findings of Objective 2:

Risteska, M., Donmez, B., Chen, H. Y. W., & Modi, M. (2018). Prevalence of engagement in single vs. multiple types of secondary tasks: Results from the Naturalistic Engagement in Secondary Tasks (NEST) dataset. *Transportation Research Record: Journal of the Transportation Research Board*.

Chapter 2

2 Literature Review

This chapter provides the background and the motivating literature for both research objectives tackled in this thesis. The purpose of this literature review is to point out the research gaps in driver distraction literature. Section 2.1 presents a motivating literature for the first research objective regarding drivers' distraction engagement behaviours and visual attention allocation as a function of varying environmental demands. The section starts by defining driver distraction and elaborating why distractions with visual-manual components are the most detrimental to safety. Following this, it introduces the importance of visual attention allocation metrics for studying driver distraction and then reviews the background literature examining adaptation behaviours under distracted driving. Lastly, background literature on the safety-relevance of different environmental conditions is presented. Section 2.2 presents the background for studying engagement in multiple types of secondary tasks vs. single. Section 2.2 starts by reviewing the literature regarding driving performance and safety degradation due to distractions from both controlled and naturalistic studies. Following this, it introduces the research gap regarding the potential effects from engagement with more than one type of secondary task.

2.1 Objective I: Driver Distraction Engagement and Glance Behaviour

Findings from naturalistic driving data and crash records have shown that distracted driving is ubiquitous. Recent analysis on SHRP2 NDS found that drivers are distracted from their primary task of driving approximately 50% of the time, and that 68% of crashes involve some type of observable distraction (Dingus et al., 2016). Further, traditional crash studies have associated 10% to 12% of all vehicle crashes to driver distraction (Gordon, 2009). Driver distraction can be defined as misallocation of attention from driving related components to a non-driving task or to an information source (Smiley, 2005). Distraction is fundamentally related to the process of attention distribution. Although attention, or the opposite, inattention, is associated with a broad class of cognitive states experienced by drivers (e.g., drowsiness or fatigue), one way to discriminate inattention from driver distraction is that distraction involves an explicit activity (e.g., dialing on the cellphone or daydreaming) that competes for drivers' limited attentional resources (Regan et al., 2009). Humans have limited attentional resources (Kahneman, 1973), and driving as a task requires drivers to accurately perceive, estimate, and process information available at the driving scene within a short period of time. Nevertheless, drivers do engage in non-driving activities mostly when the driving situation is perceived as safe.

There are three primary forms of driver distraction: visual, manual, and cognitive (Regan et al., 2009). According to the Multiple Resource Theory, if two tasks compete for similar cognitive, perceptual, or motor resources, then dual-task interference occurs (Wickens, 2002). What form of interference will lead to the greatest degradation in driving performance and increase of crash risk depends on the nature of the task itself. Consequently, in the literature, visual-manual secondary tasks have been identified as the most detrimental to safety, a finding that can be explained by the driving task itself being highly visual-manual in nature (Wickens, 2002). For example, in 1998, a test track study was conducted to test the destination entry task on four commercially available route guidance systems, three involving visual-manual demands and one based on a voice control input (Tijerina, Parmer, & Goodman, 1998). The authors found that, on average, the destination entry task performed on visual-manual systems was associated with longer completion times, longer eyes-off-road times, longer glances to the device, and greater numbers of lane exceedances. Several years later, in a test track study, Hurwitz and Wheatley (2002) investigated curvy and straight trajectories and found that visual distractors had a larger negative effect on vehicle control in contrast to auditory distractors. The authors measured vehicle control in terms of deterioration in steering wheel control and lane keeping.

The negative effects of distractions with visual-manual components have also been recognized by studies performed on naturalistic driving data. Recent evidence from analysis based on SHRP2 NDS has shown that handheld cell-phone dialing (OR=12.2) and reading/writing (OR=9) pose the highest risks compared to model driving, i.e., driving in an attentive and sober state (Dingus et al., 2016). Furthermore, Dingus et al. (2016) reported that texting on a cell phone increased crash risk by a factor of 6.1, whereas talking on a handheld cell phone increased crash risk by a factor of 2.2 when compared to model driving. These findings are consistent with the results obtained from previous literature (Klauer et al., 2006) and given that visual-manual tasks infringe on the same resources that the driving task requires, support Wickens' Multiple Resource Theory as well (Wickens, 2002). Namely, when distracted by a visual task, drivers not only time-share between the road and the off-road object, but also spend longer durations on the off-road object when completing more difficult secondary tasks (Victor, Harbluk, & Engström, 2005).

Driving is a highly visual-perceptual task (Sivak, 1998), hence a shift of the visual attention away from the forward roadway while driving has been shown to be particularly dangerous. According to analysis based on an earlier naturalistic dataset, the risk of safety-critical events doubled when the cumulative off-road glance duration exceeded 2s during the 6s period preceding an event onset (Klauer et al., 2006). In a similar study for teenage drivers, greater crash risk was observed for longer off-road glance durations as opposed to shorter ones (Simons-Morton, Guo, Klauer, Ehsani, & Pradhan, 2014). Furthermore, by comparing 24 algorithms based on a combination of glance duration, history, and location, Liang et al. (2012) found that duration of a single glance away from the forward roadway to be the most appropriate crash/near-crash risk predictor. Glance duration thresholds of 1.6s and 2s have been used in other relevant traffic safety research (e.g., Reimer et al., 2014) and NHTSA has adopted off-road glance duration of 2s as a safety critical threshold (National Highway Traffic Safety Administration, 2013).

In the real-world, drivers play a vital role in their decision to engage in a distracting activity (Lee & Strayer, 2004). As such, drivers may employ situational decision strategies of whether, when, and under what driving conditions to engage in potentially risky activities (Schömig & Metz, 2013). Although driver distraction increases crash risk, drivers are often capable of dividing their attention between secondary tasks and driving without any or with minor consequences to driving performance and safety. The lack of negative consequences can in part be explained by findings from earlier naturalistic studies, which suggest that drivers exhibit self-regulating behaviors regarding distraction engagement: e.g., being more likely to initiate cell-phone conversations and visual-manual phone tasks when stopped compared to driving at high speeds (Funkhouser & Sayer, 2012; Tivesten & Dozza, 2015). Parnell et al. (2018a) examined drivers' decision to engage in secondary tasks in both a driving simulator and an on-road study. The authors further found that different road types have different impacts on drivers' intention to engage in a distracting activity. In particular, drivers were approximately three times more willing to engage in a distracting activity on the motorways and on A-type roads than at roundabouts (Parnell et al., 2018a). In addition to drivers' decision to engage in distracting activities, other risk-reducing adaptive behaviors have been observed in other simulator studies on driver distraction. For instance, when distracted by a cell-phone conversation, drivers have been observed to be less likely to overtake slower vehicles (Charlton, 2009) and to change lanes (Cooper et al., 2009), and more likely to reduce their speed to a larger extent when driving on curves (Oviedo-Trespalacios et al., 2017).

Although prior research has found a variety of adaptive behaviors about cell-phone tasks, to the best of our knowledge, no naturalistic research to date investigated whether and how environmental demands affect driver engagement in distractions in general. Visual attention adaptation has been studied in general in on-road studies (Räsänen & Summala, 1998; Shinar, 2008; Tijerina et al., 2004), and during visual-manual phone tasks in a naturalistic study (Tivesten & Dozza, 2014). The results suggest that drivers modify their visual attention allocation based on expectancies (Räsänen & Summala, 1998; Tijerina et al., 2004) and driving demands (Shinar, 2008; Tivesten & Dozza, 2014). For example, Tivesten and Dozza (2014) found that drivers spend more time looking at the road and have fewer long off-road glances when turning and when lead or oncoming vehicles are present, both when engaged in a visual-manual phone task and not. Further, for the phone task, the authors observed longer off-road glances to be associated with lower speeds. Although prior naturalistic research found visual attention adaptation behaviours during visual-manual phone tasks, how the environmental demands affect drivers' general visual attention allocation behaviours has not yet been examined.

Distraction engagement and the associated driving performance decrements may also vary with age. For example, in the U.S., drivers 20-years-old and younger, disproportionally account for a high percentage of drivers who are involved in distracted driving crashes (Singh, 2010). This result could be due to younger drivers' lack of skill and poor judgement (Horberry et al., 2006), their tendency towards risk-taking behaviours (Mcgwin & Brown, 1999), or simply due to younger drivers being early adopters and users of technology (Lee, 2007). NHTSA's distracted driving report for 2015 states that 20-29 year-old drivers constitute the largest proportion of drivers involved in fatal distraction-affected crashes (National Center for Statistics and Analysis, 2017). In 2015, young drivers (20-29 years old) accounted for 24% of all drivers in fatal crashes (11,428 of the 48,613), and 27% of total distracted drivers (891 of the 3,183 distracted drivers in fatal crashes).

The multi-modal nature of the driving task requires visual-manual coordination (Kramer & Rohr, 1982). In addition to demands associated with distractions, different driving environments can also place a broad spectrum of cognitive and physical demands on drivers. For example, road surface (e.g., harder to stop on a slippery road) and curvature of a turn (e.g., harder to stay within a lane during a sharp turn) can increase the level of motor control demand. In this regard, previous studies have reported the safety consequences associated with the road alignment, surface condition, and weather conditions. Donmez and Liu (2015) found crash severity to be higher on curves, and Norrman, Eriksson, and Lindqvist (2000) showed that crash risk increased with road slipperiness. Moreover, in an instrumented vehicle study, a decrease in driving speed and swerving behavior was observed when smooth-surface road width was reduced via the addition of gravel (De Waard, Jessurun, Steyvers, Reggatt, & Brookhuis, 1995).

Weather conditions also impair driving (i.e., traction, stability and maneuverability) and visual scanning performance. In a crash study conducted in Calgary and Edmonton, Canada in 1993, the crash risk during rainfall conditions was found to be 70% higher than normal driving conditions (Andrey & Yagar, 1993). Weather was also found to be a major factor on highway crashes in California (Satterthwaite, 1976), with doubled crash frequency on wet days as opposed to dry days. Using data from the United States and Israel, Brodsky et al. (1988) found that during rainy weather the crash risk was two to three times higher than in dry conditions. The researchers also reported that crash risk was greater when rain followed a period of dry weather. Previous research indicates that weather conditions with poor visibility, especially rain, reduce the effectiveness of drivers' visual search (Konstantopoulos, Chapman, & Crundall, 2010). The authors observed that rain significantly affected drivers' sampling rate and processing time.

Through the analysis of a naturalistic dataset, the first objective of this thesis was to investigate whether and how drivers adapt, based on environmental demands, their secondary task engagement and visual attention allocation away from the forward scene (direction of travel). Specifically, given the literature review presented above, the goal was to provide insights into how environmental demands (visual and motor control difficulty) along with driver age (a proxy of skill and ability) and chosen speed may affect secondary task engagement and visual attention allocation. Baseline events (i.e., non-safety-critical) events from the NEST dataset were utilized for this analysis.

2.2 Objective II: Driver Engagement in Multiple Tasks

Simulator and on-road studies have found considerable amount of evidence for driving performance and safety degradation due to distractions (Regan et al., 2009). More precisely, distracted driving has been shown to degrade the longitudinal and lateral vehicle control, delay responses to hazards, elevate workload, and increase crash risk (Dingus et al., 2016; Horberry et al., 2006; Strayer & Johnston, 2001). Technological advances in recent years in personal communication devices and in-vehicle infotainment systems have generated a particular focus on the potential distracting effects of technology. For example, many controlled studies have examined the effects of prominent types of cell-phone usage: e.g., dialing (Alm & Nilsson, 1994; Brookhuis, de Vries, & de Waard, 1991; Reed & Green, 1999) and talking on the phone (McKnight & McKnight, 1993; Strayer & Drews, 2004; Strayer & Johnston, 2001). Previous research has also investigated the effects of in-vehicle technologies, such as radios (Sodhi, Reimer, & Llamazares, 2002) and navigation devices (Lee, Forlizzi, & Hudson, 2008).

The detrimental effects of driver distraction to traffic safety has been extensively researched using naturalistic settings as well. As presented earlier, recent analysis on SHRP2 data indicate that reaching for objects, manipulating objects, reading, and cell phone texting are the highest crash risk factors amongst various secondary tasks (Bakhit, Guo, & Ishak, 2018). The authors have found that these activities can increase the crash or near-crash risk by four- to eight-fold when compared to baseline driving and can be considered as high-risk distractors as they not only require multiple completion steps but also longer eyes-off-road time.

Although considerable number of studies examined driver distraction both in controlled and naturalistic settings, most studies, if not all, focused exclusively on the effects associated with one type of secondary task compared to no secondary task (i.e., model driving or baseline) or another task. In a descriptive analysis of the NEST data, Domeyer et al. (2016) found that the majority of distraction-affected SCE and baseline epochs reported in NEST include more than one type of secondary task, suggesting that engagement in multiple types of secondary tasks do occur. According to Wickens' dual-task interference theory (Wickens, 2002), it is likely that engagement in multiple types of secondary tasks can increase the demands on drivers by requiring multi-tasking and task-switching. Taking this phenomenon into account, it is possible that the distraction effects reported in previous crash risk studies are confounded by the presence of other secondary tasks. Thus, engagement in multiple types of secondary tasks appears to be a neglected topic in the field of traffic safety research. Therefore, in addition to studying how environmental demands affect engagement in distractions in general, this thesis further investigates the prevalence of engagement in multiple types of secondary tasks within different environmental demands. The goal was to investigate and compare the prevalence of engagement in single vs. multiple types of secondary tasks in distraction-affected safety-critical events (crashes/near-crashes) and baselines (model driving) reported in the NEST dataset.

Chapter 3

3 Naturalistic Driving Studies

Naturalistic driving studies capture drivers' natural behavior during everyday trips and provide data collected outside of the contrived settings used in experiments. They provide a unique opportunity to capture the conditions in which drivers engage in secondary tasks and to assess the extent to which they adapt their behavior based on the environmental demands. In these studies, participating vehicles are equipped with onboard advanced data-acquisition devices including cameras and various sensors that continuously monitor driving behavior, vehicle maneuvers, and external conditions for an extended period of time while participants drive their vehicles naturally. The details of driver behaviour and the environment are captured (e.g., road surface, curvature, weather and lighting conditions) along with vehicle kinematics during both safety-critical moments and normal driving scenarios.

The 100-Car Study was the first naturalistic driving study designed to collect a large volume of driving data over an extended period (i.e., ~13 months) (Dingus et al., 2006). The study included 102 primary drivers from northern Virginia. The resulting database provided valuable driver behaviour information that could not be obtained by conventional research methods, such as extreme cases of driving behavior and performance, including severe drowsiness, impairment, judgment error, risk taking, willingness to engage in secondary tasks, aggressive driving, and traffic violation (Dingus et al., 2006). This study allowed for the first time the recording of crashes with much greater detail than police reports. Further, it allowed for the recording of lower severity crashes and near-crashes that could not be included in police-report databases. Although the 100-Car Study provided valuable insights into driver behaviour, the sample was small, and the data was not nationally representative as it was collected from only one area in the United States (Northern Virginia/Washington, DC, metro area). However, the 100-Car study was first of its kind and it was designed to serve as a pilot to a much larger naturalistic study, the Second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS).

SHRP2 is the largest NDS conducted to date and captured around 50 million miles of continuous driving and 2 petabytes of video, kinematic, and audio data (Dingus et al., 2015). The SHRP2 NDS monitored approximately 3,400 drivers during a 3-year data collection period between 2010 and 2013. The naturalistic driving data was collected from a nationally representative sample across six states in the United States: Washington, Florida, New York, North Carolina, Pennsylvania, and Indiana. To date, there are 1,549 crashes and 2,705 near-crashes identified in the SHRP2 database (Hankey, Perez, & Mcclafferty, 2016). For each event, various data types are extracted, such as event summary and driver socio-demographics.

The benefits of NDS have been recognized on the international stage as well. UDRIVE—eUropean naturalistic Driving and Riding for Infrastructure & Vehicle safety and Environment—is the first large-scale European NDS on cars, trucks, and powered two-wheelers (Barnard, Utesch, Van Nes, Eenink, & Baumann, 2016). This European NDS was conducted in different regions within the borders of European Union, such as France, Germany, Netherlands, Poland, UK, and Spain. Moreover, there are NDS that have been performed or are ongoing in other countries as well, such as in Japan (Uchida, Kawakoshi, Tagawa, & Mochida, 2010) and Australia (Regan et al., 2013).

3.1 NEST Dataset

The NEST dataset was created from the SHRP2 data by Virginia Technical Transportation Institute, contracted by and under the supervision of Toyota Collaborative Safety Research Center (Owens et al., 2015). NEST was sampled from the data of SHRP2 drivers who had at least one safety critical event (SCE) where secondary task engagement was identified to be a potential contributing factor. Thus, NEST consists of a sample representing drivers who are likely at an elevated risk for distraction-affected crashes. Overall, 236 SCEs and 944 baseline events from 204 drivers were included in NEST.

3.1.1 Sampling of NEST Safety Critical Events from SHRP2

Safety critical events (SCEs) in NEST were sampled from SHRP2 while SHRP2 data ingestion was in progress. NEST included only events where secondary task engagement was judged as a potential contributing factor by data reductionists. The NEST project followed SHRP2 definitions of crashes, near crashes, and the severity levels associated with crashes (Hankey et al., 2016). Overall, the final NEST database ended up containing 236 SCEs.

Table 1 includes definitions of the SCEs, and the total number of events from each category included in NEST. Given that the number of events were controlled in the NEST sampling strategy, while SHRP2 database has 37% crashes and 63% near-crashes, NEST has 67% crashes and 33% near-crashes. Thus, NEST is a stratified sample from SHRP2, but not a random sample.

It is important to note that data reduction for NEST overlapped with SHRP2 data reduction. While NEST data reduction concluded in October 2014, SHRP2 data reduction was completed in its entirety in early 2015. Cross-checking SHRP2 InSight database suggests that NEST database was able to capture the majority of level I and II severity crashes in SHRP2 related to secondary task engagement, but only a portion of the relevant level III and IV crashes. Also, NEST oversampled near-crashes to achieve a larger number of near crashes in the database.

Table 1: Definitions (adopted from NEST user guide) and number of safety critical events

Safety Critical Event	**Definition**	**Frequency**
Crash Level I: Most Severe	Any crash that includes an airbag deployment; any injury of driver, pedal cyclist, or pedestrian; a vehicle rolls over; a high Delta V; or that requires vehicle towing. Injury if present should be sufficient to require a doctor's visit, including those self-reported and those apparent from video. A high Delta V is defined as a change in speed of the subject vehicle in any direction during impact greater than 20mph (excluding curb strikes) or acceleration on any axis greater than +/-2g (excluding curb strikes).	36
Crash Level II: Police-Reportable Crash	A police-reportable crash that does not meet the requirements for a Level I crash. Includes sufficient property damage that it is police reportable (minimum of ~$1500 worth of damage, as estimated from video). Also includes crashes that reach an acceleration on any axis greater than +/-1.3g (excluding curb strikes). If there is a police report this will be noted. Most large animal strikes and sign strikes are included here.	39
Crash Level III: Minor Crash	Most crashes not included above are Level III crashes. Includes physical contact with another object but with minimal damage. Includes most road departures (unless criteria for a more severe crash are met), small animal strikes, all curb and tires strike potentially in conflict with oncoming traffic, and other curb strikes with an increased risk element	44

Safety Critical Event	Definition	Frequency
	(e.g., would have resulted in worse had curb not been there, usually related to some kind of driver behavior or state).	
Crash Level IV: Low-Risk Tire Strike	Tire strike only with little/no risk element (e.g., clipping a curb during a tight turn).	40
Near Crash	Any circumstance that requires a rapid evasive maneuver by the subject vehicle, or any other vehicle, pedestrian, cyclist, or animal to avoid a crash. A rapid, evasive maneuver is defined as steering, braking, accelerating, or any combination of control inputs that approaches the limits of the vehicle capabilities.	77

3.1.2 Sampling of NEST Baseline Events from SHRP2

Four baselines epochs (20s long each) were sampled from the same driver for each SCE coded in NEST. Baseline epochs are periods of driving that do not include a crash or near-crash event, sometimes referred to as 'model' driving. If a driver had more than one SCE (e.g., 3 SCEs) captured by NEST, they would have more baselines (e.g., 12 baselines) presented in NEST, compared to those who had only one SCE. Baselines were also sampled first from the available baselines reduced concurrently for SHRP2 analysis, followed by additional identification and reduction of baselines to meet the goal of 4 baselines per SCE coded. Given the sampling criteria of both SHRP2 and NEST, baselines in NEST fall under three categories:

- *Balanced baselines:* selected and coded as part of SHRP2 based on stratified sampling to control for exposure. The number of baselines extracted for each participating driver depends on the number of hours that the driver drove but did not drive slower than 5 mph for more than 2 seconds. At least one baseline was extracted for every driver.

- *Additional baselines:* selected and coded initially as part of SHRP2 based on distance driven, but after final adjustment were deemed to be extra from the balanced baselines. In total, SHRP2 extracted 20K balanced baselines and 12K additional baselines.

- *Null:* baselines that were selected and coded for NEST specifically, when the balanced and additional samples together did not provide sufficient number of baselines required by NEST (i.e., 4 baselines per SCE).

3.1.3 Coding of Events

In NEST, detailed coding of the events was extended beyond the standard SHRP2 data reduction process since NEST was designed to provide a richer description of driver distraction engagement (Owens et al., 2015). SCEs and baselines in NEST dataset were coded for 30s and 20s respectively. Specifically, SCEs were coded for 30s: 20s prior to, and 10s after the precipitating event, i.e., the state of environment or action that initiated the crash or near crash event sequence. Baseline epochs, without a precipitating event by definition, were coded for 20s. Figure 1 below visualizes the coding scheme for both types of events reported in NEST. In contrast to NEST coding scheme, both of SCEs and baseline in SHRP2 data were coded for 6s. In SHRP2 data, secondary task engagement included only indicators of the presence of specific secondary task immediately preceding an SCE or during a baseline event.

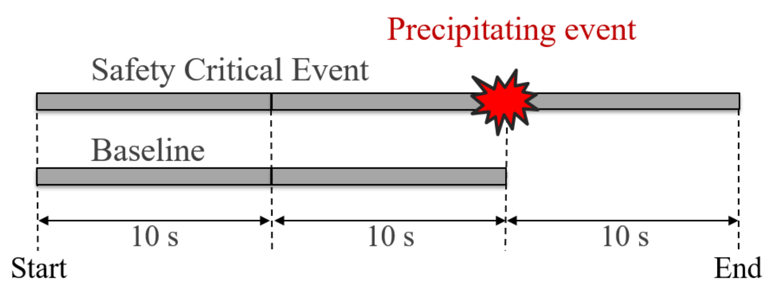


Figure 1: Data coding epochs for SCEs and baseline events in NEST.

The NEST dataset provides two types of variables: sequential data coded at 10 Hz (~200 frames per event) and data aggregated over 10s long epochs. The sequential data consists of: (1) frame-by-frame manually annotated video sequences that describe driver's glance direction, hand placement, and secondary task engagement, and (2) vehicle kinematic data including GPS speed, x-y-z axis acceleration, gear position, and brake pedal state. Table 2 presents the complete vehicle kinematics signals available in NEST. In contrast to sequential data coding, environmental variables (i.e., surface condition, alignment, locality, traffic density, and lighting) and secondary task engagement reported in this dataset only provide a high-level description for each event; the high-level descriptive variables for the driving environment were coded once for each 10s epochs, whereas the high-level descriptive variables for secondary task engagement were coded up to six times for each 10s epoch. For example, over a 10s epoch the driver may have been reported to engage in a cell-phone task in addition to a conversation with a passenger.

Table 2: Vehicle kinematics data available in the NEST dataset

Vehicle Kinematics	Description	Units
Brake Pedal	Relative position of brake pedal	-
Gear Position	Position of gear	-
Gas Pedal	Relative position of gas pedal	-
Speedometer	Speed indicated on the speedometer	km/h
GPS Speed	Speed measured by GPS	km/h
x-acceleration	Longitudinal acceleration/deceleration	g
y-acceleration	Lateral acceleration/deceleration	g
z-acceleration	Vertical acceleration/deceleration	g
Pitch	Angular velocity of vehicle along y	deg/s
Yaw	Angular velocity of vehicle along z	deg/s
Steering wheel position	Angle of steering wheel	deg

Furthermore, for all SCEs and baseline events, NEST also performed a trip-level, categorical coding on secondary task engagement across the entire trip, up to 20 minutes. For trips longer than 20 min, the earlier part of the trip was also coded but at a rate of 2 min for every 10 minutes of driving; see Figure 4 in Owens et al. (2015) for the exact sampling method used. Video coding of a trip marked start and end points of all secondary task engagements, and categorized these engagements based on level of complexity as:

- *Simple:* tasks that can generally be completed without hand movement or eyes or with only a very quick glance and movement/touch
- *Moderate:* tasks that generally require 1 hand involvement with repeated or extended action and/or 1 -3 brief (< 2 second) glances
- *Complex:* tasks that generally involve both hands and/or repeated or extended (> 2 second) glances, or require cognitive multitasking

3.1.4 NEST and Crash Risk

SHRP2 Naturalistic Driving Study utilized a case-cohort design. This is a hybrid design that combines characteristics of cohort and case-control studies. In SHRP2, cohorts are the group of drivers stratified based on driver characteristics (e.g., age and gender). Cases are the crashes, and controls are the baselines. Although all cases are coded, it is not feasible to code all baseline data, thus SHRP2 utilized a sampling strategy to identify the baseline epochs that would be coded. The particular strategy utilized was selected to approximate crash risk rate ratios (Guo & Hankey, 2009). The following example adapted from Guo and Hankey (2009) illustrates the approximation used (Table 3).

Table 3: Crash risk rate approximation example

	Exposure (e.g., cell-phone used)	**No Exposure** (e.g., cell-phone not used)
Cases (Crashes)	A (# of crashes with cell-phone use)	B (# of crashes w/o cell-phone use)
Controls (Baselines)	C (# of baselines with cell-phone use)	D (# of baselines w/o cell-phone use)

Although a cohort design is used for the selection of drivers, as stated earlier, the same approach cannot be feasibly used for the time variant factors observed in SHRP2 (e.g., weather, cell-phone use). If a cohort design is used, exposure information would be predetermined (i.e., $A+C$ and $B+D$) and then the outcome (# drivers who crash and who do not crash) would be observed; the ratios $A/(A+C)$ and $B/(B+D)$ would represent crash risk given cell-phone and no cell-phone use, respectively. Similarly, the ratios A/C and B/D would present the odds of a crash given cell-phone and no cell-phone use, respectively.

However, with a case-control design, where the number of controls (i.e., baselines) are selected by the experimenters, the ratios $A/(A+C)$ and $B/(B+D)$ do not represent crash risk. Given that the experimenter manipulates the controls, the factor which determines whether an observation is a case or a control should be seen as a fixed factor, whereas the exposure information (i.e., whether there was cell-phone use vs. not) should be seen as the random (or stochastic) factor. Although the researchers and practitioners are interested in the risk of a crash given cell-phone use vs. not, what they can model is the relative frequency of cell-phone use given a crash $A/(A+B)$ vs. a baseline $C/(C+D)$. The ratios A/B and C/D represent exposure odds, in other words the odds of cell-phone use given a crash and no crash, respectively. The Exposure Odds Ratio (EOR) can then be calculated as follows:

$$EOR : \frac{A/B}{C/D} = \frac{x \mid \text{crash}}{x \mid \text{baseline}} \tag{1}$$

where x is the odds of cell phone usage. For selecting the controls, SHRP2 used random sampling stratified by participant and proportion of time driven to achieve a total of 20,000 baseline scenarios (Hankey et al., 2016). Under this sampling scheme, EOR is approximately equal to the Risk Rate Ratio (RRR) calculated as follows:

$$RRR : \frac{\dfrac{A}{\text{time travelled with cellphone}}}{\dfrac{B}{\text{time travelled without cellphone}}} \tag{2}$$

For the approximation to hold, the following should be satisfied:

$$\frac{C}{D} \sim \frac{\text{time travelled with cellphone}}{\text{time travelled without cellphone}} \tag{3}$$

Given that it is not yet feasible to accurately identify the exact amount of time the participants drove with and without a cell-phone for the long duration of a naturalistic study, one must sample the baseline periods to extract this exposure information. If a large enough random sample is drawn from the baseline epochs of each driver, then C/D would be representative of the ratio: time travelled with a cell phone / time travelled without a cell phone.

Given that NEST data selection also followed a case-control design, the selection of cases and controls from the SHRP2 data is instrumental in determining how the NEST dataset can be used. Although it was originally planned to utilize the entire SHRP2 data for NEST extraction, due to project timeline issues, only some of the SHRP2 data could be used. Further, unfortunately, there appears to be no way of knowing what type of a sub-sample NEST represents and thus one should expect biases in using EORs obtained from NEST data to approximate crash risk rate ratios.

3.1.5 Limitations

While NEST dataset provides valuable information regarding secondary task engagement in a naturalistic setting, it is important to note various limitations arising mainly from the sampling strategies:

- NEST does not have baseline events from drivers who did not have an SCE associated with secondary task engagement. Thus, all conclusions made from NEST data should acknowledge that are for drivers who had at least one SCE associated with secondary task engagement.

- NEST does not have SCEs that are not associated with secondary task engagement. Thus, one cannot make any conclusions on SCEs without secondary task engagement.

- NEST SCEs were selected based on the judgement of the data reductionist: SCEs where secondary task engagement was deemed to be a contributing factor were only selected.

- NEST data reduction took place in 2014, completed in October 2014 (hence did not include the potential events or baselines reduced from SHRP2 data after this date). NEST neither consists of all SHRP2 SCEs relevant to secondary task engagement, nor was drawn from the complete set of SHRP2 events and baselines.

    - Unlike the SHRP2 baseline sampling procedure, NEST baselines were not sampled to control for exposure.

    - There was no known order (e.g., by time, by site, or through a statistically random order) to the data reduction process of SHRP2. Given that NEST data was extracted before SHRP2 data was ingested entirely, NEST is not a true random sample of SHRP2. Therefore, NEST dataset cannot be used for assessing crash risk.

    - NEST includes only 204 drivers that ended up in a safety-critical event caused by secondary task engagement. This is not a large sample size and it is probably biased in a number of ways. First, given that NEST is a subsample of SHRP2 data, there might be some biases related to population demographics from the SHRP2 recruitment process. Second, NEST is likely biased towards drivers that are at an increased risk of distraction-affected crashes given that it only includes drivers that ended up in a safety-critical event caused by secondary task engagement.

3.2 Limitations of Naturalistic Driving Studies

Although the NDS methods overcome a range of limitations associated with conventional approaches, there are some potential methodological drawbacks associated with NDS. First, NDS is an expensive approach given the resources needed in terms of sample recruitment, data gathering, data storage, and data analysis. For example, the equipment installed in the participants' vehicles (e.g., cameras, sensors, GPS, radar, accelerometers), and their maintenance requires a great deal of material and labour cost. This is, however, just one fraction of the cost associated with NDS. The high volume of recorded data requires a further labour-intensive processing and analytical work, such as data mining, processing and coding, to identify and extract the particular events of interest (e.g., safety-critical situations, distraction engagements, judgement error). Second, crashes are rare events and thus very large sample sizes are needed to yield sufficient crash events in NDS. Third, given that NDS monitors drivers' everyday commutes, it has no control over the influences around the participants. Hence, the same participant could be associated with different baseline events that differ in terms of driving conditions, time of the day, or even driver state. Lastly, biases might be introduced by NDS coding methodology given that it is up to the data reductionist's perspective to judge and label a particular situation or driving behaviour. For example, some of the NDS glance coding may result in lower accuracies given that the item/area that the driver is looking at is usually inferred from the gaze direction and driving situation. This could potentially lead to mislabeled glances such as "over the shoulder" when in fact the driver is talking to a passenger on the back seat. Also, due to the same reasons, NDS lists only observable distractions as secondary task types given that it cannot capture engagement in cognitive distractions.

Chapter 4

4 The Effect of Environmental Demands on Secondary Task Engagement and Glance Behaviours

4.1 Introduction

As stated in the Introduction, the aim for Objective 1 was to investigate drivers' distraction engagement behaviours and visual attention allocation as a function of varying environmental demands. Through the analysis of NEST, this chapter investigated whether and how drivers adapt, based on the environmental demands, their secondary task engagement and visual attention allocation away from the forward scene (direction of travel). This chapter utilized the baseline (i.e., non-safety-critical) events from the NEST dataset. Secondary task engagement and non-forward glance behaviors were analyzed with environmental demands, GPS speed, and driver age as predictor variables. In particular, environmental demand was explored within the study of driving context. Environmental demand was defined to consist of two constructs, visual and motor control difficulty, based on the following NEST variables: locality, traffic density, lighting, weather, surface condition, and alignment. Speed was included to better capture the environmental demands, and driver age was adopted as a proxy for driving skill and ability given that age is known to correlate with driving skill (Carr, Jackson, Madden, & Cohen, 1992) and information processing abilities (Maltz & Shinar, 1999; Panek, Barrett, Sterns, & Alexander, 1977).

4.2 Method

This section begins by providing a detailed description of the dependent and explanatory variables used in our analysis; it then proceeds to present our statistical modeling approaches.

4.2.1 Dependent Variables

4.2.1.1 Secondary Task Engagement

The first dependent variable was whether the driver engaged in a secondary task or not during a given baseline event (20s). There are 40 different types of secondary tasks observed in NEST baselines, which are listed in Table 4. It should be noted that more than one secondary task type could be coded per epoch, and two epochs were coded per baseline. Although the NEST dataset listed the presence of passengers/children with no interaction as secondary tasks, we categorized these cases under no secondary task engagement. Moreover, secondary task types that were coded as unknown or N/A were excluded. In total, there were 613 baselines with secondary task engagement, and 194 baselines without secondary task engagement used in the model. Detailed NEST secondary task type variable descriptions can be found in Appendix A.

Table 4: Secondary task types observed in NEST baselines with the number of epochs each task type was observed in

Secondary Task Engagement	NEST Secondary Task Type	Number of Epochs
Yes	Adjusting/monitoring climate control	21
	Adjusting/monitoring other devices integral to vehicle	17
	Adjusting/monitoring radio	88
	Inserting/retrieving CD	2
	Applying make-up	4
	Biting nails/cuticles	37
	Brushing/flossing teeth	2
	Combing/brushing/fixing hair	9
	Removing/adjusting jewelry	5
	Removing/inserting/adjusting contact lenses or glasses	8
	Other personal hygiene	32
	Cell phone, other	144
	Talking/listening on cell phone	92
	Viewing PDA/ other handheld device	3
	Dialing hand-held cell phone	4
	Texting on cell phone	132
	Locating/reaching PDA/ other handheld device	1
	Locating/reaching/answering cell phone	44
	Drinking	28
	Eating	32
	Dancing	42
	Talking/singing	283
	Looking at an object external to the vehicle	105
	Looking at pedestrian	5
	Other external distraction	86

Secondary Task Engagement	**NEST Secondary Task Type**	**Number of Epochs**
	Looking at previous crash or incident	1
	Moving object in vehicle	2
	Object in vehicle, other	65
	Reaching for food-related or drink-related item	14
	Reaching for object that is a manufacturer-installed device	2
	Reaching for object, other	24
	Reaching for personal body-related item	3
	Reaching for/lighting/smoking/extinguishing cigar/cigarette	32
	Passenger in adjacent or rear seat - interaction	342
	Child in adjacent or rear seat - interaction	18
	Pet in vehicle	11
No	Child in adjacent seat - no interaction or cannot tell	6
	Child in rear seat - no interaction or cannot tell	50
	Passenger in adjacent seat - no interaction or cannot tell	116
	Passenger in rear seat - no interaction or cannot tell	25

4.2.1.2 Glance Behaviour

To create the outcome variable, the original NEST glance behavior variable was further grouped into two glance directions: “forward” and “non-forward” glances. Table 5 presents the definitions of forward and non-forward glances provided in NEST.

Table 5: NEST Eye Glance variable definitions

Glance Direction	**NEST Eye Glance Type**	**Definition**
Forward	Forward (Center)	Glance out the forward windshield directed towards the direction of the vehicle’s travel.
Non-forward	Left Windshield	Glance out of the forward windshield where the driver appears to be looking specifically out of the left/right margin of the windshield (e.g., as if scanning for traffic before turning or glancing at oncoming traffic). The glance location is clearly not in the direction of travel (e.g., at road signs or buildings).
	Right Windshield	
	Rear-view Mirror	Glance toward the rear-view mirror or equipment located around it.
	Left Window/Mirror	Glance to the left/right side mirror or window.
	Right Window/Mirror	

Glance Direction	**NEST Eye Glance Type**	**Definition**
	Over-The-Shoulder	Glance over either of the participant's shoulders.
	Instrument Cluster	Glance to instrumented cluster underneath the dashboard.
	Center Stack	Glance to the vehicle's center stack (vertical).
	Cell Phone	Glance at a cell phone, other electronic communication device, or cell-phone related equipment (e.g., chargers), no matter where it is located.
	iPod (or similar)	Glance at an iPod or other personal digital music device no matter where it is located.
	Interior Object	Glance to an identifiable object in the vehicle other than a cell phone, including personal items brought in by participants, any part of their body, electronic devices other than cell phones, and OEM installed devices that don't fall into other categories. Glances to the center console are also included here.
	Passenger	Glance to a passenger.
	No Eyes Visible. Eyes Are Off-Road.	Driver's eyes/face not visible. However, it is clear that the participant is not looking at the roadway.

Drivers' attention allocation away from the forward scene (direction of travel) was analyzed through four dependent variables: (1) percent time of non-forward glances out of the total baseline event duration, (2) number of non-forward glances, (3) number of non-forward glances > 1.6s, and (4) number of non-forward glances > 2s. These glance duration thresholds (i.e., 1.6s and 2s) have been used in other related research (e.g., Reimer et al., 2014); 2s has been adopted as a safety critical threshold (National Highway Traffic Safety Administration, 2013), whereas 1.6s threshold originates from in-vehicle task performance studies which found that drivers do not, on the average, allow their single glances exceed 1.6 seconds (Wiervville, 1993). The calculation of glance durations included transition times according to ISO 15007 (International Organization for Standardization, 2013), and excluded the frames where the NEST eye glance variable was coded as "no video", "eyes closed", "no eyes visible - glance location unknown", and "other". Four baselines were removed as glance location was coded as unknown for the entire event.

4.2.2 Explanatory Variables

The driving context was captured using NEST variables describing the environment around the time of an event, such as: locality, traffic density, lighting, weather, surface condition, and alignment. Two environmental demand types that the environmental context may impose on the drivers were considered: visual difficulty and motor control difficulty. It should be noted that the same level of environmental demand is not expected to induce the same level of workload on each driver. The perceived workload would depend on the driver skill/ability and chosen speed, and their interaction. Thus, in addition to the two environmental demand variables, GPS speed at the beginning of an event and driver age were included in our models as explanatory variables. Driver age was used as a proxy for driver skill and capabilities.

4.2.2.1 Environmental Demands

Although NEST provides an extensive list of explanatory variables that can characterize environmental demands (Appendix A), given its relatively small sample size, it was infeasible to include all these variables separately in our models. Hence, aggregations were performed to create meaningful groupings with reasonable sample sizes. In the end, environmental demand was captured through two explanatory variables: visual difficulty and motor control difficulty.

Figure 2 shows an overview of how these constructs were created from six NEST variables that describe the environment: locality, traffic density, lighting, weather, surface condition, and alignment.

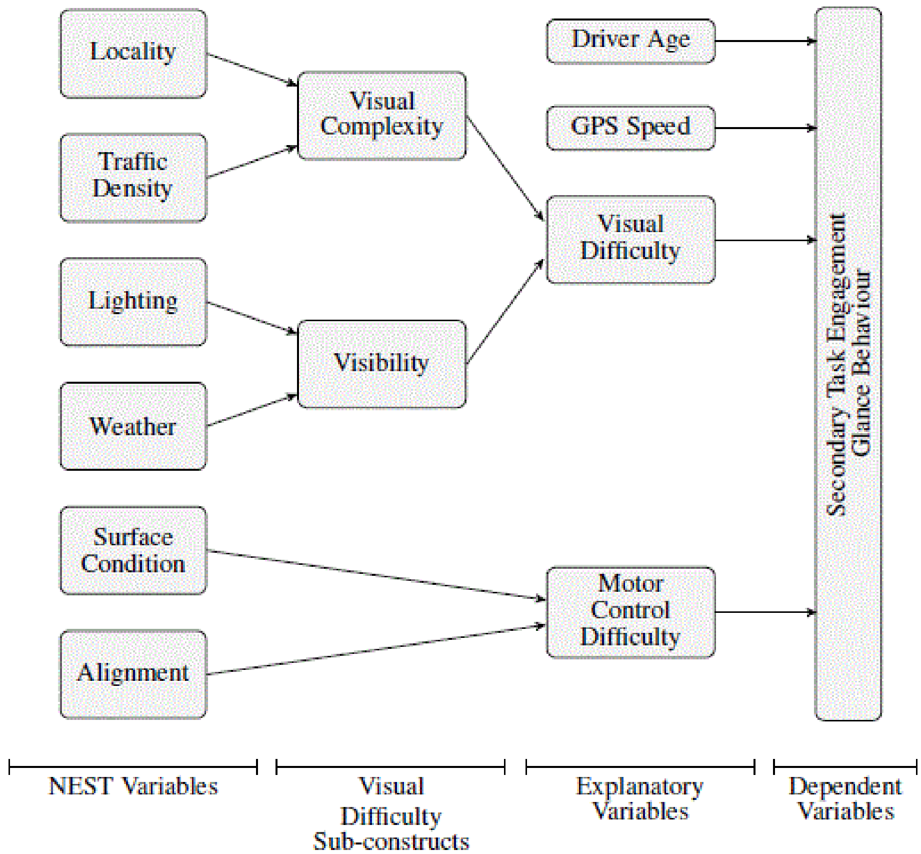


Figure 2: Model covariates and the creation process of the visual and motor control difficulty constructs for the secondary task engagement and glance behaviour models.

4.2.2.1.1 Visual Difficulty

The visual complexity associated with an environment affects visual search performance (Donderi, 2006). Given that drivers are under a continuous exposure of a vast array of visual information while driving, visual complexity of the driving environment is one factor that can affect the level of visual demand placed on drivers. Thus, visual complexity is one sub-construct of visual difficulty and describes the density of static and dynamic elements of the driving scene that the driver needs to observe and track (i.e., traffic signs, vehicles, pedestrians, cyclists, intersections), and is expected to be affected by locality (e.g., "open country" vs. "urban") and traffic density. Another sub-construct that can affect visual demand is visibility, which describes the lighting and weather conditions that may influence driver's ability to perceive these elements.

For example, time of day affects the severity and prevalence of crashes (Clarke et al., 2006), with crash risk being four times higher at night (Williams, 2003). Further, poor visibility due to adverse weather conditions, especially rain, has been shown to decrease the effectiveness of drivers' visual search (Konstantopoulos et al., 2010).

The visual difficulty construct was thus created from two sub-constructs (visual complexity and visibility), which were in turn created from the following NEST variables: locality, traffic density, lighting, and weather. Figure 4, Table 6, and Table 7 presents the correspondence of visual difficulty levels (lower and higher) to its sub-constructs and the associated NEST variables. The groupings and category labels were largely based on the NEST and SHRP2 variable descriptions; however, two researchers also reviewed a subsample of the SHRP2 Insight Data Access Website video sequences to assess the level of visual complexity associated with different localities and traffic levels of service (LOS or traffic density; Transportation Research Board, 2000). Example snapshots are presented in Figure 3 and Appendix B. Three baseline events had to be dropped from our analysis due to missing information on visual difficulty.

Table 6: Environmental demand constructs and their associated levels

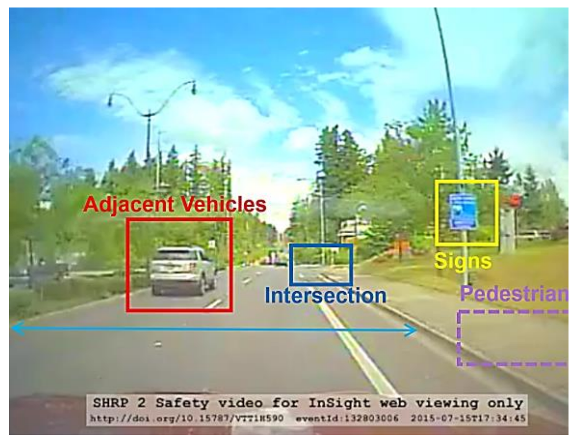
Environmental Demand Construct Creation			Description
Visual Difficulty *Lower*, *Higher* See Figure 4	Visual Complexity *Low*, *Med*, *High* See Table 7	Locality *Low*, *Med*, *High* See Table 7	Low if both epochs consist of low locality (open residential, open country, and interstate/bypass/divided highway with no traffic signals); high if at least one epoch includes high locality (urban, school, church, playground and construction zone); medium otherwise. Categorization based on one epoch if the other had missing or “unknown” data. If an epoch was coded as “other”, then baseline dropped from analysis.
		Traffic Density *Low*, *Med*, *High* See Table 7	Low if both epochs had low level of service (LOS A and B); high if at least one epoch had high level of service (LOS D, E, and F); medium otherwise. Categorization based on one epoch if the other had missing or “unknown” data.
	Visibility	Lighting *Daylight*, *Non-daylight*	Daylight if daylight for both epochs; non-daylight otherwise (darkness–lighted or not, dawn, dusk). Categorization based on one epoch if the other had missing or “unknown” data.
		Weather *Normal*, *Poor*	Normal if no adverse conditions during the baseline; poor otherwise (fog, heavy rain, mist or light rain, snowing).
Motor Control Difficulty *Lower*: Dry Surface and Straight Road n = 534 *Higher*: All other conditions n = 273		Surface Condition *Good*, *Poor*	Good if dry for both epochs; poor otherwise (icy, snowy, wet, gravel/dirt). Categorization based on one epoch if the other had missing or “unknown” data.
		Alignment *Straight*, *Curved*	Straight if straight road for both epochs; curved otherwise. Categorization based on one epoch if the other had missing or “unknown” data.

Table 7: Levels of visual complexity, locality, and traffic density

Visual Complexity	Locality	Traffic Density
Low	Low: Open country; open residential; interstate/bypass/divided highway with no traffic signals	Low: LOS A, B – Free flow or flow with some restrictions

Visual Complexity	Locality	Traffic Density
Med	Low	Med: LOS C – Stable flow, maneuverability and speed more restricted
	Low	High: LOS D, E, F – Unstable or forced flow
	Med: Business; industrial; bypass/divided highway with traffic signals; moderate residential	Low
	Med	Med
	High: Construction zone; playground; school; urban	Low
High	Med	High
	High	Med
	High	High

a) Locality: Open Residential; LOS C.



b) Locality: Business/Industrial; LOS A.

c) Locality: Urban; LOS A.

Figure 3: Visual complexity example scenarios: a) Low; b) Medium; c) High.

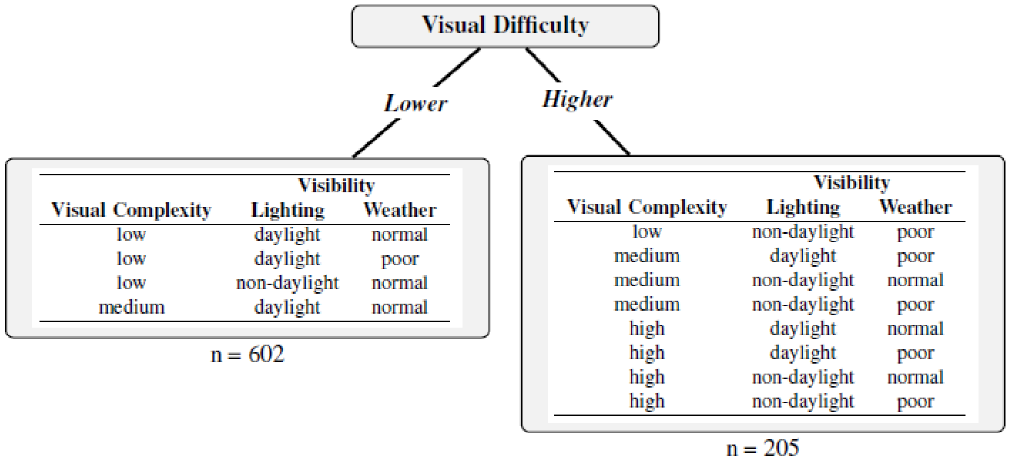


Figure 4: Levels of visual difficulty construct.

4.2.2.1.2 Motor Control Difficulty

A key aspect of driving workload is the amount of effort a driver exerts to laterally and longitudinally control the vehicle. Despite the driving speed, motor control demands experienced by the driver depend on the driving environment, such as the road surface (e.g., harder to stop on a slippery road) and curvature of a turn (e.g., harder to keep within a lane during a sharp turn) which was supported from previous literature. For example, crash severity has been found to be higher on curves (Donmez & Liu, 2015), and crash risk has been shown to increase with road slipperiness (Norrman et al., 2000). Moreover, in an instrumented vehicle study, a decrease in driving speed and swerving behavior was observed when smooth-road surfaces were reduced via the addition of gravel (De Waard et al., 1995). Hence, motor control difficulty is the second environmental construct used in our models to describe the lateral and longitudinal vehicle control demands imposed on the driver (e.g., road curvature is expected to increase lateral control demand, whereas wet road surface is expected to increase longitudinal control demand). Intuitively, it was created from two NEST variables: surface condition and alignment as presented in Table 6.

4.2.2.2 Driver Age and GPS Speed

Driving a vehicle safely requires a wide range of skills and abilities. As noted earlier the same level of environmental demand is not expected to induce the same level of workload on each driver. The perceived demand would also depend on the driver skills and capabilities, their chosen speed, and the interactions among the two. Thus, in addition to the two environmental demand variables, driver's age (a proxy of skill and ability) and GPS speed at the beginning of the baseline event were also included in our models. NEST categorizes driver age into 15 levels, ranging between 16 and 89. To aid statistical power, we aggregated these 15 levels into four: 16-24 (n=118), 25-34 (n=31), 35-64 (n=26), 65-over (n=26). Overall, age information for three drivers was missing in the NEST dataset, leading to the loss of 12 baseline events for our analysis. Further, there were 117 baselines that had missing GPS speed information. At the end, the analysis included a total of 807 baseline events.

4.2.3 Statistical Models

The statistical analysis was carried out in SAS University Edition. Secondary task engagement, i.e., whether the driver engaged in a secondary task or not, was analyzed in a logistic regression model using the GENMOD procedure. Percent time of non-forward glances was analyzed with a mixed linear model using the MIXED procedure. To satisfy the mixed linear model assumptions, a logarithmic transformation was performed on the dependent variable as follows: $\log(\%\, time\ of\ \ nonforward\, glances + 1)$. Total number of non-forward glances was analyzed through a Poisson model using the GENMOD procedure. The logarithm of the baseline event duration was introduced as an offset variable given the slight variability observed across different baseline lengths (~ 20s). As for number of non-forward glances longer than 1.6 s and number of non-forward glances longer than 2 s, we had to group the response variable into three bins/categories (0, 1, and ≥ 2), given that non-forward glances that were long in duration were infrequent. Ordered logit models were built for these variables in GENMOD.

For the models that utilized the GENMOD procedure, repeated measures were accounted for through generalized estimated equations. For the MIXED procedure, participant was introduced as a random factor. All models started with the following explanatory variables: visual difficulty (lower, higher), motor control difficulty (lower, higher), driver age (16-24, 25-34, 35-64, or 65-

over), GPS speed at the start of the baseline, and all two-way interactions of these variables. Backward selection was used to drop non-significant interaction terms from the final models.

4.2.3.1 Logistic Regression Model

Given that one of our goals was to evaluate distractions in general, the first dependent variable examined in this chapter was whether the driver engaged in a secondary task or not during a given baseline event (20s). The logistic regression model setup is as follows. Define

$$Y_{\mathrm{i}} = \begin{cases} 1, & \text{if a driver engaged in a secondary task} \\ 0, & \text{Otherwise} \end{cases} \tag{4}$$

Let ρ_i be the probability of engaging in a secondary task within 20s for an event *i*. The observed Y_i is assumed to follow a Bernoulli distribution.

$$Y_i \sim Bernoulli\left(\rho_i\right) \tag{5}$$

This probability is associated with a set of covariates by a logit link function,

$$\ell ogit\ (\rho_i) = \log\left(\frac{\rho_i}{1-\rho_i}\right) = \mathrm{X}_i\beta \tag{6}$$

where X_i is the matrix of predictors for individual event *i*, and β is the vector of regression parameters. The exponential of regression parameter, $\exp(\beta_j)$, is the odds ratio (OR) for the j^{th} exploratory variable.

4.2.3.2 Linear Mixed Model

One of the dependent variables used to investigate drivers' attention allocation away from the forward scene (direction of travel) was percent time of non-forward glances. Given that we had several observations per driver, the linear predictor contains random effects in addition to the usual fixed effects, hence the data was modelled using linear mixed models. Linear mixed models are an extension of simple linear models to allow both fixed and random effects. A fixed effect refers to the model coefficients that remain constant across all observations, whereas random effects are allowed to vary over different clusters of the data. The random effect terms act as perturbations to the fixed effects and increase model flexibility and decrease the overall model variance (Lord & Mannering, 2010; Ge, Hutcherson, Tang, & Gu, 2017).

The mixed effect logistic regression model setup is as follows:

$$Y_i = X_i\beta + Z_i\gamma + \varepsilon \tag{7}$$

where Y_i is the percent of time glancing non-forward modelled via its transformation $\log(\%\, time\ of\ nonforward\, glances + 1)$, X_i is the matrix of predictors with fixed effects (i.e., visual difficulty, motor control difficulty, driver age, and GPS speed) for an individual event i, β is the vector of regression parameters, Z_i is the matrix of predictors with random effects (i.e., participant), γ is the vector of random effect parameters, and ε is the vector of residuals.

4.2.3.3 Poisson Regression Model

Total number of non-forward glances is our second glance metric tackled in this analysis, and represents discrete rates collected within a fixed interval of time. Because total number of non-forward glances are non-negative integers, a standard ordinary least-squares regression is not appropriate. Poisson distribution explains number of arrivals of an event over a given internal:

$$\rho(y_i) = \frac{\exp(-\lambda_i)\lambda_i^{y_i}}{y_i!} \tag{8}$$

where $\rho(y_i)$ is the probability of the given interval of 20s period *i* having y_i non-forward number of glances (non-negative integers), and λ_i is the expected rate of non-forward glances for the interval of 20s (*i*). Poisson regression models are estimated by $\lambda_i = \exp(\beta X_i)$, where X_i is a is the matrix of predictors variables and β is the vector of regression parameters.

4.2.3.4 Ordered Logit Models

Finally, the dependent variables investigating number of non-forward glances longer than 1.6 s and longer than 2 s were grouped into three bins/categories: 0, 1, and ≥ 2. Given the ordinal nature of the dependent variables, these measures were modelled as a generalized linear model with ordinal dependent variables— ordered logit models. The ordered logit model setup is as follows. Define

$$Y_i = \begin{cases} 0, & \text{if no glances} \geq 1.6s/2s \\ 1, & \text{if one glance} \geq 1.6s/2s \\ 2, & \text{if two or more number of glances} \geq 1.6s/2s \end{cases} \tag{9}$$

Recall the binary logit model:

$$\ell ogit\ (\rho_i) = \log\left(\frac{\rho_i}{1-\rho_i}\right) = \mathrm{X}_i \beta \tag{10}$$

For ordered logit model we consider cumulative probabilities. Let ρ_i be the probability of exhibiting numbers of non-forward glances longer than 1.6/2s for each of the bins/categories *i*. The cumulative odds are:

$$\begin{aligned} \theta_0 &= \frac{p_0}{p_1 + p_2} \\ \theta_1 &= \frac{p_0 + p_1}{p_2} \end{aligned} \tag{11}$$

The last category (i.e., i = 2) doesn't have odds associated with it since the probability of exhibiting two or more glances longer than 1.6/2s is 1, given that $p_0 + p_1 + p_2 = 1$. The ordinal logistic is then,

$$\ln(\theta_i) = \alpha_i + \beta \mathrm{X} \tag{12}$$

where $i = 0,1, .. k\text{-}1$, and k is the number of bins/categories defined above. Note, the intercept α_i is increasing. That is, $\alpha_0 \leq \alpha_1 \leq \alpha_2$.

4.3 Results

4.3.1 Secondary Task Engagement

The final logistic regression model included visual difficulty (χ^2 (1) = 4.32, p =.04), motor control difficulty (χ^2 (1) = 2.38, p =.12), driver age (χ^2 (3) = 5.76, p =.12), speed (χ^2 (1) = 3.90, p =.048), and speed and motor control difficulty interaction (χ^2 (1) = 3.30, p =.07). The results showed that drivers appear to adapt their secondary task engagement based on the environmental demands, and their speed also plays a role. Higher visual difficulty conditions were associated with a decreased likelihood of secondary task engagement, see Figure 5 (OR = 0.65, 95% CI = 0.43, 0.98). Speed was also significant, and its interaction with motor control difficulty was marginally significant at p = .07. Follow-up contrasts revealed that a speed increase is associated with a decrease in the likelihood of distraction engagement in higher motor control difficulty situations (for an increase in speed of 10 km/h OR = 0.88, 95% CI = 0.79, 0.98, p = .02) but not for lower motor control difficulty situations (for an increase in speed of 10 km/h OR = 0.99, 95% CI = 0.92, 1.06, p = .76).

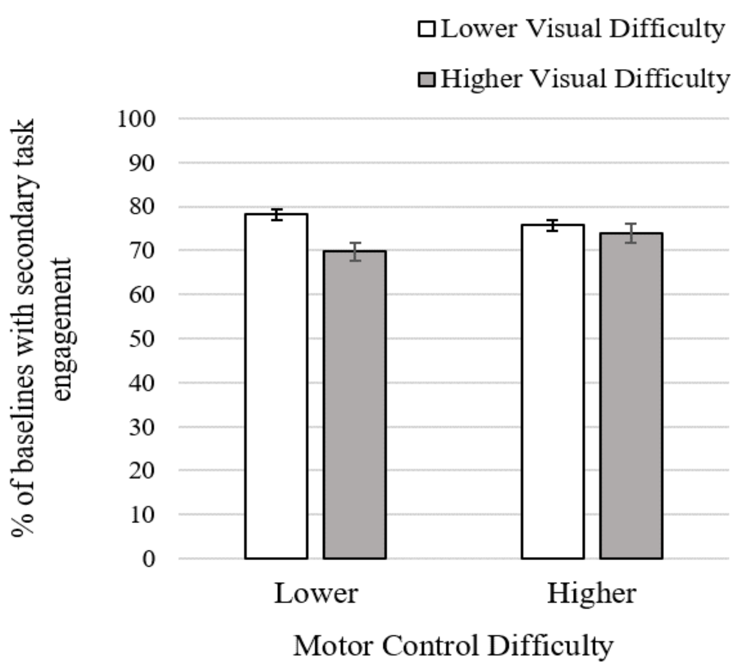


Figure 5: Percentage of baselines with secondary task engagement (vs. none) for different environmental demand levels.

4.3.2 Glance Behaviour

For percent time of non-forward glances, visual difficulty ($F(1, 797) = 8.47$, $p = .004$) was significant, whereas motor control difficulty ($F(1, 796) = 2.03$, $p = .15$), driver age ($F(3, 199) = 1.93$, $p = .13$), and speed ($F(1, 789) = 0.01$, $p = .93$) were not. Overall, higher visual difficulty was associated with a reduced percentage of time looking non-forward (Figure 6). Visual difficulty was also significant for rate of non-forward glances (χ^2 (1) = 4.33, p =.04), which was estimated to be 11% lower in the higher visual difficulty condition compared to lower visual difficulty (95% CI = 1, 20), see Figure 7. Driver age was also significant (χ^2 (3) = 16.30, p =.001), with drivers 35-over exhibiting reduced rates of non-forward glances compared to younger drivers. The rate of non-forward glances was 24% and 20% lower for drivers 65-over compared to drivers 16-24 (95% CI = 10, 35, p = .001) and 25-34 (95% CI = 2, 34, p = .03), respectively. Similarly, the rate of non-forward glances was 22% and 18% lower for drivers 35-64 compared to drivers 16-24 (95% CI = 8, 33, p = .002) and 25-34 (95% CI = 0.5, 32, p = .04), respectively. Motor control difficulty (χ^2 (1) = 0.94, p =.33) and speed (χ^2 (1) = 0.58, p =.45) were not significant for this dependent variable.

For number of glances longer than 1.6 s (the top subfigure on Figure 8), visual difficulty (χ^2 (1) = 5.46, p =.002) was significant, speed (χ^2 (1) = 3.15, p =.08) was marginally significant, and motor control difficulty (χ^2 (1) = 0.06, p =.81) and driver age (χ^2 (3) = 6.32, p =.10) were not significant. The odds of exhibiting more glances longer than 1.6 s was 38% lower (OR = 0.62, 95% CI: 0.42, 0.93) in the higher visual difficulty condition compared to lower visual difficulty. An increase of 10 km/h in speed was associated with a marginally significant decrease of 5% in odds of exhibiting more glances longer than 1.6 s (OR = 0.95, 95% CI: 0.89, 1.01).

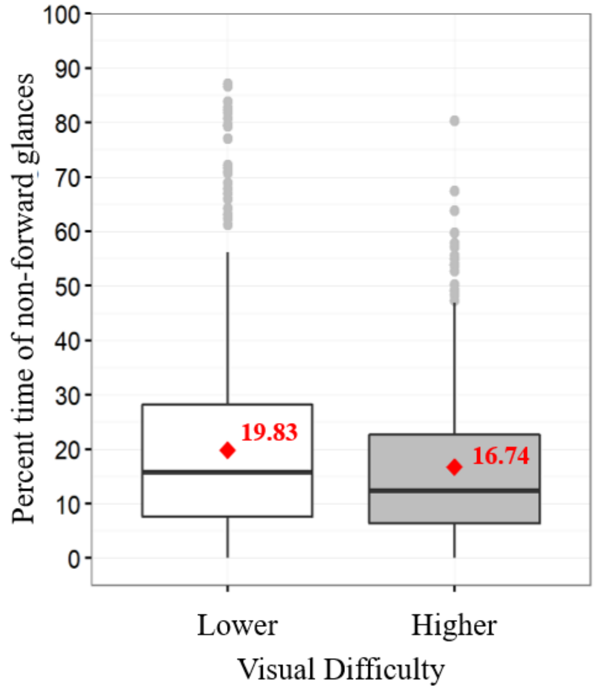


Figure 6: Boxplots (showing quartile information and means via red diamonds) for percent time of non-forward glances.

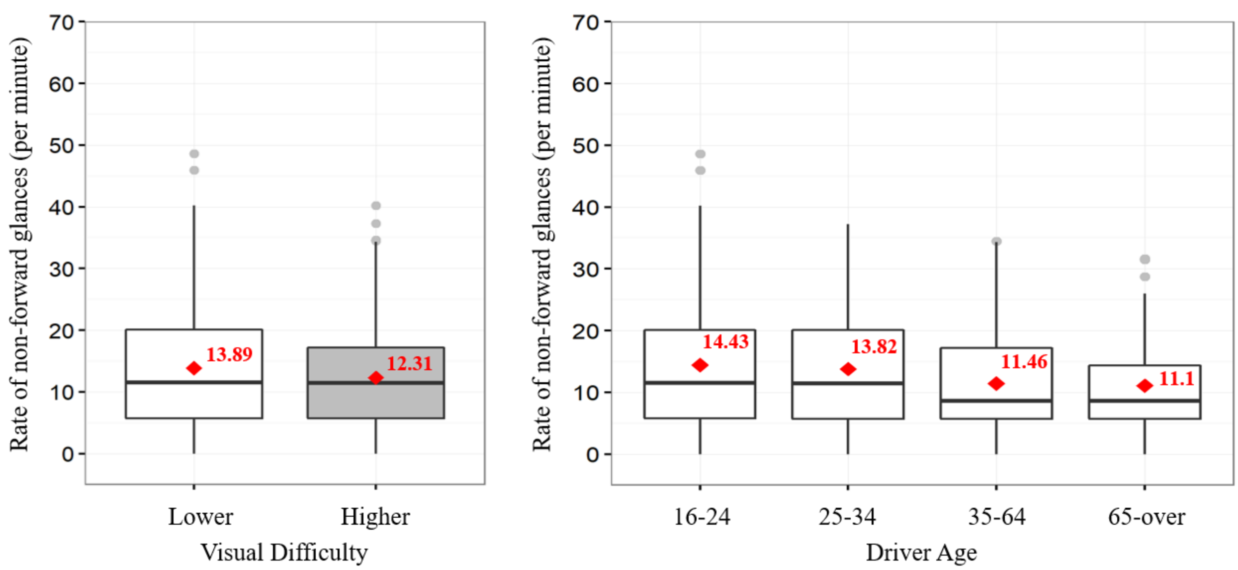


Figure 7: Boxplots (showing quartile information and means via red diamonds) for rate of non-forward glances (per minute) across (left subfigure) visual difficulty, and (right subfigure) driver age.

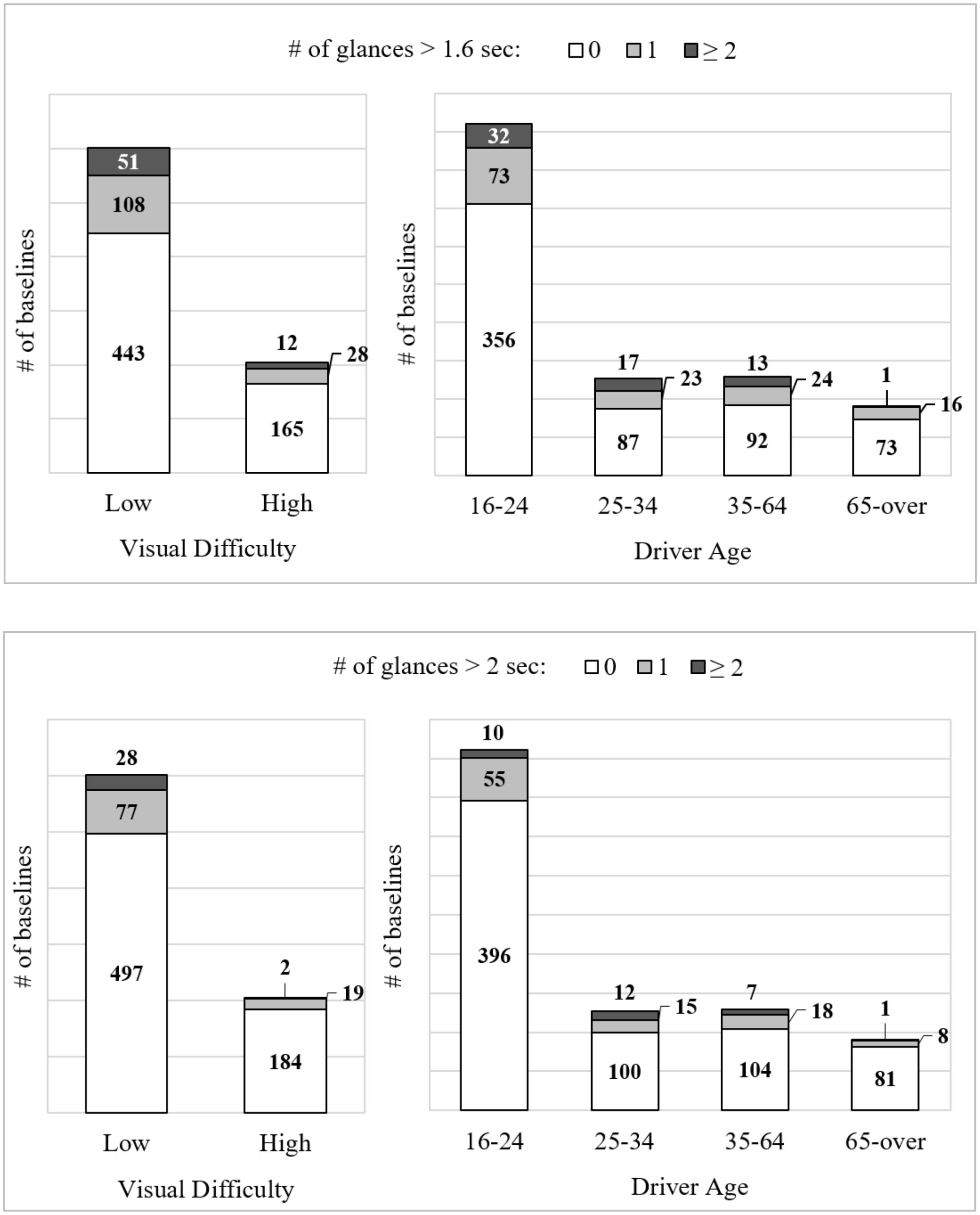


Figure 8: Distribution of non-forward glances (top subfigure) longer than 1.6 s and (bottom subfigure) longer than 2s.

For number of glances longer than 2 s (the bottom subfigure on Figure 8), visual difficulty (χ^2 (1) = 7.04, p =.0008) and speed (χ^2 (1) = 4.57, p =.03) were significant, driver age (χ^2 (3) = 7.31, p =.06) was marginally significant, and motor control difficulty (χ^2 (1) = 1.18, p = .28) was not significant. The odds of exhibiting more glances longer than 2 s was 51% lower (OR = 0.49, 95% CI: 0.29, 0.83) in the higher visual difficulty condition compared to lower visual difficulty. An increase of 10 km/h in speed was associated with a significant decrease of 7% in odds of exhibiting more glances longer than 2 s (OR = 0.93, 95% CI: 0.86, 0.99). As for age, which was marginally significant, drivers 65-over appeared to be less likely to exhibit glances longer than 2 s compared to drivers 25-34 (OR = 0.36, 95% CI: 0.16, 0.82) and 35-64 (OR = 0.43, 95% CI: 0.19, 0.99).

4.4 Discussion

This work investigated whether drivers adjust their secondary task engagement and non-forward glances (i.e., not in the direction of travel) based on environmental demands. For this purpose, we utilized the Naturalistic Engagement in Secondary Task (NEST) dataset (Owens et al., 2015). Environmental demand was captured through two sub-constructs: visual difficulty and motor control difficulty. Driver age and chosen speed were also considered given that perceived demand may vary across individuals and based on the speed of travel. Overall, the results suggest that environmental demands do have a relation to secondary task engagement and glance behaviors. Drivers decreased their secondary task engagement in a risk reducing direction. Further, their non-forward glances were also affected by environmental demands.

Specifically, the likelihood of secondary task engagement was found to be lower in higher visual difficulty situations compared to lower ones. Higher visual difficulty also was associated with a lower percent time looking non-forward, lower frequency of non-forward glances, as well as a lower likelihood of exhibiting long glances, with the likelihood of glances longer than 2 s being reduced to a larger extent compared to glances longer than 1.6 s. Motor control difficulty had an effect on secondary task engagement through an interaction with speed. An increase in speed was associated with a decrease in the likelihood of engagement in higher motor control difficulty situations but not in lower ones. It should be noted that SHRP2 and hence NEST have a relatively significant amount of missing speed information, which likely resulted in a loss of power in our analysis. Although raw data presented in Figure 5 may indicate that there was an interaction between visual and motor control difficulty, only the main effect of visual difficulty was significant. Even though statistical significance was observed, it is important to note that the effect on secondary task engagement appears to be relatively small (Figure 5). Dingus et al. (2016) reported that in SHRP2 drivers engaged in distractions during 51.93% of baselines, whereas we observed a higher rate of secondary task engagement of around 70%. This could be due to the fact that NEST dataset was designed to explicitly capture driver distraction which may have resulted in a more liberal way of distraction engagement coding or it might be because the NEST sample included drivers who had at least one SCE related to distraction. In general, the results should be interpreted in light of the fact that NEST data only includes drivers who were involved in at least one distraction-related crash or near crash. Thus, they are not necessarily representative of the entire driving population, but a particularly at risk one for distraction-affected safety critical events.

The findings on the likelihood of secondary task engagement for different environmental demands provide a novel contribution to the literature given that earlier naturalistic studies, which identified similar adaptive behaviors, focused specifically on cell-phone tasks (Funkhouser & Sayer, 2012; Tivesten & Dozza, 2015). On the other hand, prior on-road and naturalistic studies investigated driver glance behaviors in general (i.e., not necessarily specific to cell-phone tasks), and found that drivers modify their visual attention allocation based on expectancies (Räsänen & Summala, 1998; Tijerina et al., 2004) and driving demands (Shinar, 2008; Tivesten & Dozza, 2014). The glance findings in this work provide support to these earlier studies. For example, we found that drivers reduce their longer non-forward glances (>2s), which can be particularly risky (Klauer et al., 2006; Simons-Morton et al., 2014), to a larger extent than shorter ones (1.6s). Similarly, Tivesten and Dozza (2014) found that higher driving demands result in shorter off-road glances. It should be noted that we had to focus on non-forward glances, some of which might have been relevant to the driving task at hand and hence not a distraction (e.g., looking at road signs). Given the level of glance coding provided in NEST, we were not able to identify such situations. Additional coding is needed to obtain a more detailed picture of drivers' glance behaviors as they perform a variety of secondary tasks. Moreover, given that this objective only utilized the baselines, we could not further investigate if secondary task engagement differs across different event types (i.e., SCEs vs. baselines). Future work should explore if secondary task engagement alters between different event types and different severity levels associated with SCEs.

Age was only found to be significant for rate of non-forward glances. Drivers 35 and older had reduced rates of non-forward glances compared to those who were younger. It is possible that older drivers, especially those who are 65 and older, may have experienced age related effects of restricted head movements (Isler, Parsonson, & Hansson, 1997), thus were less likely to look away from the forward roadway, or may have experienced changes in eye movements due to declines in visual information processing abilities (Maltz & Shinar, 1999). On the other hand, middle-aged and older drivers may simply be less inclined to engage in visual secondary tasks, which are in part technology-related (e.g., texting) as categorized in NEST (see Table 4). Previous studies have shown that older drivers (e.g., Parnell et al., 2018; Pöysti et al., 2005) are less likely to report technology-related distraction engagement compared to their younger counterparts. It is perhaps surprising then to see a lack of age effect in our analysis of secondary task engagement. However, we note that our secondary task engagement variable does not differentiate the nature of the task types (e.g., visual, manual, or visual-manual) and include less visually intensive distractions, of which age may not be a factor (e.g., talking, interaction with passenger). Considering all secondary tasks together, different age groups may not modulate their task engagement differently, or the lack of effect may be due to the relatively low sample size overall or within some of the age groups. Further, given that age is known to correlate with driving skill (Carr et al., 1992) and information processing abilities (Maltz & Shinar, 1999; Panek et al., 1977), age was used as a proxy of skill and ability in our models; however, further data is needed to more reliably control for skill and ability when investigating the effects of environmental demand on secondary task engagement.

Although this work provided a novel framework of categorizing different environmental demands, the categorization was exploratory in nature and some variables that were used in the labeling of visual difficulty (e.g., level of service), may have also affected motor control difficulty. For example, traffic density is expected to increase visual complexity, but it may also increase motor control difficulty with potentially a larger number of braking responses required (Brookhuis et al., 1991; De Waard, Kruizinga, & Brookhuis, 2008). With a larger sample size, the variables that may overlap across the two constructs may be treated separately in statistical models. Further work is needed in general for characterizing environmental demand, which can enhance existing distraction detection algorithms (e.g., Vanysek et al., 2005), as well as the performance of driver support systems (e.g., Trivedi and Cheng, 2007) that can warn the drivers or take over control. Given that the environmental variables provided in NEST are the same as they are in SHRP2, future analysis of the SHRP2 data can utilize our approach to provide deeper insights for a larger population.

Finally, although the results suggest that environmental demands do have a relation to secondary task engagement and glance behaviors and that drivers seem to be decreasing their engagement in secondary activities in a risk reducing direction, previous literature shows that some secondary tasks as well as inopportune short off-road glances increase crash risks (Dingus et al., 2016; Victor et al., 2015). Therefore, interventions are still needed to help drivers better modulate when and where they engage in secondary tasks, and how they allocate their visual attention on the road. For example, different feedback displays have demonstrated to be promising for mitigating driver distraction (Donmez, Boyle, & Lee, 2007).

Chapter 5

5 Examining the Prevalence of Drivers' Engagement in Multiple Types of Secondary Tasks

5.1 Introduction

As mentioned in the Introduction, in this thesis the aim of Objective 2 was to investigate the prevalence of engagement in multiple types of secondary tasks within different environmental demands. Through inferential statistics, this chapter compared the prevalence of engagement in single vs. multiple types of secondary tasks in distraction-affected safety-critical events (SCEs: crashes/near-crashes) and baselines reported in the NEST dataset. A logit model was built to compare the odds of engaging in single vs. multiple types of secondary tasks with event type (SCE, baseline) as a predictor. NEST provides detailed information about the driving environment, which provides the opportunity to investigate and control for the effects of the environmental context on secondary task engagement type. Findings from naturalistic studies suggest that drivers exhibit self-regulating behaviours when engaging in secondary activities. For instance, Funkhouser and Sayer (2012) found that drivers initiated cell-phone conversations more frequently during low-speed conditions and participated in visual or manual phone tasks more frequently when stopped. Likewise, Tivesten and Dozza (2015) reported that drivers were more likely to initiate visual-manual phone tasks while standing still compared to while driving at high speeds. Therefore, environmental demand, GPS speed, and driver age were included in the model as a way of capturing the driving demands experienced by the driver, which may have impacted their secondary task engagement behaviour, in particular, whether they engaged in more than one type of secondary task in a given epoch. In this chapter, the environmental demand variable refers to the overall demand imposed on the drivers by the driving context, and is defined to be a combination of both visual and motor control difficulty. Driver age was used as a proxy for driver skill and ability.

5.2 Method

This section begins by presenting the dependent variable and explanatory variables used in the model. Following this, the statistical modeling approach is described. NEST provides an extensive list of variables. Given the relatively small sample size, it was infeasible to include all these variables separately in our model. Hence, aggregations were performed to create meaningful groupings of NEST variables, with reasonable sample sizes within each group. After describing in detail how our model variables were created, we present an overview of the statistical model.

It should be noted this analysis excluded the third 10s epoch coded in NEST for SCEs, which represents the period from the precipitating event to the crash/near-crash. It is reasonable to assume that this period is inherently different than the 20s preceding the precipitating event and may represent significant shifts in secondary task engagement, which is a point for future research.

5.2.1 Dependent Variable

NEST provides an extensive list of secondary tasks (Table 8), with each 10s epoch providing information of up to a maximum of 6 different secondary tasks. Some of these tasks appear to be complementary to each other, which may not suggest a shift in task type when they occur together in the same epoch (e.g., viewing PDA vs. operating PDA). Instead, the drivers may be expected to perform some of these tasks together or in sequence as they complete a higher-level task (e.g., to operate a PDA, the driver may first have to locate/reach the PDA). Thus, we aggregated the NEST secondary tasks into nine more general secondary task types as presented in Table 8. These nine secondary task types relate to generally distinct objects and/or activities. Detailed NEST secondary task types variable descriptions can be found in Appendix A.

To create the outcome variable used in our model, we identified whether the driver engaged in multiple types of secondary tasks in a given epoch or not. The event was then labeled as "engagement in multiple types of secondary tasks" if the driver engaged in multiple types of secondary tasks in at least one of the 10s epochs. All other events were labeled as "engagement in single secondary task type". Events that included unknown and N/A were excluded from our analysis. Further, events that involved writing/reading and pet interaction were too infrequent for these tasks to be in their own categories. These tasks also did not fit well within the other nine task types, so they were excluded from our analysis. Finally, although NEST considered the presence of passengers or children with no interaction as secondary tasks, we did not. Thus, SCEs (n = 11) and baselines (n = 228) which were associated with only these NEST secondary tasks were excluded from our analysis. Further, three baseline events and one SCE were removed due to missing information about the environment given that environmental demand was a variable included in our model. In total, 218 SCEs and 704 baseline events were included in our analysis from a total of 204 drivers.

Table 8: Secondary task types used in our analysis and their corresponding NEST secondary tasks

Secondary Task Type	NEST Secondary Tasks
Visual/manual interactions with vehicle integrated device/control	Adjusting/monitoring (a) climate control, (b) radio, (c) other devices integral to vehicle Inserting/retrieving CD
Personal hygiene	Applying make-up Biting nails/cuticles Brushing/flossing teeth Combing/brushing/fixing hair Removing/adjusting jewelry Removing/inserting/adjusting contact lenses or glasses Other personal hygiene
Interaction with carried-in device	Dialing hand-held (a) cell phone, (b) cell phone using quick keys Texting on cell phone Locating/reaching/answering cell phone Cell phone, other Operating PDA/other hand-held device Locating/reaching PDA/other handheld device Viewing PDA/other handheld device PDA/other handheld device, other
Talking on hand-held cell phone	Talking/listening on hand-held cell phone
Drinking/eating	Drinking Eating
Dancing/singing	Dancing Talking/singing
Outside distraction	Looking at (a) an object external to the vehicle, (b) pedestrian, (c) previous crash or incident Other external distraction Distracted by construction

Secondary Task Type	NEST Secondary Tasks
Reaching/manipulating object	Moving object in vehicle Object (a) in vehicle, other, (b) dropped by driver Reaching for (a) food-related or drink-related item, (b) object that is a manufacturer-installed device, (c) object, other, (d) personal body-related item, (e) lighting/smoking/extinguishing cigar/cigarette
Passenger interaction	Passenger in adjacent or rear seat – interaction Child in adjacent or rear seat – interaction

5.2.2 Exploratory Variables

5.2.2.1 Event Type

SCEs and baselines represent the events of interest in this analysis. However, we wanted to investigate whether the severity of an SCE made a difference as well. Thus, the predictor 'event type' was assigned to three levels: baseline (n = 704), lower severity SCE (n = 107), and higher severity SCE (n = 111). The categories of lower and higher severity SCE were generated from the SHRP2 SCE severity levels by taking sample size into account (Table 9).

Table 9: NEST SCE severity levels and severity categories used in our analysis

NEST SCE Severity Levels	Frequency	SCE Severity Categories
Crash Level I: Most severe	34	Higher (n = 111)
Crash Level II: Police-reportable crash	38	
Crash Level III: Minor crash	39	
Crash Level IV: Low-risk tire strike	38	Lower (n = 107)
Near-crash	69	

5.2.2.2 Environmental Demand

Six NEST variables describing the environment around the time of an event were used to capture environmental demand. Each of these variables had various levels and was coded in NEST once to three times per event. Therefore, these variables and their levels needed to be grouped to have a reasonable sample size within each environmental demand level used in our model.

In creating the environmental demand variable, two constructs were considered: motor control difficulty and visual difficulty (Section 4.2.2.1). Environmental demand variable was created from these two constructs, and was also assigned two levels: lower and higher. Environmental demand was labeled to be lower if both motor control difficulty and visual difficulty were deemed to be lower (n = 461, e.g., industrial locality with free traffic flow in normal weather conditions on a straight road), it was labeled to be higher otherwise (n = 461, e.g., busy urban areas with medium traffic density during rainy weather). Cases where the road surface was dry, and the road was straight were deemed to correspond to lower motor control difficulty; all other cases were labeled as higher motor control difficulty. As for visual difficulty, the categorization was more complex given that the NEST variables which made up this construct had significantly more levels. An example for lower visual difficulty is interstate/bypass/divided highway with no traffic lights, level of service C, daylight, and normal weather. An example for higher visual difficulty is interstate/bypass/divided highway with no traffic lights, level of service A, non-daylight, and poor weather. The grouping and labeling performed were largely based on the NEST and SHRP2 variable descriptions; however, two of the authors also reviewed a subsample of the SHRP2 Insight Data Access Website video sequences to assess the level of visual complexity associated with different localities and traffic levels of service.

As mentioned earlier, the same level of environmental demand is not expected to induce the same level of workload on each driver. The perceived workload would depend on the driver skills, their chosen speed, and the interactions among the two along with environmental demand level. Thus, in addition to environmental demand, GPS speed at the beginning of an event (the very first frame coded for the event) and driver's age (a proxy of skill and ability) were also included in our model as predictor variables.

5.2.2.3 Driver Age

As discussed earlier, driver age was used in our model to capture skill and ability. Table 10 presents the original NEST age groups, as well as the five categories we created to obtain a reasonable minimum sample size within each category.

Table 10: NEST age groups and age categories used in our analysis

NEST Age Groups	Frequency	Age Categories
16-19	49	16-19 *(n=49)*
20-24	69	20-24 *(n=69)*
25-29	20	25-34 *(n=31)*
30-34	11	
35-39	2	35-64 *(n=26)*
40-44	1	
45-49	3	
50-54	4	
55-59	7	
60-64	9	
65-69	5	65-over *(n=26)*
70-74	3	
75-79	7	
80-84	8	
85-89	3	
Missing Age Data	3	missing

5.2.3 Statistical Model

A logistic regression model was built to compare the odds of engaging in single vs. multiple types of secondary tasks for different event types (i.e., SCEs and baselines). Given that NEST only included SCEs that involved secondary task engagement, baselines included in our model were those that also involved secondary task engagement (n = 704). The outcome variable was whether the driver engaged in multiple types of secondary tasks in either or both of the first two 10s epochs of an event, or not. Further analysis on the two 10s epochs independently were carried out, but similar results were obtained. Therefore, we only report our results that considered the two 10s epochs together.

The predictor variables that were included in the model are as follows: event type (baseline, lower severity SCE, higher severity SCE), environmental demand (lower, higher), GPS speed at the start of the event, driver age (16-19, 20-24, 25-34, 35-64, 65-over), and all two-way interactions of these variables. Repeated measures were accounted for through generalized estimating equations. Backward selection was used to drop non-significant interaction terms from the final model. The model was built in SAS University Edition using the GENMOD procedure. Figure 9 below presents the model covariates tested along with how the environmental demand variable was created.

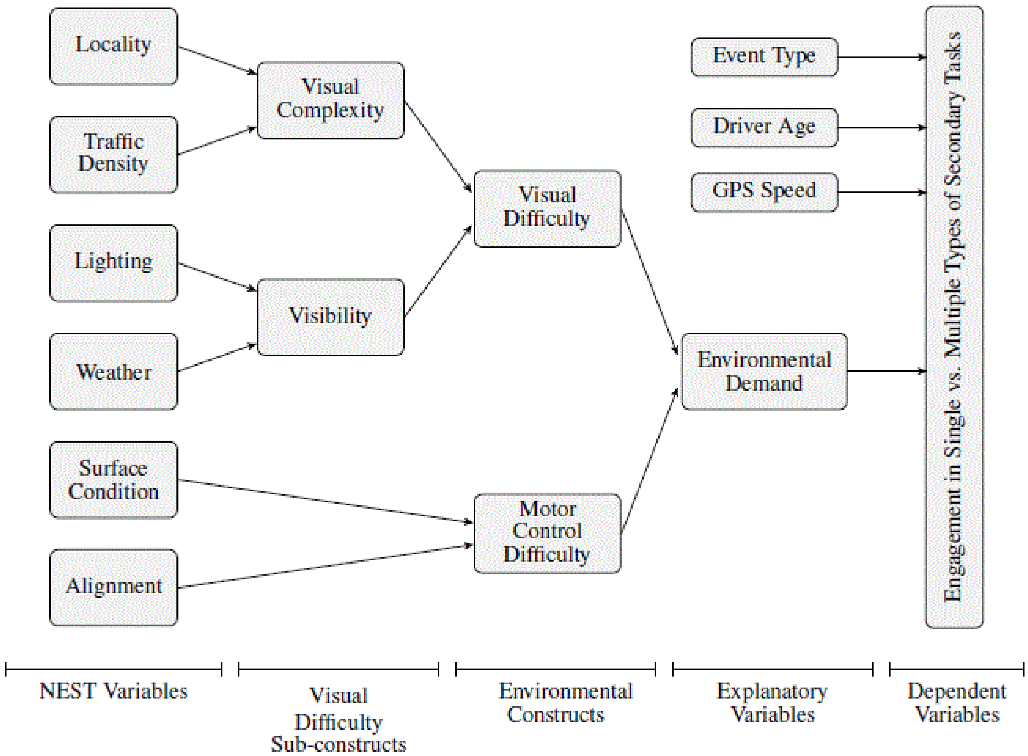


Figure 9: Model covariates and the creation process of the environmental demand variable for the model examining single vs. multiple type of secondary task.

5.2.3.1 Logistic Regression Model

Our goal was to evaluate drivers' engagement in multiple types of secondary task in a given 10s epoch or not. The logistic regression model setup is as follows. Define

$$Y_i = \begin{cases} 1, & \text{if driver in event i engaged in multiple tasks} \\ 0, & \text{Otherwise} \end{cases} \tag{13}$$

Let ρ_i be the probability of engaging in multiple types of secondary task within 20s for an event *i*. The observed Y_i is assumed to follow a Bernoulli distribution.

$$Y_i \sim Bernoulli\left(\rho_i\right) \tag{14}$$

This probability is associated with a set of covariates by a logit link function,

$$\ell ogit(\rho_i) = \log\left(\frac{\rho_i}{1-\rho_i}\right) = \mathrm{X}_i\beta \tag{15}$$

where X_i is the matrix of predictors for individual event *i*, and β is the vector of regression parameters. The exponential of regression parameter, $\exp(\beta_j)$, is the odds ratio (OR) for the j^{th} exploratory variable.

5.2.4 Descriptive Analysis of Secondary Task Types

In addition to our statistical model, we conducted preliminary descriptive analysis to investigate how frequently different task types occurred within an epoch as well as how frequently they occurred together with another task type within an epoch.

5.3 Results

The final statistical model included event type, $\chi2(2) = 30.75$, $p < .0001$, environmental demand, $\chi2(1) = 1.28$, $p = .26$, and driver age, $\chi2(4) = 8.13$, $p = .09$. Overall, GPS speed information was found to be missing from 42 crashes, 10 near-crashes, and 85 baseline events. Thus, the non-significant main effect of GPS speed was excluded from the final model in order not to lose any additional statistical power. None of the interaction terms were significant and had been dropped from the model ($p > .05$).

The results showed that the likelihood of engagement in multiple types of secondary tasks (as opposed to in a single secondary task type) was more likely to occur during SCEs compared to baselines (Figure 10); lower severity SCEs vs. baselines: Odds Ratio (OR) = 2.10, 95% Confidence Interval (95% CI) = 1.36, 3.24, p = .0008; higher severity SCEs vs. baselines: OR =

2.75, 95% CI = 1.84, 4.11, p < .0001. No significant difference was observed between lower severity and higher severity SCEs, p > .05.

Even though from Figure 10 it appears that there might be an interaction effect between event type and driver age, the interaction was not statistically significant as mentioned earlier. Only the main effect of driver age was marginally significant as reported above. With a marginal statistical significance, drivers 65 years old and over were less likely to engage in multiple types of secondary tasks (as opposed to a single secondary task) compared to other age groups; 16-19 year olds: OR = 0.45, 95% CI = 0.26, 0.78, p = .005; 20-24 year olds: OR = 0.56, 95% CI = 0.33, 0.95, p = .03; 25-34 year olds: OR = 0.60, 95% CI = 0.33, 1.09, p = .09; 35-64 year olds: OR = 0.56, 95% CI = 0.29, 1.07, p = .08.

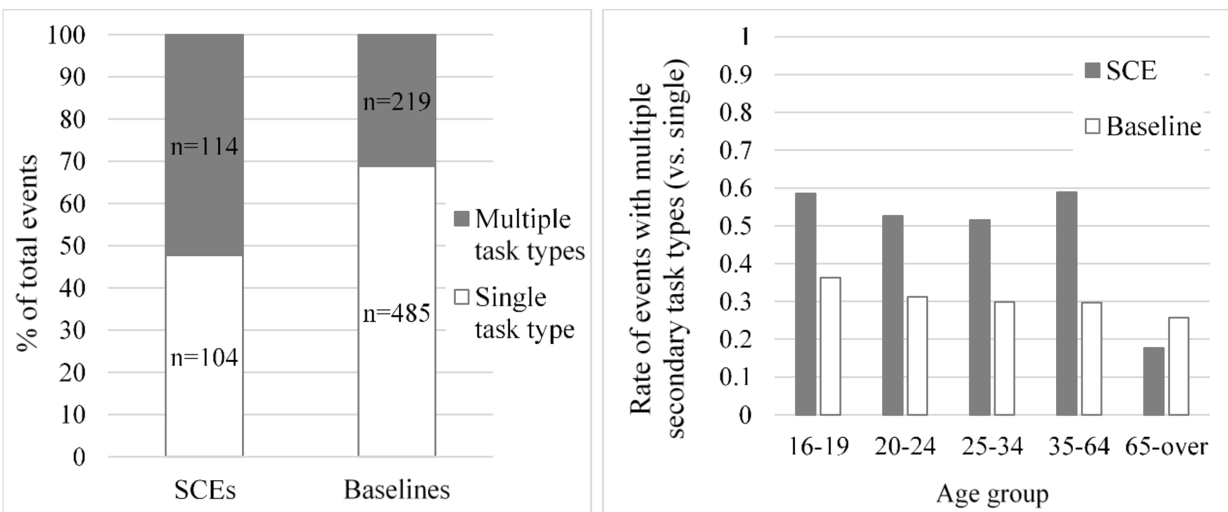


Figure 10: (Left subfigure) The frequency and percentage of SCEs and baselines with single vs. multiple types of secondary task engagement; (Right subfigure) Rate of events (type: SCEs and baselines) with multiple types of secondary engagement (as opposed to single) across different age groups.

5.3.1 Preliminary Descriptive Analysis of Secondary Task Types

Table 11 presents the number of times different secondary task types were observed alone within a 10s epoch, as well as the number of times they were observed together with other task types within a 10s epoch. For the latter number, an epoch could have been included more than once in the total count, as a 10s epoch could have more than two secondary task types.

The most common task type observed alone in the baseline epochs were *"passenger interaction"*, followed by *"dancing/singing"* and *"interaction with carried-in device"*. For SCEs, the list consisted of *"interaction with carried-in device"*, *"passenger interaction"*, and *"reaching/manipulating object"*. The most common task types that were observed together in baseline epochs were the same as the most common pairs observed together in SCE epochs: dancing/singing + interaction with carried-in device, dancing/singing + outside distraction, and outside distraction + passenger interaction.

Table 11: Number of times different secondary task types were observed within a 10s epoch alone and together with another task type

			# of times task type observed together with another task type							
Secondary Task Type	**Event Type**	**# of times task type observed alone**	**Visual/manual vehicle center stack**	**Personal hygiene**	**Interaction with carried-in device**	**Talking on hand-held cell phone**	**Drinking/ eating**	**Dancing/ singing**	**Outside distraction**	**Reaching/ manipulating object**
Visual/manual vehicle center stack	Baseline	58	-							
	SCE	12								
Personal hygiene	Baseline	54	8	-						
	SCE	12	7							
Interaction with carried-in device	Baseline	**189**	13	4	-					
	SCE	**79**	4	3						
Talking on hand-held cell phone	Baseline	76	3	2	9	-				
	SCE	32	1	1	8					
Drinking/eating	Baseline	29	1	2	3	0	-			
	SCE	5	3	0	0	0				
Dancing/singing	Baseline	**215**	16	14	**25**	0	3	-		
	SCE	20	7	7	**18**	0	1			
Outside distraction	Baseline	96	15	2	17	4	5	**29**	-	
	SCE	33	6	7	14	5	3	**25**		
Reaching/ manipulating object	Baseline	59	7	5	12	0	15	15	9	-
	SCE	**34**	6	5	11	3	9	11	7	
Passenger interaction	Baseline	**243**	14	10	16	1	7	7	**28**	23
	SCE	**53**	10	4	6	3	3	2	**20**	14

Note: Prevalent cases highlighted.

5.4 Discussion

This work investigated engagement in single vs. multiple types of secondary tasks in distraction-affected safety-critical events (SCEs: crashes/near-crashes) and baselines reported in the Naturalistic Engagement in Secondary Tasks (NEST) dataset. Engagement in multiple types of secondary tasks was observed in 52% of the distraction-affected SCEs and 31% of the baselines involving secondary task engagement. Moreover, our statistical model revealed that engagement in multiple types of secondary tasks was significantly more likely (as opposed to engagement in a single secondary task) during SCEs compared to baselines. The severity of the SCEs was also considered but no statistical difference between the lower and higher severity levels was found.

Overall, it appears that engagement in multiple secondary task types is prevalent in both distraction-affected SCEs and baselines but is more likely in SCEs than baselines. Most crash risk studies to date have reported the effects associated with one type of secondary task when it appears that in reality these effects may be confounded by the presence of other secondary tasks. For example, the prevalence rates of different distraction types and the associated crash/near-crash risks reported in (Dingus et al., 2016) do not consider whether drivers engaged in more than one distraction type. Therefore, the numbers reported in Dingus et al. (2016) and other naturalistic studies of crash risk only capture part of the story. The NEST dataset is a small portion of the SHRP2 data, and based on its sampling methodology, is not appropriate for crash risk calculations. Future research can use SHRP2 data or other naturalistic driving data to conduct similar analysis to the ones reported in this work and calculate crash risks associated with engagement in single vs. multiple types of secondary tasks.

Although this work presents some preliminary descriptive analysis, future research should also further investigate which types of secondary tasks are more likely to occur together, and whether there are patterns that may explain such groupings (e.g., the type of attentional resources claimed by different secondary tasks). The limited sample size of the NEST database prevented us from making conclusions about the different multiple task combinations that the drivers engaged in. It is possible for drivers at times to engage in multiple secondary tasks without a significant degradation in their driving performance. Drivers may be able to self-regulate their attention allocation efficiently across the driving task and multiple types of secondary tasks, especially if these secondary tasks claim attentional resources that are not central to the driving task at hand (Wickens, 2002, 2008). SHRP2 data can be used to assess prevalence of different multiple secondary task combinations, but also crash risks associated with the more prevalent ones. The prevalence and crash risk findings from SHRP2 data can also inform controlled studies (e.g., simulator or instrumented vehicle) investigating how driving performance is affected by multi-tasking situations that are commonly experienced by drivers or that are associated with increased crash risks.

Our results also showed that, although marginally significant, drivers 65 years old and over were less likely to engage in multiple types of secondary tasks compared to younger age groups. Risk reducing compensatory behaviors for older drivers have been reported in previous studies (Donorfio, D'Ambrosio, Coughlin, & Mohyde, 2009; Reimer et al., 2013). Further research is needed to identify whether the reduction observed in our analysis is 1) intentional to compensate for decreasing cognitive and motor abilities, 2) a result of a cognitive saturation with multiple types of secondary tasks that older drivers experience more than other age groups, or 3) an effect of generational differences in driving styles and technology use. Further, raw data seemed to indicate that there might be an interaction effect between event type and driver age. An increased sample size may reveal stronger effects for age-related factors. Sample size may have also played a role in the lack of significance for the environmental demand variable. It might also be that environmental demand may not have an influence on engagement in single vs. multiple types of secondary tasks or that our categorization of environmental demand needs to be improved. We could not identify any previous literature systematically classifying environmental demand in driving. Thus, our categorization was a first attempt that was exploratory in nature. Further research is needed for quantifying environmental demand.

The results presented in this paper should be interpreted considering the fact that NEST data only includes drivers who have had at least one distraction-affected crash/near-crash. Thus, they are not necessarily representative of the entire driving population, but a particularly at risk one for distraction-affected crashes.

Chapter 6

6 Conclusion and Future Work

6.1 Driver Distraction Engagement and Glance Behaviour

This thesis demonstrated that environmental demand has a relation to drivers' secondary task engagement and glance behaviors. To minimize the risk of distracted driving, drivers appear to adapt their secondary task engagement and non-forward glances based on environmental demands. Specifically, the likelihood of secondary task engagement was found to be lower in higher visual difficulty situations compared to lower ones. Higher visual difficulty also was associated with a lower percent time looking non-forward, lower frequency of non-forward glances, as well as a lower likelihood of exhibiting long glances. Motor control difficulty had an effect on secondary task engagement through an interaction with speed. An increase in speed was associated with a decrease in the likelihood of engagement in higher motor control difficulty situations but not in lower ones. Thus, drivers modulate their secondary task engagement based on environmental demands, and their speed also plays a role.

These findings on secondary task engagement and visual attention based on different environmental demands provide a novel contribution to the traffic safety literature given that earlier naturalistic studies, which identified similar adaptive behaviors, focused specifically on cell-phone tasks (Funkhouser & Sayer, 2012; Tivesten & Dozza, 2015). Further work is needed for studying environmental demand to enhance existing distraction detection algorithms (e.g., Vanysek et al., 2005) and improve driver support systems (e.g., Trivedi and Cheng, 2007) that can warn the drivers or take over control. Distraction detection algorithms and driver support systems can further make use of adaptive user interfaces to formulate more effective and intelligent strategies to further support drivers when the demands increase. For example, if the system detects that the driver is in a situation that demands a high level of motor control due to curvy road and slippery surface, incoming calls or text messages can be filtered or postponed thereby minimizing any unnecessary secondary task engagement. Further, given that the environmental variables provided in NEST are the same as they are in SHRP2, future analysis of the SHRP2 data can utilize our approach to provide further insights for a larger population.

6.2 Driver Engagement in Multiple Tasks

Further, this thesis showed that engagement in multiple secondary task types is prevalent but is more likely in distraction-affected SCEs than baselines. Most crash risk studies to date have reported the effects associated with one type of secondary task when it appears that in reality these effects may be confounded by the presence of other secondary tasks. For example, the prevalence rates of different distraction types and the associated crash/near-crash risks reported in Dingus et al. (2016) do not consider whether drivers engaged in more than one distraction type. Therefore, the numbers reported in Dingus et al. (2016), Bakhit et al. (2018), and other naturalistic studies of crash risk only capture part of the story. Given that NEST is not appropriate for crash risk calculation as explained in Chapter 3, future research can use SHRP2 data or other naturalistic driving data to conduct similar analysis to the ones reported in this thesis and calculate crash risks associated with engagement in single vs. multiple types of secondary tasks.

Although this work presented some preliminary descriptive analysis, future research should also further investigate which types of secondary tasks are more likely to occur together, and whether there are patterns that may explain such groupings (e.g., the type of attentional resources claimed by different secondary tasks). SHRP2 data can be used to assess prevalence of different multiple secondary task combinations, but also crash risks associated with the more prevalent ones. The prevalence and crash risk findings can also inform controlled studies (e.g., simulator or instrumented vehicle) investigating how driving performance is affected by multi-tasking situations that are commonly experienced by drivers or that are associated with increased crash risks.

The results of this thesis also showed that, although marginally significant, drivers 65 years old and over were less likely to engage in multiple types of secondary tasks compared to younger age groups. Risk reducing compensatory behaviors for older drivers have been reported in previous studies (Donorfio et al., 2009; Reimer et al., 2013). Additional research is needed to identify whether the reduction observed in our analysis is 1) intentional to compensate for decreasing cognitive and motor abilities, 2) a result of a cognitive saturation with multiple types of secondary tasks that older drivers experience more than other age groups, or 3) an effect of generational differences in driving styles and technology use.

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Appendix A: Description of NEST Variables

Table A - 1: NEST secondary task types, descriptions available from NEST data dictionary, and aggregated secondary task categories created in this project

NEST Secondary Task Variable	Description	Secondary Task Category
Adjusting/monitoring climate control	Subject vehicle driver interacts with in vehicle climate control system either by touching the climate control buttons, glancing at the climate control on dashboard, or adjusting climate control vents.	Visual/Manual Vehicle Center Stack
Adjusting/monitoring other devices integral to vehicle	When the driver interacts with a manufacturer-installed device other than those listed in other categories, either by touching or glancing at the device. This includes interaction with seat belt, door locks, window, sun visor, etc. Does not include driving critical tasks, such as turn signal, wipers, headlights, gear shift, speedometer.	
Adjusting/monitoring radio	Subject vehicle driver interacts with in vehicle radio/audio system either by touching the radio buttons on dashboard or steering wheel, or glancing at the radio on dashboard.	
Inserting/retrieving CD	Subject vehicle driver picks up CD, cassette, or other music storage device (other than MP3 player) in vehicle and/or inserts it into radio, presses any subsequent buttons to get device to play/rewind/fast forward and then play, or driver presses button to eject device and then places it somewhere in vehicle.	
Applying make-up Biting nails/cuticles Brushing/flossing teeth Combing/brushing/fixing hair Removing/adjusting jewelry Removing/inserting/ adjusting contact lenses or glasses Other personal hygiene	When the driver attends to personal hygiene in some manner. Examples include applying make-up or lotion, shaving, blowing nose in a tissue, tooth-brushing, instilling eye drops, combing/brushing hair, putting on/removing jewelry, putting on/removing glasses, and purposeful adjustment of clothing (i.e., removing or putting on clothing, buttoning/unbuttoning clothing, zipping/unzipping clothing, tying or loosening neckties, carefully rolling up sleeves, and putting on/removing a hat). NOTE: Combing/Brushing hair does not include brushing bangs out of eyes with hands or absently twirling long hair. The driver needs to be purposely adjusting his or her hair by using a brush or comb, tying hair back, or looking in the mirror while using hand to adjust hair. NOTE: If a driver uses his/her fingernails to clean teeth, only coded as a distraction if the driver is also looking at him/herself in a mirror as he/she does it. If the driver uses his/her fingernails to clean teeth without looking in a mirror, it is not considered a distraction and is not coded as such. NOTE: Checking self in mirror without also performing a qualified hygiene task (such as applying make-up) is not considered a distraction task and is not coded as such. If, however, the driver locates and reaches for a handheld mirror from a purse or within the car (coded as "Reaching for object that is not manufacturer-installed"), then looks at him/herself in that mirror, this would be coded as "Personal Hygiene." NOTE: The following items are not considered distractions in the Detailed Secondary Task reduction and were not coded as such in the frame-by-frame analysis UNLESS they were performed while the driver is obviously looking at self in a mirror or the task involves both hands and/or associated glances from the driving task: scratching, yawning, biting nails, sneezing, coughing, licking/biting lips, rubbing face/beard, twirling hair, brushing bangs out of eyes, picking nose, picking face, cleaning teeth with tongue, cleaning teeth with fingernail.	Personal Hygiene
Cell phone, other	Subject vehicle driver is interacting with a cell phone in some manner (e.g., looking at a cell phone or just holding it, but not necessarily manipulating the cell phone in any way), or action does not fit in any other category. Includes plugging phone into charger, cleaning screen, putting on headset, etc.	Unknown interaction with carried-in device
PDA/ other handheld device Other	Subject vehicle driver is interacting with an electronic tablet device in some manner not described in other categories. Includes plugging tablet into charger, cleaning screen, headset, holding without manipulating, etc.	

NEST Secondary Task Variable	Description	Secondary Task Category
Talking/listening on cell phone	Subject vehicle driver is talking on a handheld phone or has phone up to ear as if listening to a phone conversation or waiting for person they are calling to pick up the phone. If driver has an earpiece or headset, the driver must be observed talking repeatedly.	
Viewing PDA/ other handheld device	Subject vehicle driver is holding and looking at an electronic tablet device, but not pressing any buttons.	
Dialing hand-held cell phone	Subject vehicle driver is pushing number buttons on a cell phone or touch screen to dial a number or browse/check something else on their cell phone (this would also include reading the phone number from a sheet of paper).If unsure whether driver is texting or dialing/browsing, code as dialing.	
Dialing hand-held cell phone using quick keys	Subject vehicle driver is pushing quick key buttons (e.g., speed dial) on a cell phone to dial a number or check something else on their cell phone (this would also include reading the phone number from a sheet of paper). Maximum number of buttons is 6, else code as "dialing handheld phone".	
Operating PDA/ other hand-held device	Subject vehicle driver is pressing buttons on or using the touch screen on the electronic tablet device.	**Visual/Manual interaction with carried-in device**
Texting on cell phone	Subject vehicle driver is pressing buttons or a touch screen on the cell phone to create and/or send a text message.	
Locating/reaching PDA/ other handheld device		
Locating/reaching/answering cell phone	Subject vehicle driver is glancing to find cell phone, reaching towards his/her cell phone, and/or flipping phone open or pressing a button to answer a call. If more than one distraction happens (e.g., driver looks for phone, reaches for it and then answers it), the last frame number would be the last step in this sequence (e.g., answering cell phone). Once phone is at driver's ear or conversation has clearly begun, code as the appropriate "talking" category.	
Drinking	When the driver has food that will be put in his/her mouth with or without a utensil like a fork, spoon, knife, chopsticks etc., or when the driver moves a drink toward his/her mouth.	**Drinking/Eating**
Eating		
Dancing	When the driver is moving his/her arms, head, or other body part (such as tapping fingers, hands, or feet) in time with the beat of music.	
Talking/singing	When the driver is moving lips as if talking or singing a song or responding to stimulus by nodding head, shaking head “no,” smiling, or laughing. Mark this if the driver is talking, singing, nodding head, shaking head “no,” smiling, or laughing and it does not appear to be related to interaction with a passenger. Only use this distraction if a passenger cannot be seen in the video or if the driver is not looking in the direction of a passenger and does not turn their head or otherwise appear to be communicating with someone.	**Dancing/Singing**
Looking at an object external to the vehicle	Subject vehicle driver is looking outside of the vehicle in the direction of an object not in a construction zone) on the side of the road (e.g., a box).	
Looking at pedestrian	Subject vehicle driver is looking outside of the vehicle in the direction of a pedestrian (not in a construction zone) either on the side of the road or in front of them (i.e., using a cross walk or riding a bike at a red light).	
Other external distraction	Subject vehicle driver is looking outside of the vehicle for purposes not described in previous categories, or for an unknown reason when glance is not considered to be part of the driving task. Includes looking at vehicle ahead in adjacent lane.	**Outside Distraction**
Looking at previous crash or incident	Subject vehicle driver is looking outside of the vehicle in the direction of what is obviously an accident or similar incident.	
Distracted by construction	Subject vehicle driver is looking outside of the vehicle in the direction of a construction zone. A construction zone would be defined as the presence of a barrel, person in a hard hat, construction equipment or vehicles.	

NEST Secondary Task Variable	Description	Secondary Task Category
Moving object in vehicle	An object inside the vehicle, which is not being held by the driver or passenger(s) (if present) is in motion, either due to the motion of the vehicle or due to another passenger throwing the object. Ex. object fell off seat when driver stopped hard at a traffic light.	**Manipulating Object in Vehicle**
Object in vehicle, other	Subject vehicle driver clearly is looking at, handling, holding, or manipulating an object (visible or not) or thing located in the vehicle, other than those listed in other categories.	
Object dropped by driver	Subject vehicle driver is initially holding something and drops it and the driver then immediately picks it back up, taking the driver's attention away from the driving task.	
Reaching for food- related or drink-related item	Subject vehicle driver is looking for or reaching for any item related to eating or drinking. If the driver is already in the process of eating, and is just picking up food repeatedly to put in mouth, code as the appropriate eating category. This reaching task is for the initial locating, reaching, and preparing food or drink to be eaten.Ex. reaching for cup, utensils, plate, food. Once the item is in hand and being moved with the intent to use, code as appropriate usage category (e.g., eating).	**Reaching Object**
Reaching for object that is a manufacturer-installed device		
Reaching for object, other	Subject vehicle driver reaches for an object not described in any other category.	
Reaching for personal body-related item		
Reaching for/Lighting/Smoking/Extinguishing cigar/cigarette	Driver puts the cigar/cigarette in mouth and last touches cigar/cigarette before the process of lighting it has begun OR stops reaching for cigar/cigarette OR the hand holding the cigar/cigarette is still and the driver is not moving to light it. Driver starts to let go of lighter, OR (in the case of an in dash lighter), when lighter is placed back in dashboard and driver lets go of it OR last glance to either of these devices (whichever occurs last). This would be the last frame number before driver starts to move cigar/cigarette towards ashtray or device for extinguishing cigar/cigarette OR if driver puts lit cigar/cigarette down (e.g., to rest in ashtray) OR driver passes the lit cigar/cigarette to the passenger.	
Writing	Subject vehicle driver is writing with a pen/pencil or using a stylus on a tablet.	**Writing/reading (including tablet)**
Reading	Subject vehicle driver is reading material that is in vehicle (i.e., not reading external signs, or center stack display)	
Passenger in adjacent seat - interaction	A front seat passenger is visible or not visible, but the subject vehicle driver is clearly interacting with a passenger (other than a child) in the adjacent/front seat. This could be talking, listening, reacting to (i.e., laughing), gesturing towards, moving toward or away from the passenger, or reaching to take something from or give something to the passenger. If age of passenger is unable to estimate, use this category.	**Passenger Interaction**
Passenger in rear seat - interaction	A rear seat passenger (other than a child, or age unable to estimate) is visible or not visible, but the driver is clearly interacting with a passenger (other than a child) in the rear seat. This could be talking, listening, reacting to (i.e., laughing), moving toward or away from the passenger, or reaching for the rear seat passenger. If age of passenger is unable to estimate, use this category.	
Child in adjacent seat - interaction	Child is visible or not visible, but the driver is clearly interacting with a child in the front adjacent seat. This could be talking, listening, reacting to (i.e., laughing), or moving toward or away from the child (i.e., reaching for a child, not object, or avoiding a pat from the child).	**Child/pet Interaction**
Child in rear seat - interaction	A child is visible or not visible in the rear seat, and the driver is clearly interacting with a child in the rear seat. This could be talking, listening, reacting to (i.e., laughing), or moving toward or away from the child (i.e., reaching for a child, not object, or avoiding a pat from the child).	
Pet in vehicle	Any interaction with a pet in the vehicle, including holding, petting, talking to, or moving pet or interacting with pet carrier.	

NEST Secondary Task Variable	Description	Secondary Task Category
Child in adjacent seat - no interaction or cannot tell		No Distraction
Child in rear seat - no interaction or cannot tell		
Passenger in adjacent seat - no interaction or cannot tell		
Passenger in rear seat - no interaction or cannot tell		
No secondary task observed	The subject vehicle driver is not engaged in any (or any additional for V21 and 25) observable secondary tasks and is attentive to the driving task.	

Table A - 2: NEST surface condition types, descriptions available from NEST data dictionary, and aggregated surface condition categories created in this project

NEST Surface Condition Variable	Description	Surface Condition Categories
Dry	There is no foreign material (rain, snow, oil, etc.) on the roadway in the area of the event (nothing on the road to affect the driving task).	**Good**
Wet	Roadway is completely or partially wet in the area of the event (not snowy, icy, muddy, or oily).	**Worse**
Snowy	There is some amount of unmelted snow or slush on the roadway in the area of the event (no ice on the road in the area of interest).	**Worse**
Icy	There is some amount of ice on the roadway in the area of the event.	**Worse**
Gravel/Dirt Road	The road surface consists of gravel or dirt. Not paved. Use this option only if weather related options above do not also apply.	**Worse**
Unknown		**Unknown**

Table A - 3: NEST alignment types, descriptions available from NEST data dictionary, and aggregated alignment categories created in this project

NEST Alignment Variable	Description	Alignment Categories
Straight	Roadway alignment is straight in the vicinity of the event.	**Straight**
Curve Left	Roadway alignment is curved to the left in the vicinity of the event.	**Curved**
Curve Right	Roadway alignment is curved to the right in the vicinity of the event.	**Curved**
Unknown	Cannot determine roadway alignment due to limitations in video views, lighting, visual obstructions, or limited perspective.	**Unknown**

Table A - 4: NEST locality types, descriptions available from NEST data dictionary, and aggregated locality categories created in this project

NEST Locality Variable	Description	Locality Categories
Business/industrial	Any type of business or industrial structure is present, but is not as dense as an Urban Locality. (If there are also houses visible, this category takes precedence over Open residential and Moderate residential).	**Medium**
Bypass/divided highway with traffic signals	Vehicle is travelling on a bypass or divided highway with traffic signals (no other category description is visible) at the time of the Precipitating Event. (Often appears as "Open Country", but with more lanes and/or as a divided road.)	**Medium**
Construction zone		**High**
Interstate/bypass/divided highway with no traffic signals	Vehicle is travelling on an interstate, bypass, or divided highway with no traffic signals (regardless of what buildings can be seen), at the time of the Precipitating Event.	**Low**
Moderate Residential	An area where multiple houses or apartment buildings are present, but is not as dense as an Urban Locality.	**Medium**
Open country	Other than the roadway, there is nothing but vegetation visible during the time surrounding the Precipitating Event that is described in any of the other categories. Road is not an Interstate or a bypass/divided highway with traffic signals. (Often appears as rural roads, 2 lanes undivided.)	**Low**
Open residential	Rural to semirural areas where there may be only one or a few houses around (i.e., farmland).	**Low**
Playground	One or more involved vehicle passes any type of playground or children's playing field at the time of the Precipitating Event.	**High**
School	One or more involved vehicles passes any type of school building or is in a school zone at the time of the Precipitating Event, including adult learning institutions.	**High**
Urban	Higher density area where blocks are shorter, streets are a mix of one and two way, and traffic can include buses and trams. (This category takes precedence over others when either businesses and/or residences are present.)	**High**
Church	One or more involved vehicle passes a church building at the time of the Precipitating Event.	**High**
Other	Locality at the time of the Precipitating Event is one not described in other categories (ex. in campground).	**Other**

Table A - 5: NEST traffic density types, descriptions available from NEST data dictionary, and aggregated traffic density categories created in this project

NEST Traffic Density Variable	Description	Traffic Density Categories
Level-of-service A: Free flow	LOS A represents a free flow traffic with a leading vehicle present in at least one lane. However, individual drivers are still virtually unaffected by the presence of others in the traffic stream. Freedom to select desired speeds and to maneuver within the traffic stream is extremely high. The general level of comfort and convenience provided to the motorist, passenger, or pedestrian is excellent.	**Low**
Level-of-service B: Flow with some restrictions	LOS B is still in the range of stable flow, but the presence of other users in the traffic stream begins to be noticeable. Freedom to select desired speeds is relatively unaffected, but there is a slight decline in the freedom to maneuver within the traffic stream from LOS A. The level of comfort and convenience provided is somewhat less than at LOS A, because the presence of others in the traffic stream begins to affect individual behavior.	**Low**
Level-of-service C: Stable flow, maneuverability and speed are more restricted	LOS C is still in the range of stable flow, but marks the beginning of the range of flow in which the operation of individual users becomes significantly affected by interactions with others in the traffic stream. The selection of speed is now affected by the presence of others, and maneuvering within the traffic stream requires substantial vigilance on the part of the driver. The general level of comfort and convenience declines noticeably at this level.	**Medium**
Level-of-service D: Unstable flow - temporary restrictions substantially slow driver	LOS D represents a high density, but stable flow. Speed and freedom to maneuver are severely restricted, and the driver or pedestrian experiences a generally poor level of comfort and convenience. Small increases in traffic flow will generally cause operational problems at this level.	**High**
Level-of-service E: Flow is unstable, vehicles are unable to pass, temporary stoppages, etc.	LOS E represents operating conditions at or near the capacity level. All speeds are reduced to a low, but relatively uniform value. Freedom to maneuver within the traffic stream is extremely difficult, and it is generally accomplished by forcing a vehicle or pedestrian to "give way" to accommodate such maneuvers. Comfort and convenience levels are extremely poor, and driver or pedestrian frustration is generally high. Operations at this level are usually unstable, because small increases in flow or minor perturbations within the traffic stream will cause breakdowns.	**High**
Level-of-service F: Forced traffic flow condition with low speeds and traffic volumes that are below	LOS F represents forced or breakdown flow. This condition exists wherever the amount of traffic approaching a point exceeds the amount which can traverse the point. Queues form behind such locations. Operations within the queue are characterized by stop and go waves, and they are extremely unstable. Vehicles may progress at reasonable speeds for several hundred feet or more, then be required to stop in a cyclic fashion. LOS F is used to describe the operating conditions within the queue, as well as the point of the breakdown. It should be noted, however, that in many cases operating conditions of vehicles or pedestrians discharged from the queue may be quite good. Nevertheless, it is the point at which arrival flow exceeds discharge flow, which causes the queue to form, and level of service F is an appropriate designation for such points.	**High**
Unknown	Cannot determine the traffic density due to limitations in video views, lighting, visual obstructions, or limited perspective.	**Unknown**

Table A - 6: NEST lighting types, descriptions available from NEST data dictionary, and aggregated lighting categories created in this project

NEST Lighting Variable	Description	Lighting Categories
Darkness, lighted	It is dark during the Precipitating Event, but the roadway is sufficiently lighted. (Vehicle may be outside or inside a parking structure or tunnel.)	**Non-daylight**
Darkness, not lighted	It is dark during the Precipitating Event, and the roadway is not lighted. (Vehicle may be outside or inside a parking structure or tunnel.)	**Non-daylight**
Dawn	The time of day during the Precipitating Event is sunrise.	**Non-daylight**
Daylight	The Precipitating Event occurs in daylight, such as occurs in after dawn but before dusk.	**Daylight**
Dusk	The time of day during the Precipitating Event is sunset.	**Non-daylight**
Unknown	Cannot determine the lighting conditions due to limitations in video views, lighting, visual obstructions, or limited perspective.	**Unknown**

Table A - 7: NEST weather types, descriptions available from NEST data dictionary, and aggregated weather categories created in this project

NEST Weather Variable	Description	Weather Categories
Fog	There is fog visible at the time of the Precipitating Event.	**Poor**
Heavy Rain	It is raining steadily at the time of the Precipitating Event. (Code wet road in Surface Condition.)	**Poor**
Mist or Light Rain	There is mist in the air or light rain at the time of the Precipitating Event.	**Poor**
Snowing	It is snowing at the time of the Precipitating Event. (Code snow or slush on road in Surface Condition.)	**Poor**
No adverse conditions	There are no adverse atmospheric conditions at the time of the Precipitating Event (no conditions described in other categories).	**Normal**
Unknown	Cannot determine the weather at the time of the Precipitating Event due to limitations in video views, lighting, visual obstructions, or limited perspective.	**Unknown**

Appendix B: Driving Context Snapshot Examples

Figure B - 1: Low visual complexity locality example: Open residential. This image and the following ones are snapshots from the SHRP2 InSight Website; the annotations on the images are created by the authors.

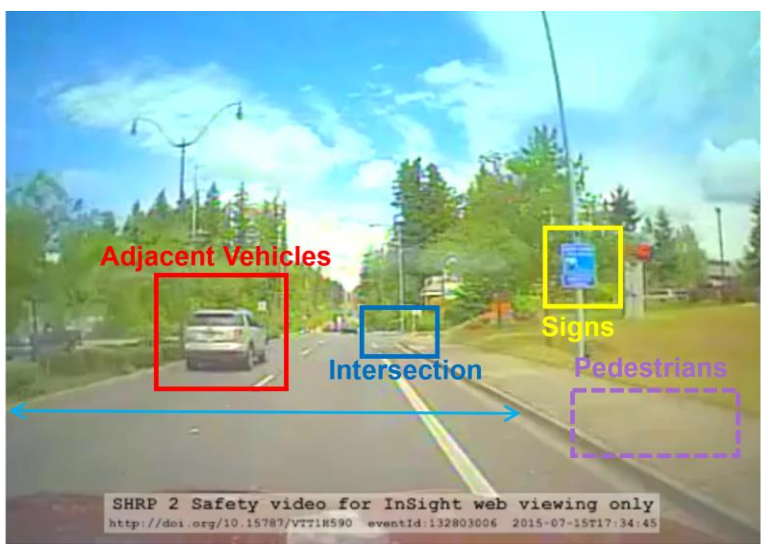

Figure B - 2: Medium visual complexity locality example: Business/industrial.

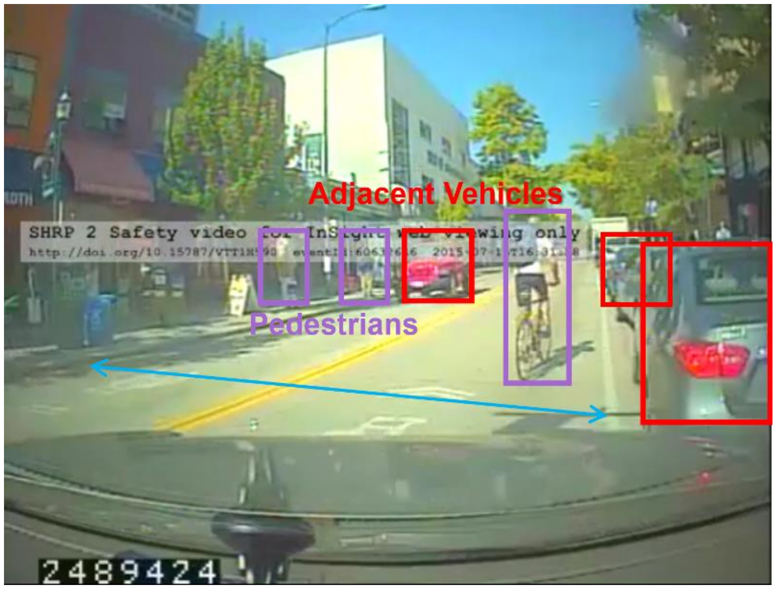

Figure B - 3: High visual complexity locality example: Urban.

Figure B - 4: Lower visual difficulty example: Interstate/bypass/divided highway with no traffic lights, high traffic density: LOS D, daylight, normal weather.

Figure B - 5: Lower visual difficulty example: Interstate/bypass/divided highway with no traffic lights, low traffic density: LOS B, non-daylight, normal weather.

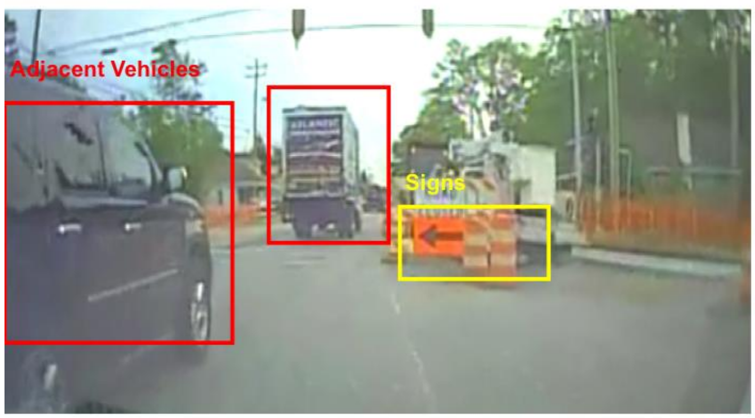

Figure B - 6: Higher visual difficulty example: construction zone; medium traffic density: LOS C, daylight, normal weather.

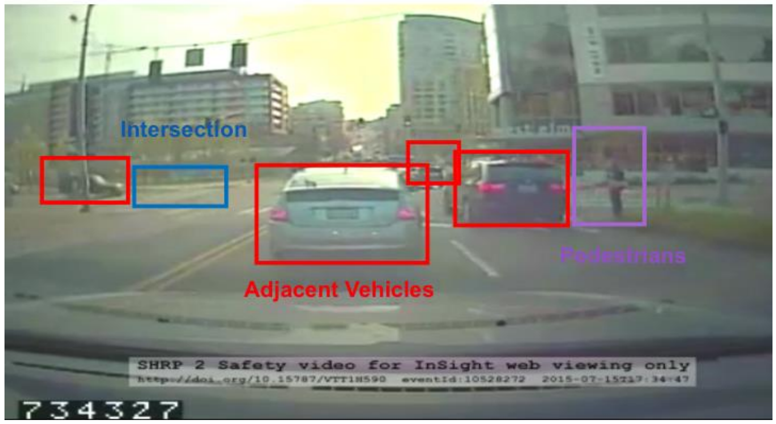

Figure B - 7: Higher visual difficulty example: Urban, high traffic density: LOS D, daylight, normal weather.

Figure B - 8: Higher visual difficulty example: Interstate/bypass/divided highway with no traffic lights, low traffic density: LOS A, non-daylight, poor weather.